My Smartphone Knows I am Hungry

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Logging by Input

https://jawbone.com/up
Use Devices to Track Eating

HapiFork
Use Devices to Track Eating

Yatani et al. BodyScope Ubicomp 2012

Rahman et al. BodyBeat, MobiSys 2014
Need Specialized Hardware
Can your smartphone **unobtrusively** predict your food eating behavior?
Can your smartphone unobtrusively predict your food eating behavior? purchases
Our Work

unobtrusively collect behavior data

build predictive model

predict buy food or not

2014-06-17
Dataset – Evidence

• 25 students, 10 weeks
• Smartphone app runs 24/7 in the background to collect:
  - Conversation
  - Physical activity
  - Sleep
  - Location
  - Bluetooth colocation
  - Wi-Fi scan log
Dataset – Ground Truth

• We collected dinning records
  • Purchase time
  • Location
  • Account
  • Cost

• We don’t know what they bought

<table>
<thead>
<tr>
<th>Purchase Time</th>
<th>Location</th>
<th>Account</th>
<th>Type</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>04/11/2013 01:57:26</td>
<td>Novack Cafe</td>
<td>Dining DBA</td>
<td>Debit</td>
<td>$3.55</td>
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<tr>
<td>04/11/2013 10:10:31</td>
<td>Collis Cafe</td>
<td>Dining DBA</td>
<td>Debit</td>
<td>$7.45</td>
</tr>
</tbody>
</table>
Roadmap

• Motivation
• **Design Challenges**
• Approach
• Results
• Conclusion
Why Not Just Use Location?
Not the Case for Campus
Why Not Use Time?
No Distinct Mealtimes
Roadmap

• Motivation
• Design Challenges
• Our approach
• Results
• Conclusion
Our Approach

• Unobtrusively monitor user behavior
• Identify food purchasing related behaviors
• Build a predictive model
Prediction Pipeline

• Training phase

![Diagram showing the prediction pipeline with steps for behavioral data, feature extraction, features, purchase history, and classifier with training connections.]
Prediction Pipeline

- Prediction phase
Features Related to Food Purchase

- Location
- Arrival time / Leaving time
- Conversation
- Physical activity

Previous Location

Current Location

- Location
- Arrival time
Prediction Pipeline

• Prediction phase

behavioral data → feature extraction → features → classifier → training

features → purchase history → classifier

behavioral data → feature extraction

buy food or not
Approach: Training Set Selection

- Select training data based on **personalization** and **adaptation**.

One size does not fit all.

Behavior changes over time.

Use latest n weeks data to train

- week 1
- week 2
- week 3
- week 4
- week 5
- week 6
- week 7
Prediction Pipeline

• Prediction phase:

- **Behavioral data**

  - Feature extraction
  - Purchase history

- **Features**

  - Classifier

- **Training**

  - Buy food or not

- **Behavioral data**

  - Feature extraction
Approach: Classifier

• Classification and Regression Trees (CART)

• Handles categorical data (location) and numerical data (behavioral)
Roadmap

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Evaluation Setup

• Schemes for comparison
  • Random guessing: flip a coin
  • Generic: one size fits all model
  • Personalized: personalized model but without adaptation
  • Our model: personalization and adaptation

• Metrics
  • **Accuracy**: % of correct predictions
  • **Precision**: % of correct predictions in all positive predictions
  • **Recall**: % of identified real true cases
Key Result

- Random guessing < generic < personalized < our model (personalized and adapted)
Roadmap

- Motivation
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- Approach
- Results

- **Conclusion**
Conclusion and Limitation

- Proposed a simple predictive model of food purchases
  - 74% accuracy using smartphone sensing data

- Limitations
  - Cannot predict what food student would buy
  - Do not cover food purchases beyond student ID card
  - Do not know when they ate their food
  - Limited to student body
Future Work

• How can we unobtrusively track what we bought?
Future Work

• How to generalize the model?
Future Work

• How to unobtrusively detect eating?
Future Work

• Food intervention
Thanks!
Backup
What Features are more predictive

- Current location
- Arrival time
- Prev. location departure time
- Physical activity
- Prev. location arrival time
- Conversation duration
- Prev. location
- Conversation freq.

Feature importance:

- Current location: 0.25
- Arrival time: 0.18
- Prev. location departure time: 0.16
- Physical activity: 0.16
- Prev. location arrival time: 0.14
- Conversation duration: 0.10
- Prev. location: 0.08
- Conversation freq.: 0.05