CS 528 Mobile and Ubiquitous Computing

Lecture 10a: Attention, Boredom, Intelligent Notifications, Smartphone Overuse

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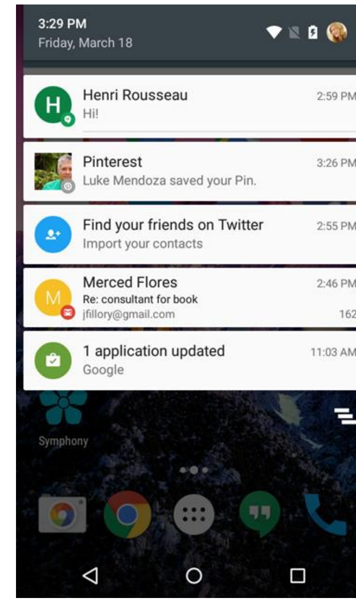
Designing Content-Driven Intelligent Notification Mechanisms, Mehrota *et al*, Ubicomp 2015

Notifications Galore!

- Too many apps now push notifications to user
  - Arrival of email
  - Friend commented on Facebook
  - Battery too low



- Notifications interrupt, distract user if they arrive at an wrong (inopportune) time

- Notifications at inopportune time:
  - Increase task completion time, errors
  - Annoy the user

Goal: Intelligently Notify at Opportune Time

- We would like to deliver each notification at the "right time", (e.g. when user is free, available)

- How to determine the "Right time" to deliver a notification?

- **Prior work:** focused on right context (times, locations) to deliver ALL messages. E.g.
  - When user is switching from app 1 to app 2 (e.g. going from Facebook app to YouTube)
  - Specific time of day (e.g evening), location (e.g home) or activity type (e.g. sitting)

“Right Time” Depends on Message Content

- But “right time” depends on **what notification** is (content)
- Example, if in meeting working on a project
  - Notification from buddy just to chat is distracting
  - Notification from project collaborator is great! Could be a solution

Motivation - What is an Opportune Moment?

- Study about determining right time to deliver notifications,
  - when the user will answer it immediately

- Factor in
  - **Where:** user's context
  - **What:** Message content
  - **Who:** Social relationship between sender and receiver

- **Performance metric:** Aim to
  - reduce user response time
  - Increase acceptance rate of notifications

Study Design

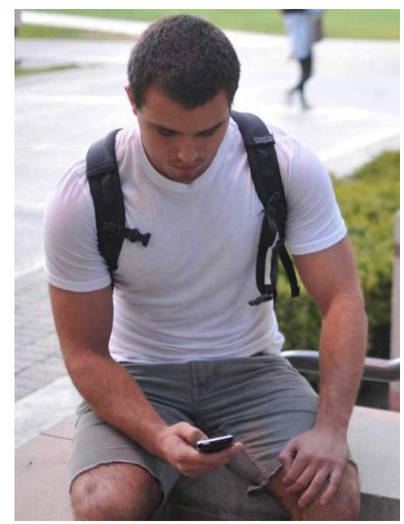
- Real, in-the-wild notifications
- 35 users, 3 weeks
  - Published on Google Play Store
  - Ages 21-31
  - Advertised at University of Birmingham (UK)
- Simulateously tracked 1) 70,000 notifications,2) 4,096 Interruptibility questionnaire responses and 3) auto-sensed data

Labels (for classifier)

User Interruptibility Responses (EMA)

Autosensed data

Data Gathering app, automatically sense
- Context, social situation, etc



Interruptibility EMA Questions

- User-supplied interruptibiity labels

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

Table 2. Questions and their options from NotifyMe questionnaire.

Time Measures (arrival time, Response time, etc) Features Extracted From Auto-Sensed Data

Feature	Description
Arrival time	Time at which a notification arrives in the notification bar.
Removal time	Time at which a notification is removed from the notification bar.
Response time	Difference between arrival and removal time.
Notification response	Whether the notification was clicked or not (boolean).
Sender application	Name and package of an application which triggers a notification.
Notification title	Title of a notification displayed in the notification bar.
Alert type	Signals used to alert the user for a notification: sound, vibrate, and LED.
Physical activity	Current activity of a user.
Location	Current location of a user.
Surrounding sound	Whether the user is in a silent environment or not (boolean).
WiFi connectivity	Whether the phone is connected to a WiFi or not (boolean).
Proximity	Whether the user was proximate to the phone in the last one minute or not (boolean).
Phone's status	Whether the phone was in use in the last one minute or not (boolean).
Ringer mode	Current ringer mode: sound, vibrate and LED.

Table 1. Description of features from the NotifyMe dataset.

Time measures

Features Extracted
From auto-sensed data

NotifyMe Data Gathering App

- Runs in background
- Passively tracks notifications
- Context in which notifications posted
- Context tracked using Android Activity Recognition API, ESSensorManager (homegrown)

Methodology

- Data collection forms:
  - Measures notification responses (accept/decline)
    - Accept: click on notification to launch corresponding app
  - Additional 12 random NotifyMe notifications throughout the day
  - Questionnaires

Dataset

- Manually classified notifications by info type
  - Work
  - Social
  - Family
  - Other

- “Accepting” notifications = launching the app (within 10 mins of notification’s arrival)

Categorized notifications by type of app that generated it, relationship with person

