Context-aware system for proactive personalized service based on context history
Jongyi Hong, Eui-Ho Suh, Junyoung Kim, SuYeon Kim

Recognizing and predicting context by learning from user behavior
Rene Mayrhofer, Harald Radi, Alois Ferscha

Context-Aware Implementation based on CBR for Smart Home
Tinghuai Ma, Yong-Deak Kim, Qiang Ma, Meili Tang, Weican Zhou
DOI 10.1109/WIMOB.2005.1512957
Some slides reused from last year

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CMSC818G - Spring 2013
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Context-aware system for proactive personalized service based on context history

Motivation

• Users want to receive personalized services or products based on individual preferences and their context
• Under the same context, different users may prefer different services.
• Difference based on age, gender, interests etc
Major Contribution

• **Service Personalization**
  – System to provide personalized context aware recommendations

• For the purpose of this paper, user profile is different from context
Use Case
System Framework

Data Gathering Layer

Context Management Layer

Preference Management Layer

Application Layer
Data Gathering Layer

• Raw contexts (sensor data)
  – Location, noise, temperature, light etc
• User profile
  – Age, gender, job, hobby, cost of living etc
• Selected services
  – History
Context Management Layer

• 1: Infers the current high-level context
• 2: Manages context history
• 3: Filter the dataset
Context Management Layer

• 1: Infers the current high-level context
  – Learnt from the raw context
  – Uses ML algorithms eg Bayesian networks, DTs, KNNs etc
  – Users can also define rules

(?user rdf:type Person)^(?user locatedIn ?Bed)^{(light status Off) ? (?user status Sleeping)
Context Management Layer

• 2: Manages context history
  – User profile, high-level context, service chosen
  – Hierarchical ontology
    • Common ontology
    • Domain-specific

<table>
<thead>
<tr>
<th>User ID</th>
<th>Sex</th>
<th>Age</th>
<th>High-level Context</th>
<th>Selected services (Destination)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kimji</td>
<td>M</td>
<td>25</td>
<td>Dinner</td>
<td>Family restaurant</td>
</tr>
<tr>
<td>Kang</td>
<td>F</td>
<td>20</td>
<td>Shopping</td>
<td>Department store</td>
</tr>
<tr>
<td></td>
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<td></td>
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</tbody>
</table>
Context Management Layer

• 3: Filter the dataset

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</tr>
<tr>
<td>Kange</td>
<td>F</td>
<td>20</td>
<td>Dinner</td>
<td>Chinese restaurant</td>
</tr>
</tbody>
</table>

Data Gathering Layer

Context Management Layer

Preference Management Layer

Application Layer
Preference Management Layer

• 1: Determine user preference from filtered dataset for a given context
• 2: Predict next service, based on selected service
Preference Management Layer

• 1: Determine user preference from filtered dataset for a given context
  – Learn a DT on filtered data
    • Fast
    • Easy to understand
    • Handles categorical and numerical data
    • Easily handles missing value
    • Scalable
    • Not sensitive to outliers
  – Suggest top K services
Preference Management Layer

Decision Tree for Dinner

Data Gathering Layer
Context Management Layer
Preference Management Layer
Application Layer
Preference Management Layer

- 2: Predict next service, based on selected service
  - Use association rule to extract relationship between service sequences
  - Apriori algorithm
Application Layer

- Provides recommendations and manages feedback
  - A rejected service is stored as context history
Strengths

• Does not require the user to manually enter preferences
• Can provide recommendations to new users
• Learn from behavior of other users
Weaknesses

• Feedback can be used to model user behavior
• Are repeated recommendations good?
  – Restaurants vs car service center
• Batch algorithms process the same data several times – Go online!
• HMM instead of association rules?
• Scalability
• No notion of ‘stale’ context
Recognizing and predicting context by learning from user behavior

Rene Mayrhofer, Harald Radi, Alois Ferscha
Proceedings of the International Conference on Advances in Mobile Multimedia (MoMM2003)
Why?

- “PDA” = Personal Digital Assistant
  - Today, we call these “Smartphones”
- Problem 1: User is actually assisting the device!
- Problem 2: Good human assistants are proactive, but devices are reactive!

If a “Personal Computer” or “Personal Digital Assistant” (PDA) would live up to its name, it should instead adapt to the user, offering implicit, intuitive and sometimes invisible interfaces.

In 2003, this Treo 270 was state-of-the-art! Its user manual is 257 pages long!
Example Use Cases

- I go to prayers every morning from 7:30-8:30, and every evening from 15 minutes before sunset to 20 minutes after sunset. Turn off my phone ringer during these times.

- I call my mother every other day at 8:30pm. Show me a “call mom” button.

- I turn off my phone every night because Swedish researchers say that GSM signals keep the body awake. I want my phone to figure out when I go to sleep and when I wake up.

- I get home from work every day at 6pm. Turn up the thermostat.
  - This should sound familiar...
How?

- Proactivity
  - An architecture to make PDAs proactive by predicting future user context
  - What does it mean to be proactive?

Responsive, Reactive, Proactive

- Responsive - responds to a request
- Reactive - reacts to an event
- Proactive - Anticipates and performs an action

Proactive context-aware computing
Preeti Bhargava
**What does it mean to be “proactive”?**

- System output depends on state

- **Reactive System**: Output $b_t$ at time $t$ only depends on current and implicitly on past states:
  
  $$b_t = \lambda(q_t)$$

  where $q_t = \langle q_{t-1}, a_{t-1} \rangle$ - current state based on last state and input.

