A little background ...

- Engineering and Computer Science background
- Worked at Intel & UC-Berkeley
- Focus on human-computer interaction

- Direct the Ubicomp Lab at CMU
  - Context-aware computing
  - Focus: understanding and modeling of human behavior: interaction with environment, people and devices
  - Domains: healthcare, sustainability, education, automotive, user experience, robots, LBS, personal informatics and behavior change, sensor-based interfaces, ...
dwellSense
(PhD work Matthew Lee): PervasiveHealth 2011, CHI 2012, CHI 2014
Computational Behavioral Imaging
Computational Behavioral Imaging
Computational Behavioral Imaging

• People already carry them
• Interactions with information: virtual
• Social engagement: social
• Loads of sensors: physical
Computational Behavioral Imaging

- Phones are behavioral imaging devices
- Can be used to extract and model routines and behaviors
- Develop apps that change usage behavior and to improve user experiences and lives
- Leverage personalized meaning from an individual’s own big data
Assumption: We all have smart phones

- What is a smart phone?
  - Android, iPhone, Nokia, Windows Mobile, BlackBerry, ...

- Feature phone vs. smart phone
  - Feature phone “runs its own unique software but not a true and complete mobile OS”
  - Smart phone “runs a complete mobile OS”
    - “offers more advanced computing ability and connectivity than a feature phone”
Dumb phones

- We live in a time of dumb phones
- Knows almost nothing about me
  - Explicit preferences
  - Contacts
  - Running applications
- Hardly knows when I'm mobile/fixed, charging/not charging
- Doesn’t know me or what I’m doing

WHY???
Research Goal

• Want to build a smart phone that
  – Collects and learns a model of human behavior with every interaction
  – From the moment the phone is purchased and turned on
  – Uses behavior information to improve interaction and the user experience
  – Do this opportunistically
    • Your noise is my signal!
    • Big Data of 1
We are close

• Opportunities:
  – Amazing amounts of computation at hand
  – Memory and storage
  – Radios and communication
  – Sensors
  – Software
  – Mobile device
  – Personal device
But so far away...

• Challenges:
  – Battery
  – Raw sensors not behavior data
  – Not the sensors we always want
  – Computational complexity
  – Latency in communication
  – Basic software framework to support apps that can adapt to user behavior
  – Apps that drive innovation
What if?

• What would user experience be like if:
  – Phones managed own power based on expected usage and recharging behavior
  – Phones managed collection of apps available based on expected usage
  – Phones adapted their UI based on expected usage
  – Phones changed application behavior based on expected user behavior
Smart Phone Infrastructure

- Sensor signals
- Update screen/model

Logging system:
- Sampling
- Power mgmt
- DB

Modeling system:
- Feature extraction
- Discretization
- Modeling

Inferencing system:
- Inference models

Outputs:
- Apps
- Services

Aware Framework
Aware Framework
(awareframework.com)
PhD work of Denzil Ferreira (Oulu)

• Data collection:
  – GPS
  – Bluetooth
  – Battery
  – Wi-fi access point info
  – Cellular network info
  – Network traffic
  – Accelerometer
  – Installed apps, running apps
  – Audio settings
  – Screen settings
  – Call/text/email/calendar logs
  – ...

• Strategies for extending battery life
• Support for deploying, executing studies
• Integrated modeling and machine learning
New era of *new* smart phones just beginning

- Despite challenges, lots of opportunities to build a truly smart phone
  - Use opportunistic/passive sensing
  - Leverage human behavior
    - Collect data
    - Create effective models
    - Apply models to impact user experience
Big Data of 1

• Build compelling and useful apps that provide value in everyday life and a compelling user experience

• Think about what you can do with big data for 1 with origins in everyday activity
What can behavioral imaging enable?

