TaskyApp: Inferring Task Engagement via Smartphone Sensing

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Interruptibility and Task Engagement

- Location
- Movement
- Time of day
- Sender
- Content
- Task engagement

V. Pejovic, A. Mehrotra, and M. Musolesi, "InterruptMe: Designing Intelligent Prompting Mechanisms for Pervasive Applications," ACM UbiComp'14, Seattle, WA, USA.


V. Pejovic, A. Mehrotra, and M. Musolesi, "Investigating the Role of Task Engagement in Mobile Interruptibility," Smarttention'15 workshop, Copenhagen, Denmark.
Interruptibility and Task Engagement

- Link between task engagement and opportunity to interrupt (self-reported)
  - More skilled a person is, less she will be irritated by an interruption
  - More challenging a task is to a person, more **irritated** she will be with an interruption
  - More concentrated a person is on a task, more she will be irritated by an interruption
Theory of Multitasking

- Interference when two or more threads ask for the same resource at a time

Example from [Borst2010]
Theory of Multitasking

• Complex tasks require problem state saving/retrieving

Example from [Borst2015]
Can we automatically infer task engagement?
TaskyApp

• Can smartphones sense that their users are busy (in an office setting)?
• TaskyApp data collection app
  – Background sensing of:
    • Device movement (raw and Google Activity Recognition reported), ambient sound, location
    • BT/WiFi sensing
    • Screen status, sound settings
    • Google calendar events
  – Data labelling via experience sampling and retroactive assisted labelling
TaskyApp

- Data collection trial
  - Volunteering (with a chance of winning 50€)
  - Eight office workers for five weeks
    - 232 labelled instances (3035 unlabelled)
    - Most data between 8am and 6pm
TaskyApp – Data Analysis

• Linear regression fit with task difficulty (1-5 on a Likert scale) as a dependent variable
  – **Movement data** gives the most informative features
  – The regression explains only a small part of the data

<table>
<thead>
<tr>
<th>Variable</th>
<th>B(Std. Err.)</th>
<th>t (Sig)</th>
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</thead>
<tbody>
<tr>
<td>Acc. Y mean</td>
<td>-.038 (.02)</td>
<td>-1.82 (.068)</td>
</tr>
<tr>
<td>Acc. Z mean</td>
<td>.026 (.02)</td>
<td>1.43 (.153)</td>
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<tr>
<td>Acc. mean intensity</td>
<td>-.711 (.23)</td>
<td>-3.04 (.003)</td>
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<tr>
<td>Gyro. MCR</td>
<td>-.003 (.00)</td>
<td>-4.06 (.000)</td>
</tr>
<tr>
<td>Gyro. variance</td>
<td>.200 (.16)</td>
<td>1.24 (.217)</td>
</tr>
<tr>
<td>Hour of day</td>
<td>.067 (.02)</td>
<td>3.49 (.001)</td>
</tr>
<tr>
<td>Reg. Constant</td>
<td>8.385 (2.31)</td>
<td>3.63 (.000)</td>
</tr>
</tbody>
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N=232; $R^2=0.19$, $F=8.64$ ($p=.000$)
TaskyApp – Data Analysis

• Classify a task engagement moment as either easy or difficult depending on the sensed features
  – We experimented with different classifiers but Naïve Bayes seems to work best (probably due to the low amount of data)
    • 62.5% accuracy compared to 52.8% baseline
    • Also, leads to favourable errors – few difficult tasks predicted as easy

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<thead>
<tr>
<th></th>
<th>easy’</th>
<th>difficult’</th>
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<tbody>
<tr>
<td>easy</td>
<td>45 (19.4%)</td>
<td>62 (26.7%)</td>
</tr>
<tr>
<td>difficult</td>
<td>25 (10.8%)</td>
<td>100 (43.1%)</td>
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Task Engagement Inference

• Even in a restricted office setting smartphone-based task inference is challenging
• Movement features seem to be the most informative
• Next step – wearables
  – Sense heart rate and skin temperature
Thank you!

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