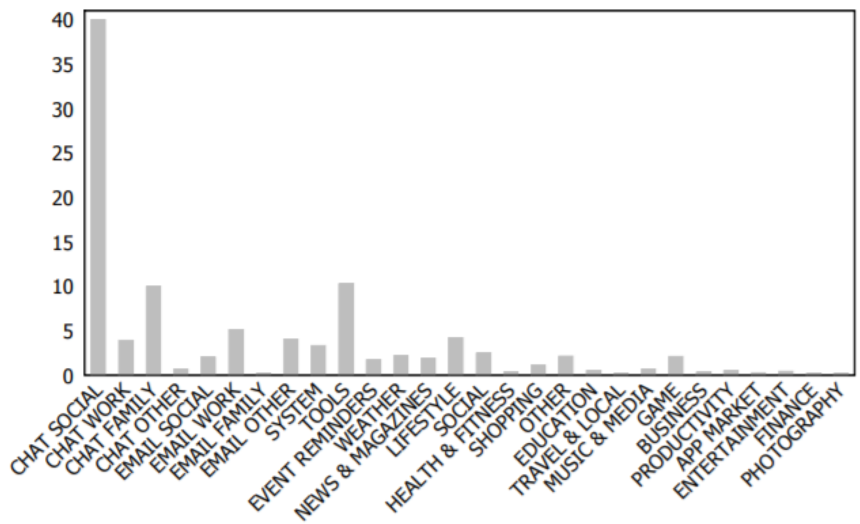


Figure 2. Percentage of notifications for each category and sub-category. The sub-categories are derived by using the recipient’s relationship with the sender.

Results

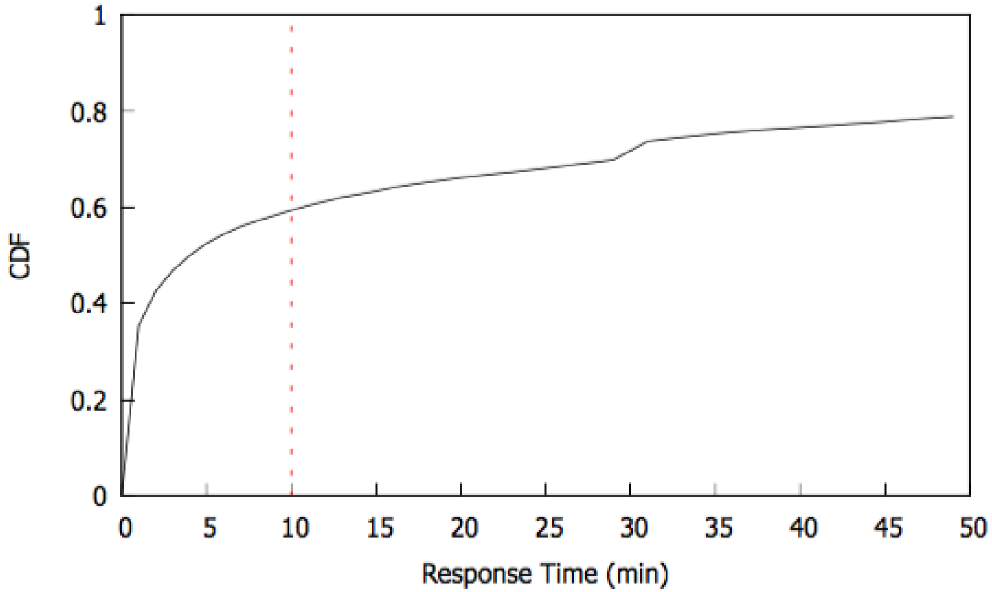


Figure 3. CDF of response time for notifications.

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

Impact of Context on Response Time

- Response time does not vary with
  - Location
    - home, workplace, the other
  - Surrounding sound
    - silent or speaking
- Response time varies with activity:
  - In vehicle < still < on foot < On bicycle

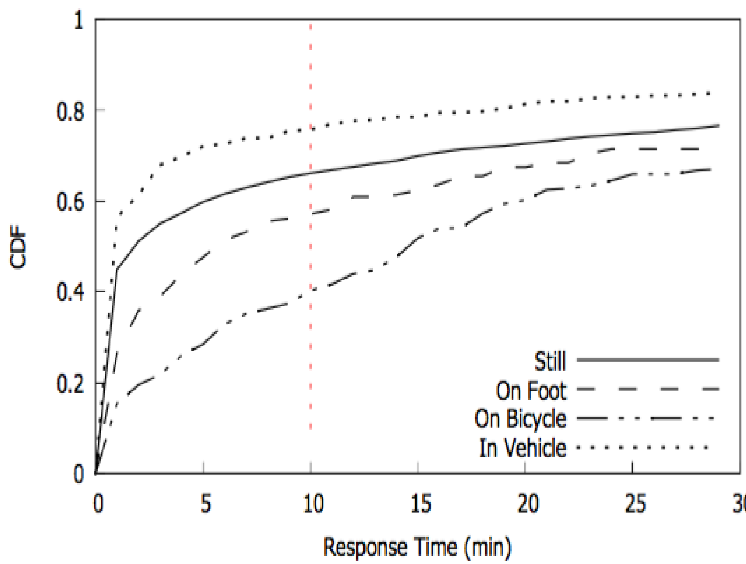


Figure 4. CDF of response time for notifications received while performing different activities.