**GPS systems** that predict where you’re going and proactively route you around traffic: (Ubicomp 2008, AAAI 2008, ICML 2010, AAMAS 2011)

**Reminder** systems that predict anomalies and routine events for families (Ubicomp 2006, 2007, CHI 2010, CHI 2011)

**Stress detection** and stress avoidance systems (with addiction population)

**Anomaly detection** for security purposes (PerCom 2014)

Detect cellphone **addiction** (Ubicomp 2013)

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**Proactively adjust battery usage** to maximize time until recharge (Pervasive 2012)

**Power management** based on predictions of use and mobility

**Predict when you’re going home** to proactively control HVAC (Ubicomp 2013)

Detect **aggressive driving** behavior, decline in driving behavior (CHI 2014)

Detect **novice driving behaviors** and support transition to expert

Detect periods of **high and low cognitive load** in drivers; and in students

**Predict office occupancy** to control energy usage (Ubicomp 2014)

Detect **types of engagement** with the phone (Mobile HCI 2014)

Identify **emotional state/mood**

Detect when multiple people are **experiencing the same situation**

Detect **symptoms of disease** and impacts of interventions

Detect predictors of **binge drinking**

…
New era of new smart phones just beginning

- Number of projects focused on user behavior
  - Navigation: NavPrescience
  - Family coordination
  - Prudent Sampling
  - Level of engagement

• Navigation market is “dead”
  – Every phone has a GPS
  – Drop in sales of PNDs
  – Google giving navigation away for “free”

• Can revitalize the navigation market with LBS
• Can revolutionize with personalized LBS
  – Need a (not very) smart phone
  – Just GPS, modeling, inferencing
  – Understand human behavior and provide valuable services
100% Travel Time
0% Distance
If costs double 73% would avoid toll roads
Fewer left-hand turns saved UPS 3 million gallons of gasoline

New York Times  (Dec. 9, 2007)
Congestion can cause frustration and “road rage”
Routes should match the driver’s skills
...and comfort level
Travel Time
Toll Costs
Fuel Costs
Safety
Stress-tolerance
Driving Skills
Can users fully specify their preferences?
“Think” with probabilities
Predict driver’s current route
Provide new routes on request that match driver’s behaviors
Route Recommendation: Shortest Path Planning

Start

Goal
Inverse Optimal Control

Find $\theta$ that explains user’s behavior.
Maximum Entropy Inverse Planning

Maximizing the **entropy** over paths:

$$\max H(P_\zeta)$$

While matching feature counts (and being a probability distribution):

$$\sum_\zeta P(\zeta) f_\zeta = f_{\text{dem}}$$

$$\sum_\zeta P(\zeta) = 1$$
Maximum Entropy Inverse Planning

Maximizing the **entropy** over paths:

\[
\max H(P_\zeta)
\]

While matching feature counts (and being a probability distribution):

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Maximum Entropy Inverse Planning

Maximizing the **entropy** over paths:

$$\max H(P_\zeta)$$

While matching feature counts (and being a probability distribution):

$$\sum_\zeta P(\zeta) f_\zeta = f_{\text{dem}}$$

$$\sum_\zeta P(\zeta) = 1$$

As uniform as possible

Performance guarantee
Reasoning Applications

• Personalized Route Recommendation
• Vehicle System Automation
• Unanticipated Hazard Warning
• Predictive LBS
• Routes that help with to-do lists
• Drive like a local
Route Preference/Behavior Modeling

• Expert Driver Data
  – 25 Taxi Drivers
  – GPS logs
  – 100,000+ Miles
Modeling Taxi Routes

(AAAI 2008)

MaxEnt better with $\alpha < 0.01$
Reasoning Applications

- Personalized Route Recommendation
- **Vehicle System Automation**
- Unanticipated Hazard Warning
- Home Automation
- Anticipating Likely Deviations
- Routes that help with to-do lists
- Drive like a local
Turn Prediction
Reasoning Applications

• Personalized Route Recommendation
• Vehicle System Automation
• Unanticipated Hazard Warning
  – Predict driver’s route and warn if it is likely to encounter congestion, accidents, poor weather, etc...
  – Recommend a new, preferred route for driver
• Predictive LBS
• Routes that help with to-do lists
• Drive like a local
Route Prediction
Destination Prediction
Family Coordination

• Largest segment of US population and growing
• Live logistically complex lives that drive aggressive and experimental use of communication technology
Why Family Life is Out of Control

Swamped with responsibilities from kids activities and jobs
Family Data Collection

- Work was carried out over 5 years
- 6 families, ~25 people
- 6 months
- GPS every minute
- Every email, text and metadata about calls
- Calendars (digital and paper)

- Phone interviews every other day
- Bi-weekly in-person interviews
- Labeled GPS, communications, stress assessment
Family Data Collection

• Need a (not very) smart phone
• Just GPS, modeling, inferencing
• Understand human behavior and provide valuable services
What did we learn from behaviors?