Impact of Content on Notification Acceptance

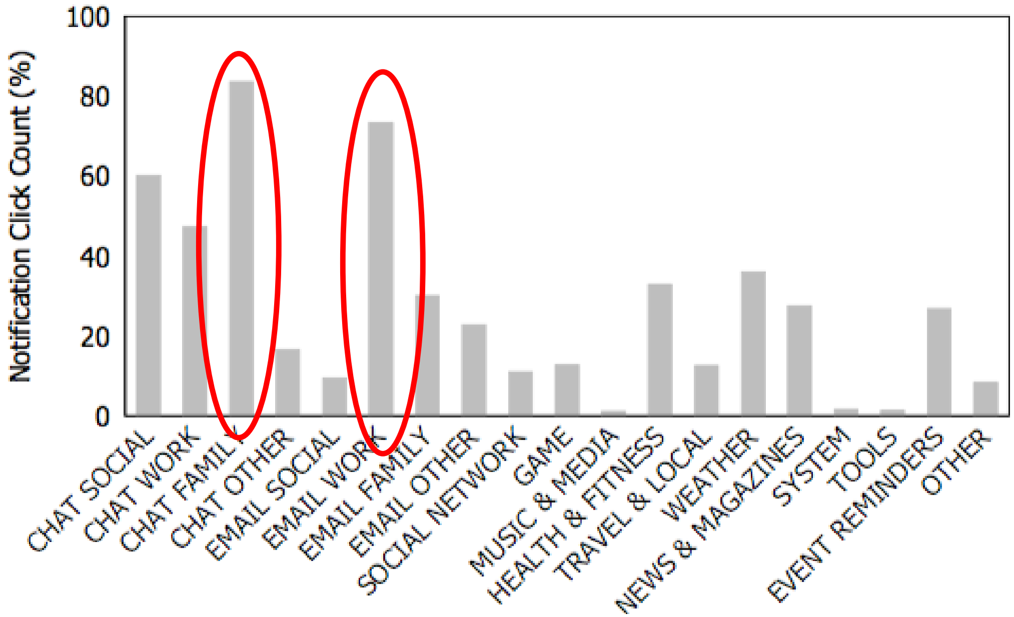


Figure 5. Click count percentages for the notifications of each category.

- Different categories of notifications have varying acceptance rate
- Chat Family and work email had highest acceptance rate

Predicting "Right Time"for a Notification: Features

- Labelled notifications accepted in <= 10 mins **accepted**
- All others labelled **declined**
- **Ranked features:** App name, notification category most important for predicting acceptance

Feature	Rank	Average IG
App Name	1	0.251
Notification category	2	0.247
Phone status	3	0.092
Location	4	0.081
Arrival hour	5	0.073
Ringer mode	6	0.056
User's activity	7	0.042
Priority	8	0.026
Alert type	9	0.024
Proximity	10	0.017
Surrounding sound	11	0.003
WiFi connectivity	12	0.001

Table 3. Ranking of features from the NotifyMe dataset.

Building the Prediction Model

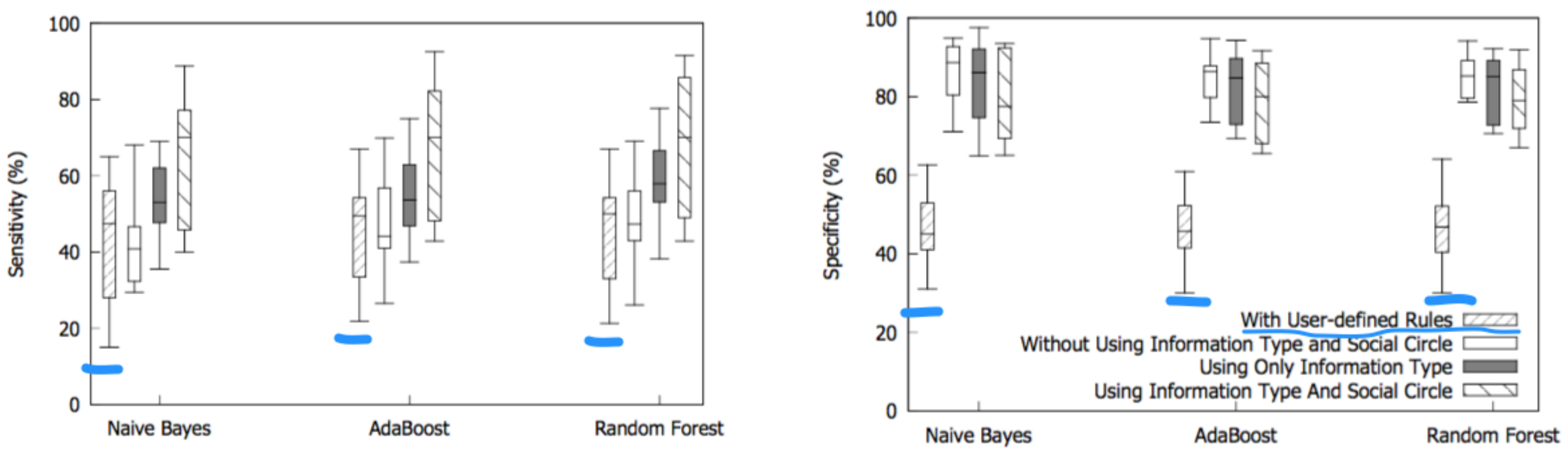
- Classify Features to Predict if Notification Accepted using three classification algorithms:
  - Naive Bayes, AdaBoost, and Random Forest
- Two approaches for building prediction models
  - Data-driven learning
  - User defined their own rules

Approaches for building the Prediction Model

- Data-driven learning that relies on quantitative evidence 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 rules (intuition)
  - notification category
  - best location
  - best time

Evaluation

- Sensitivity
  - # of predicted **accepted** notifications / total # of accepted notifications
- Specificity
  - # of predicted **declined** notifications / total # of declined notifications



- Data driven approaches beat user rules significantly
- **Best sensitivity:** Using information Type and Social Circle (70%)
- **Best specificity:** Using only information type (80%)

Conclusions

- Notification content (from who, type, etc) affected if it was accepted/declined
- The chat notification from family member or work email had highest acceptance rate
- Acceptance of a notification within 10 minutes of arrival can be predicted with sensitivity of 70% and specificity of 80%

Detecting Boredom from Mobile Phone Usage, Pielot *et al*, Ubicomp 2015

Introduction

- 43% of time, people seek self-stimulation
  - Watch YouTube videos, web browsing, social media
- **Boredom:** Periods of time when people have abundant time, seeking stimulation
- **Goal:** Develop machine learning model to infer boredom based on features related to:
  - Recency of communication
  - Usage intensity
  - Time of day
  - Demographics

Motivation

If boredom can be detected, opportunity to:

- Recommend content, services, or activities that may help to overcome the boredom
  - E.g. play video, recommend an article
- Suggesting to turn their attention to more useful activities
  - Go over to-do lists, etc

"Feeling bored often goes along with an urge to escape such a state. This urge can be so severe that in one study … people preferred to self-administer electric shock rather than being left alone with their thoughts for a few minutes"

- Pielot et al, citing Wilson et al

Related Work

- Bored Detection
  - Expression recognition (Bixler and D'Mello)
  - Emotional state detection using physiological sensors (Picard *et al*)
  - Rhythm of attention in the workplace (Mark *et al*)

- Inferring Emotions
  - Moodscope: Detect mood from communications and phone usage (LiKamWa *et al*)
  - Infer happiness and stress phone usage, personality traits and weather data (Bogomolov *et al*)

Methodology

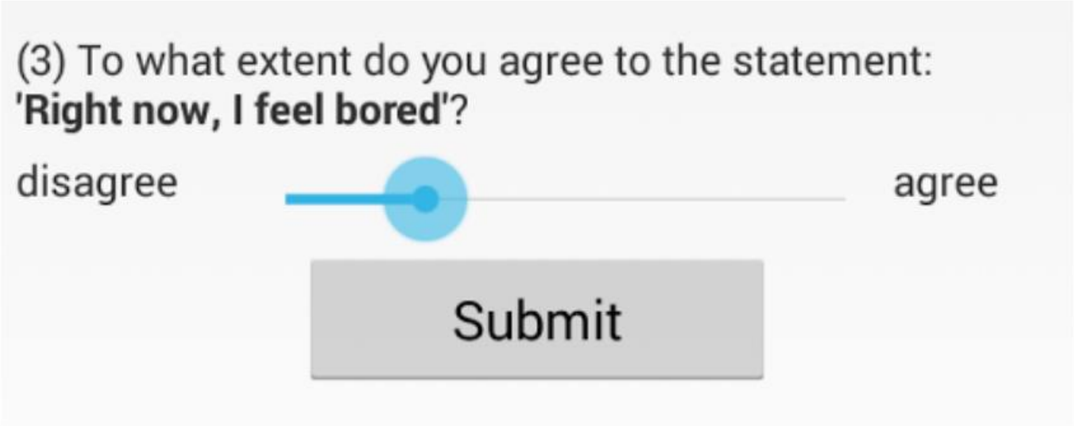
- 2 short Studies

- Study 1
  - Does boredom measurably affect phone use?
  - What aspects of mobile phone usage are most indicative of boredom?

- Study 2
  - Are people who are bored more likely to consume suggested content on their phones?

Methodology: Study 1

- Created data collection app *Borapp*
  - 54 participants for at least 14 days
    - Self-reported levels of boredom on a 5-point scale
      - Probes when phone in use + at least 60 mins after last probe
    - App collected sensor data, some sensor data at all times, others just when phone was unlocked



Study 1: Features Extracted

- **Assumption:** Short infrequent activity = less goal oriented

- Extracted 35 features, in 7 categories
  - Context
  - Demograpics
  - Time since last activity
  - Intensity of usage
  - External Triggers
  - Idling

Context	
audio	Indicates whether the phone is connected to a headphone or a bluetooth speaker
charging	Whether the phone is connected to a charger or not
day_of_week	Day of the week (0-6)
hour_of_day	Hour of the day (0-23)
light	Light level in lux measured by the proximity sensor
proximity	Flag whether screen is covered or not
ringer_mode	Ringer mode (silent, vibrate, normal)
semantic_location	Home, work, other, or unknown
Demographics	
age	The participant's age in years
gender	The participant's gender
Last Communication Activity	
time_last_incoming_call	Time since last incoming phone call
time_last_notif	Time since last notification (excluding Borapp probe)
time_last_outgoing_call	Time since the user last made a phone call
time_last_SMS_read	Time since the last SMS was read
time_last_SMS_received	Time since the last SMS was received
time_last_SMS_sent	Time since the last SMS was sent

Table 3. List of features related to context, demographics, and time since last communication activity.

Study 1: Features Extracted (Contd)

- Extracted 35 features, in 7 categories
  - Context
  - Demograpics
  - Time since last activity
  - **Intensity of usage**
  - **External Triggers**
  - **Idling**

Usage (related to usage intensity)	
battery_drain	Average battery drain in time window
battery_level	Battery change during the last session
bytes_received	Number of bytes received during time window
bytes_transmitted	Number of bytes transmitted during time window
time_in_comm_apps	Time spent in communication apps, categorized to none, micro session, and full session
Usage (related to whether it was triggered externally)	
num_notifs	Number of notifications received in time window
last_notif	Name of the app that created the last notification
last_notif_category	Category of the app that created the last notification
Usage (related to the user being idling)	
apps_per_min	Number of apps used in time-window divided by time the screen was on
num_apps	Number of apps launched in time window before probe
num_unlock	Number of phone unlocks in time window prior to probe
time_last_notif_access	Time since the user last opened the notification center
time_last_unlock	Time since the user last unlocked the phone
Usage (related to the type of usage)	
screen_orient_changes	Flag whether there have been screen orientation changes in the time window
app_category_in_focus	Category of the app in focus prior to the probe
app_in_focus	App that was in focus prior to the probe
comm_notifs_in_tw	received in the time window prior to the probe
most_used_app	Name of the app used most in the time window
most_used_app_category	Category of the app used most in the time window
prev_app_in_focus	App in focus prior to *app_in_focus*

Table 4. List of features related to usage intensity, external trigger, idling and type.