• Parents enroll their kids in lots of activities
Schedules are key

- Most don’t know schedules

<table>
<thead>
<tr>
<th>Activity</th>
<th>S15</th>
<th>Mom</th>
<th>Dad</th>
</tr>
</thead>
<tbody>
<tr>
<td>School</td>
<td>Start</td>
<td>6:35 am</td>
<td>6:40 am</td>
</tr>
<tr>
<td></td>
<td>End</td>
<td>2:25 pm</td>
<td>2:45 pm</td>
</tr>
<tr>
<td>Track</td>
<td>Start</td>
<td>2:25 pm</td>
<td>2:30 pm</td>
</tr>
<tr>
<td></td>
<td>End</td>
<td>5:00 pm</td>
<td>5:00 pm</td>
</tr>
<tr>
<td>Boy Scouts</td>
<td>Start</td>
<td>7:00 pm</td>
<td>7:00 pm</td>
</tr>
<tr>
<td></td>
<td>End</td>
<td>8:30 pm</td>
<td>9:00 pm</td>
</tr>
<tr>
<td>Paper Route</td>
<td>Start</td>
<td>5:30 pm</td>
<td>5:30 pm</td>
</tr>
<tr>
<td></td>
<td>End</td>
<td>6:30 pm</td>
<td>6:00 pm</td>
</tr>
</tbody>
</table>
Schedules are key

• Calendars hold deviations, not schedules
  – >90% of entries were deviations
Regularity and no regularity
How to Model Family Behavior

Data Sources

Ground Truth Interviews

Sensor GPS

Time

Activities

Driving State

Location

Person

Lateness

Model 2

Driver Prediction

Model 1

Ride Recognition

Destination Prediction

Model 3
How to Model Family Behavior

Frankly, it makes my little heart glad that someone with an entourage still managed to lose a child on a family day out.
Ride Recognition

- 3283 rides
- Study of co-location, co-travel, splitting off
- 90.1% precision
  (detected rides were actually rides)
- 95.5% recall
  (% of actual rides that were detected)
Predict Driver

- Use location of pickup/dropoff, day, time, distribution of drivers, last 5 drivers
- Could predict 72% after 1 week of data
- 88% with 4 weeks of training data
Forgetting a Child

- Bayesian Network
Forgetting a Child

• ROC evaluation
Other applications

• Improve family awareness
• Support advanced scheduling/planning with probabilistic calendars:
  – foregrounds travel, missing details, conflicts

• Stress prediction and management, deviation prediction from communications and movement
Prudent Sampling  (work of Jin-Hyuk Hong)

• Current/future need for mobile applications
  – Being aware of user context ALL THE TIME
  – Drawback of current mobile systems
    • Several sensors are expensive in battery usage

• Everyday behaviors and user mobility
  – Only need to activate GPS when users are moving outside
  – Cheaper sensors may predict the user context (mobility)

• Prudent sampling
  – Model and predict user context with cheaper sensors
  – Proactively manage expensive sensors based on the context
Energy Consumption of Smartphone Sensors

![Graph showing energy consumption of smartphone sensors]

- **Baseline**: Minimum energy consumption.
- **Telephony**: Energy consumption during calls.
- **Network Location**: Energy used for location services.
- **Accelerometer**: Energy used for motion detection.
- **Air Pressure**: Energy for atmospheric data collection.
- **WiFi (1min)**: Energy used for 1-minute WiFi connections.
- **Bluetooth (1min)**: Energy for 1-minute Bluetooth connections.
- **GPS**: Energy consumed during GPS navigation.