Results: Study 1

- Machine-learning to analyze sensor and self-reported data and create a classification model
  - Compared 3 classifier types
    1. Logistic Regression
    2. SVM with radial basis kernel
    3. Random Forests
    - Random Forests performed the best and was used
  - Feature Analysis
    - Ranked feature importance
    - Selected top 20 most important features of 35
  - Personalized model: 1 classification model for each person

Results: Study 1, Most Important Features

- **Recency of communication activity:** last SMS, call, notification time
- **Intensity of recent usage:** volume of Internet traffic, number of phonelocks, interaction level in last 5 mins
- **General usage intensity:** battery drain, state of proximity sensor, last time phone in use
- **Context/time of day:** time of day, light sensor
- **Demographics:** participant age, gender

Feature	*Import*	*Correlation*	*The more bored, the ..*
time_last_outgoing_call	0.0607	-0.143	less time passed
time_last_incoming_call	0.0580	0.088	more time passed
time_last_notif	0.0564	0.091	more time passed
time_last_SMS_received	0.0483	0.053	more time passed
time_last_SMS_sent	0.0405	-0.090	less time passed
time_last_SMS_read	0.0388	-0.013	less time passed
light	0.0537	-0.010	darker
hour_of_day	0.0411	0.038	later
proximity	0.0153	-0.186	less covered
gender (0=f, 1=m)	0.0128	0.099	more male (1)
age	0.0093	n.a.	+20s/40s, -30s
num_notifs	0.0123	0.061	more notifications
time_last_notif_cntr_acc	0.0486	-0.015	less time passed
time_last_unlock	0.0400	-0.007	less time passed
apps_per_min	0.0199	0.024	more apps per minute
num_apps	0.0124	0.049	more apps
bytes_received	0.0546	-0.012	less bytes received
bytes_transmitted	0.0500	0.039	more bytes sent
battery_level	0.0268	0.012	the higher
battery_drain	0.0249	-0.014	the lower

Results: Study 1

- Could predict boredom ~82% of the time
- Found correlation between boredom and phone use
- Found features that indicate boredom

Motivation: Study 2

Now that we can predict when people are bored.

- Are bored people more likely to consume suggested content?

Methodology: Study 2

- Created app *Borapp2*
- 16 new participants took part in a quasi-experiment
  - When participant was bored, app suggested newest Buzzfeed article
- Buzzfeed has articles on various topics including politics, DIY, recipes, animals and business

Methodology: Study 2 Measures

- **Click-ratio:** how often user opened Buzzfeed article / total number of notifications

- **Engagement-ratio:** How often user opened Buzzfeed article for at least 30 seconds / total number of notifications

Results: Study 2

Click-Ratio

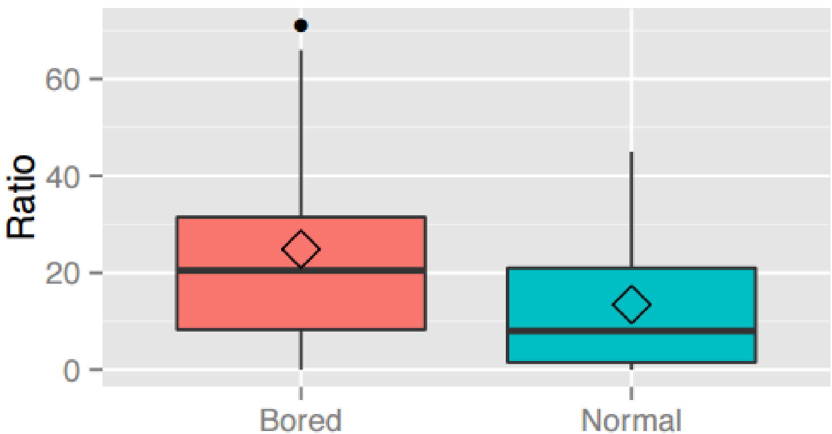


Figure 6. Click-ratio per condition.

Engagement-Ratio

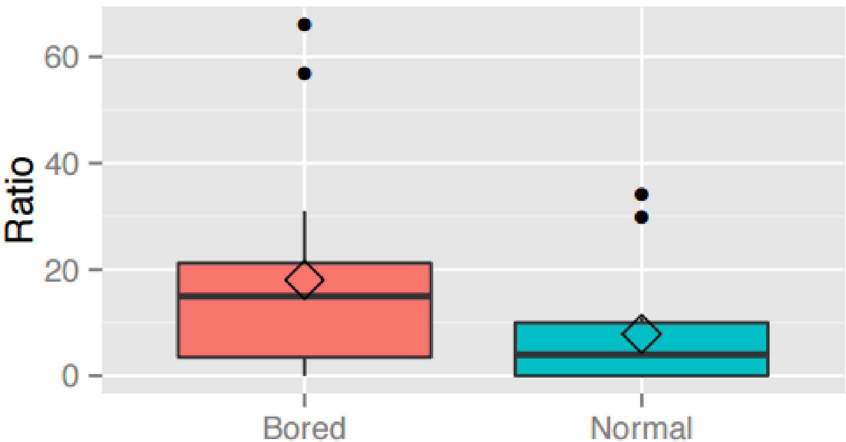


Figure 7. Engagement-ratio per condition.

- Preliminary findings: Bored Users were more likely to click on, and engage with suggested content

Hooked on Smartphones: An Exploratory Study on Smartphone Overuse among College Students, Lee *et al,* CHI 2014

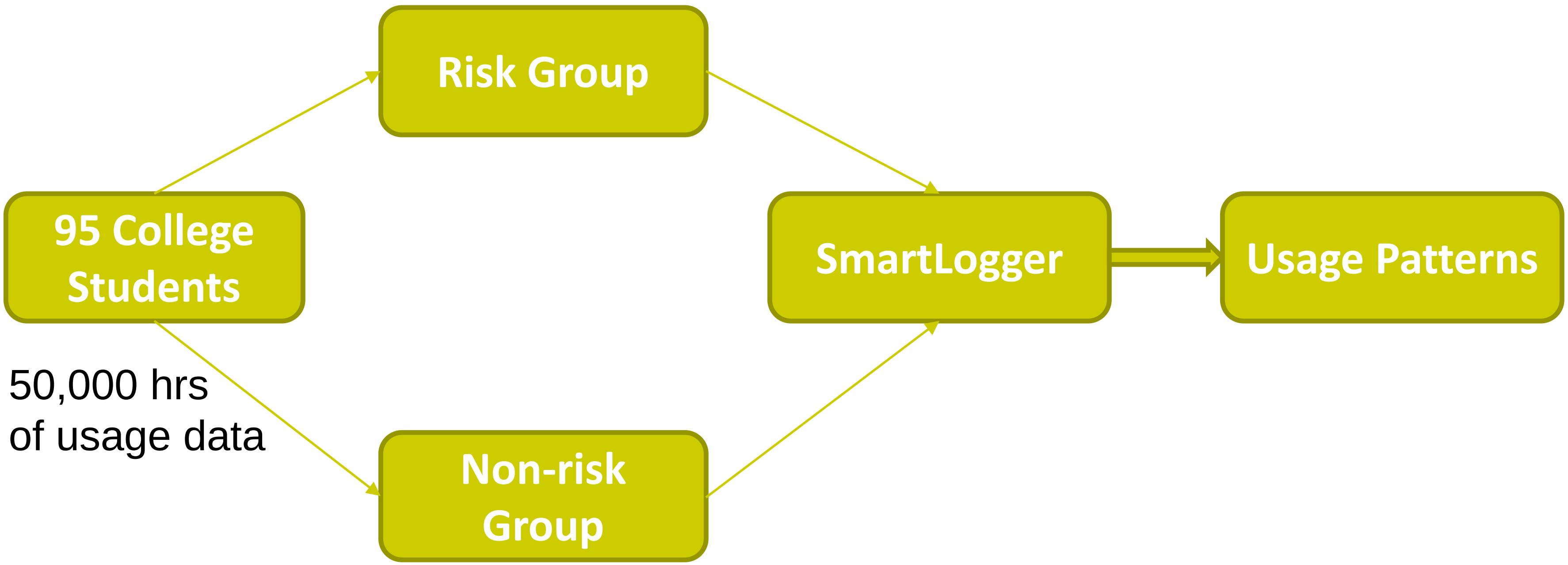
Introduction

- Smartphones now very popular, owned by 77 percent of Americans
- Sometimes overused?
- **Negative consequences:** smartphone addiction, sleep deprivation, poor mental health, disruption of social interactions, etc.

- How is smartphone overuse reflected in actual phone use?

Introduction

- Separated subjects into risk vs non-risk group based on score on **smartphone addiction proneness scale**
- Analyze usage patterns related to smartphone overuse



Is there difference in phone usage between Risk vs non-risk group?

Methodology

- Participants
  - 95 Korean College Students, Average age is 20.6 years
  - Time span: average 26.8 days in 2012

- SmartLogger: Unobtrusively logs
  - **Application events:** active/inactive apps, touch/text input, web URLs, notifications
  - **System:** power on/off, screen lock
  - **Phone events:** calls and SMS

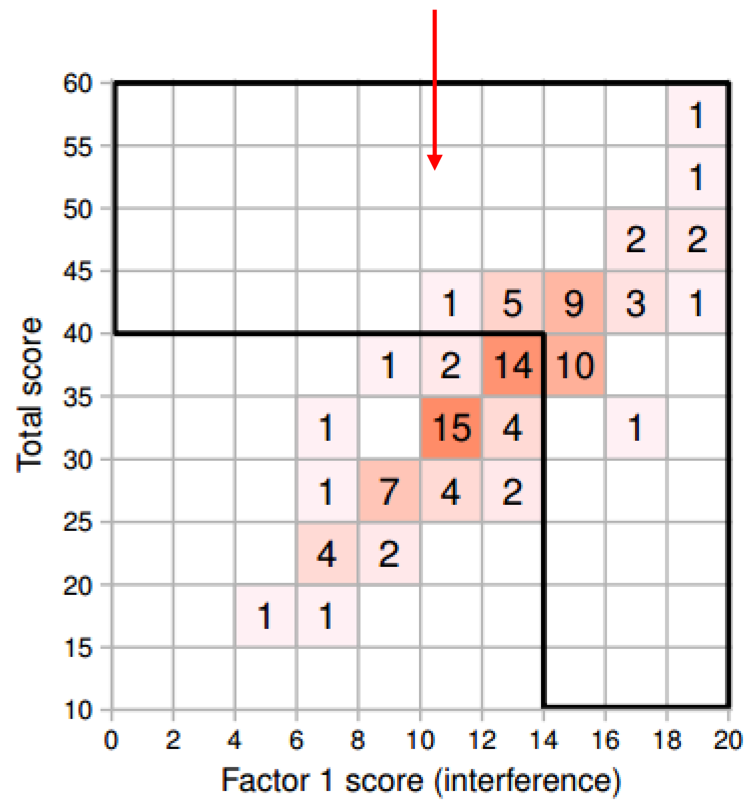
Separated Subjects: Low Risk, vs High Risk