The graph compares energy consumption in **driving**, **outdoor**, and **indoor** environments.
How to Monitor Location for 24 Hours

G2 with a full charged battery 3000mAh

\[ 3000 \times 20\% = 600 \text{mAh} \]

Simply using GPS / 100mAh = 6 hours

Using user context

60

84%
How to Monitor Location for 24 Hours

G2 with a full charged battery 3000mAh

× 20% = 600mAh

Using user context

Simply using GPS

/ 100mAh = 6 hours

84%

16%

10%

3%

2%

1%

no outside move  once in 5 minutes  twice in 5 minutes  every minute  constant
GPS Sensing Optimization

• Sensing from context sensors **EXCEPT GPS**
  – Acceleration, air pressure: 10 Hz for 1 sec/minute
  – Bluetooth & Wifi access points: every minute

• Inferring mobility
  – Feature extraction & selection
  – Probabilistic modeling
  – Frequency: once every minute when GPS is off

• Managing sensors
  – If we predict/infer outside motion, turn off context sensors & turn on GPS
  – Otherwise, turn on context sensors & turn off GPS
  – Monitor speed: control GPS and context sensors
Accuracy of Mobility Prediction
## Energy Consumption

<table>
<thead>
<tr>
<th>Model</th>
<th>If 5% required</th>
<th>If 10% required</th>
<th>If 20% required</th>
<th>If 50% required</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free sensors</td>
<td>8 mAh</td>
<td>12 mAh</td>
<td>22 mAh</td>
<td>46 + 2 = 48 mAh</td>
</tr>
<tr>
<td>Free+barometer</td>
<td>9</td>
<td>13</td>
<td>23</td>
<td>49</td>
</tr>
<tr>
<td>Free + barometer + WiFi + BT</td>
<td>46</td>
<td>48</td>
<td>54</td>
<td>69</td>
</tr>
<tr>
<td>Always GPS-on</td>
<td><strong>93</strong> mAh</td>
<td><strong>93</strong> mAh</td>
<td><strong>93</strong> mAh</td>
<td><strong>93</strong> mAh</td>
</tr>
</tbody>
</table>

### Graph

The graph illustrates the energy consumption for various applications. The x-axis represents different applications such as baseline, telephony, network_location, accelerometer, air_pressure, WiFi (1min), Bluetooth (1min), and GPS. The y-axis represents the energy consumption in mAh, ranging from 0 to 120.
The Long and the Short of Mobile Device Use Sessions
(work of Nikola Banovic, Mobile HCI 2014)
study of different types of device usage sessions
<table>
<thead>
<tr>
<th>Event</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lock screen only</td>
<td></td>
</tr>
<tr>
<td>Launcher only</td>
<td></td>
</tr>
<tr>
<td>Application use</td>
<td></td>
</tr>
<tr>
<td>Incoming phone call</td>
<td></td>
</tr>
<tr>
<td>Outgoing phone call</td>
<td></td>
</tr>
</tbody>
</table>

**Key Events:**
- **lock screen**
- **in call**
- **launcher/home**
- **screen off**
- **application**
14.5% of applications used more in reviews

48.3% of applications used in both review and engage

36.6% of applications engaged with 95% of the time
Proactive Tasks
Proactive Tasks
Proactive Tasks
Track productivity
Phone resource tracking
Privacy settings
Predictive application use
Impact and Designs
Conclusions

• Despite challenges, lots of opportunities to build a truly smart phone
  • Use opportunistic sensing
  • Leverage human behavior
    • Collect data – sensing/power and privacy challenges
    • Create effective models – infrastructure challenges
    • Apply models to impact user experience – inferencing, machine learning and app challenges
• Think about what can be done with an individual’s big data
What can behavioral imaging enable?

**GPS systems** that predict where you’re going and proactively route you around traffic: (Ubicomp 2008, AAAI 2008, ICML 2010, AAMAS 2011)

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Detect **symptoms of disease** and impacts of interventions (in progress)

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Acknowledgements

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