- Based on Smartphone Addiction Proneness Scale
- 15 questions scored on Likert scale

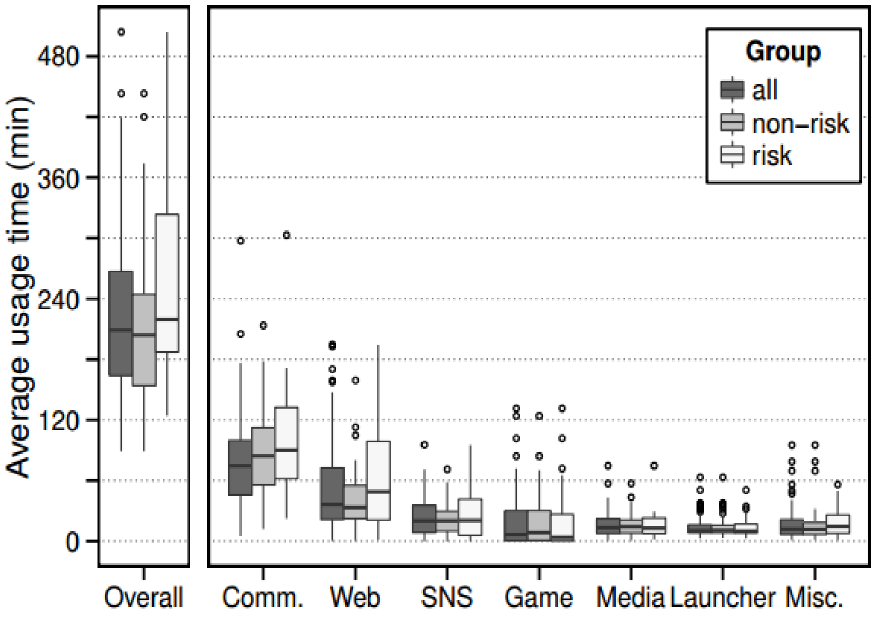
F1	*"My school grades (or work productivity) dropped due to excessive smartphone use."* *"People often complained about excessive smartphone use."*
F2	*"Using a smartphone is more enjoyable than spending time with my family or friends."* *"When I cannot use my smartphone, I feel like I have lost the entire world."*
F3	*"It would be distressing if I am not allowed to use my smartphone."* *"I become restless and nervous when smartphone use is impeded."*
F4	*"Even when I think I should stop, I continue to use my smartphone."* *"Spending a lot of time on my smartphone has become a habit."*

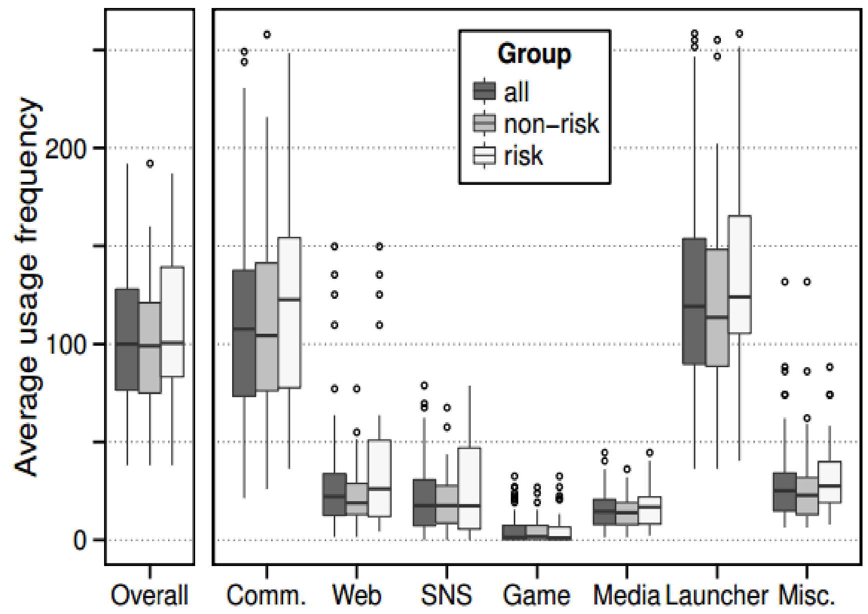
Table 1. Illustration of Smartphone Addiction Proneness Scale (its sub-factors include F1: Interference, F2: Virtual World, F3: Withdrawal, and F4: Tolerance)

High/At-risk: Total score ≥ 40 or F1 score ≥ 14



Overall Differences in Usage Patterns





Usage time: insignificant differences

Usage frequency: insignificant differences

Overall Differences in Usage Patterns

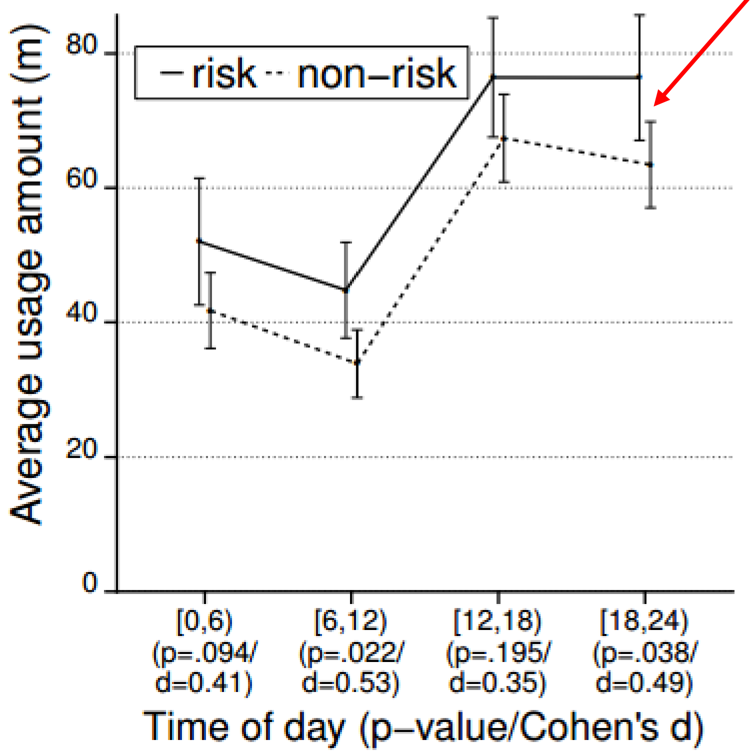
- High risk group: More total mins daily

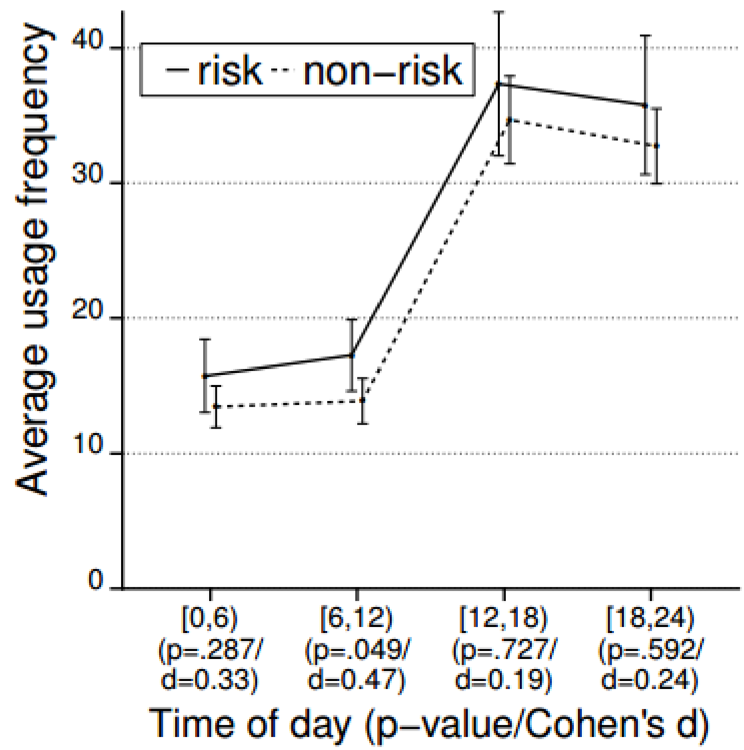
	Daily Usage	Usage Frequency	
		Session Frequency	Inter-session time
Risk Group	**253.0 min**	111.5	729.1
Non-risk Group	**207.4 min**	100.1	816.6

- High risk group: Also spent more time on their favorite apps
  - **Mean usage time of 1st ranked app:** 98 min vs 70 mins

Differences in Diurnal Usage Patterns

- High risk groups used their phones longer morning and evening





Communication App Use

- Mobile Instant Messaging (MIM) most used app- KakaoTalk
  - **Top apps:** MIM, Voice calls, SMS, E-mail
- Notifications are potential **trigger** of problematic usage behavior.

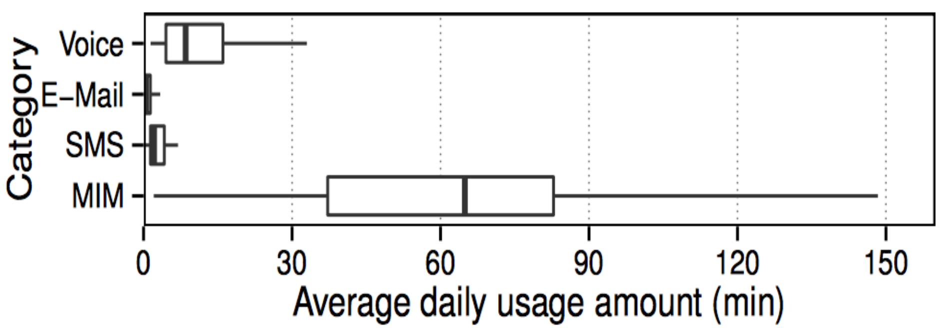


Figure 6. Usage statistics for communication apps

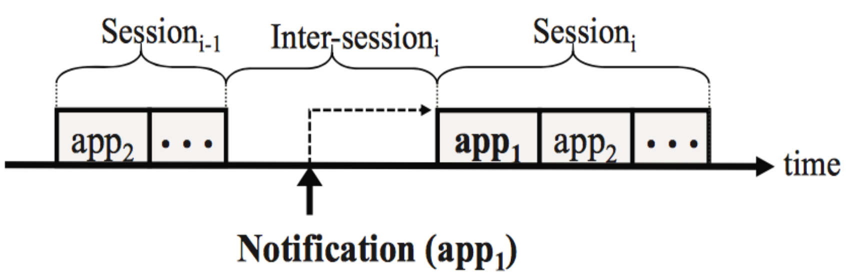


Figure 7. Illustration of an external session

Summary of Findings

- Communications App Usage
  - More than 400 notifications/day and 90% from MIMs.
  - The risk group spend significantly more time on MIM-initiated sessions

- Web Browsing app usage
  - Risk group browsed the web more often, searched for content updates more frequently.

Analytic Modeling of Usage Behavior

- Regression Analysis
  - The usage time and frequency were closely related with smartphone overuse
- Classification Analysis
  - Category-specific usage patterns were best features for classifying the groups.
- Problematic usage in form of frequent interferences
  - Instant messages interfered with different degrees: loss attention, disturb sleep pattern, interrupt social activity.