- **Proactive System**: Output $b_t$ can also depend on future states:
  
  $$b_t = \lambda(\bar{q}_t, \bar{q}_{t+1}, \bar{q}_{t+2}, \ldots, \bar{q}_{t+m})$$

  where $\bar{q}$ future states are predicted based on any/all previous states.
What kind of Context?

any information that can be used to characterize the situation of an entity, where an entity can be a person, place, or a physical or computational object.

- geographical
- physical
- organizational
- social
- user
- task
- action
- technological
- time
Architecture: Overview

- Real-Time processing
- On Embedded Systems

1. Sensor Data Acquisition
   any entity that can provide measurements:
   - Physical – e.g. microphone, Wi-Fi, Bluetooth
   - “Abstract” – e.g. currently active application
   Data collected in discrete time steps

2. Feature Extraction
   Domain-specific methods; data transformed as necessary; Feature = sample as a function of time

3. Classification
   Find common patterns: “classes” or “clusters”
   “Degrees of Membership” = probability

4. Labeling
   Map class vectors to a set of names

5. Prediction
   Forecast future context from current one
Architecture: Sensors

- We don’t really care about the data itself!
  - Unlike most other sensing applications
  - So sensors don’t have to be as intrusive
    - We can’t wire your whole body to detect your context!

- Variety and Events are much more useful

- Data remains local

<table>
<thead>
<tr>
<th>Types of Sensors</th>
<th>NOW (2003)</th>
<th>FUTURE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time</td>
<td>GPS ✓</td>
</tr>
<tr>
<td></td>
<td>Microphone</td>
<td>GSM ✓</td>
</tr>
<tr>
<td></td>
<td>Brightness</td>
<td>Compass ✓</td>
</tr>
<tr>
<td></td>
<td>Bluetooth</td>
<td>Accelerometer ✓</td>
</tr>
<tr>
<td></td>
<td>Wi-Fi</td>
<td>Tilt ✓</td>
</tr>
<tr>
<td></td>
<td>(un)docked</td>
<td>Temperature ?</td>
</tr>
<tr>
<td></td>
<td>Logged in/out</td>
<td>Pressure ✓</td>
</tr>
<tr>
<td></td>
<td>Applications</td>
<td>Bio-medical ✓</td>
</tr>
</tbody>
</table>
Architecture: Feature Extraction

- Most research is in numerical feature extraction
- We need more
  - e.g. List of nearby Bluetooth devices
- Transformations are independent and feature-specific
- Two operations required:
  - Distance Metric
  - Adaptation Operator
Architecture: Classification

Requirements:

▪ Online Learning
▪ Adaptivity
▪ Variable Topology
▪ Soft Classification
▪ Noise Resistance
▪ Limited Resources
▪ Simplicity

... find similarities in and learn recurring patterns from [...] input data.

<table>
<thead>
<tr>
<th>On-line Algorithm</th>
<th>Network Topology</th>
<th>Topology preserving</th>
<th>Competitive</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOM</td>
<td>fixed</td>
<td>yes</td>
<td>soft</td>
</tr>
<tr>
<td>RSOM</td>
<td>fixed</td>
<td>yes</td>
<td>soft</td>
</tr>
<tr>
<td>K-Means</td>
<td>fixed</td>
<td>no</td>
<td>hard</td>
</tr>
<tr>
<td>Leader</td>
<td>variable</td>
<td>no</td>
<td>hard</td>
</tr>
<tr>
<td>G K-Means</td>
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<tr>
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</tr>
<tr>
<td>LLGNG</td>
<td>variable</td>
<td>no</td>
<td>hard</td>
</tr>
</tbody>
</table>
Architecture: Labeling

- Applications are unaware of “classes” and “degrees of membership”
  - Virtually impossible for them to be aware!
    - Information Overload
      - Different on each device

- Map them to more-meaningful values
  - Simple strings

- Requires user interaction
Architecture: Prediction

Predict multiple possible future contexts

Requirements:
- Unsupervised model estimation
- On-line learning
- Incremental model growing
- Confidence Estimation
- Automatic Feedback
- Manual Feedback
- Long-term vs. short-term

No specific algorithm chosen
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Why?

“Smart Home”

How smart is it?

Adapt home behavior for user activities and environment
What kind of Context?

... a collection of discrete facts and events with numeric parameters.

- Three categories
  - Environment
  - User’s Activity
  - User’s Physiological States

- Three dimensions
  - Time
  - Environment
  - Person
How?

- Case-Based Reasoning (CBR)
  - Problem resolution where little information known about key processes and their interdependencies.
Background: Smart Homes

Georgia Tech Aware Home  MIT Intelligent Room

UC Boulder Neural Net. House
Use Cases

▪ “At noon, Mr. Lee enters the living room; the room temperature is 30°C. The air conditioning will automatically turn on to lower the temperature. At the same time, the TV will turn on and tune to the news.”

▪ “At 23:00, Mrs. Park leaves the living room and enters the bedroom. The air conditioning and TV in the living room are turned off. The light in bedroom is turned on at low brightness.”

“Simple” Scenarios

Not so simple to implement!

Too many options...
CBR

- Reuses previous cases
- Stores all cases for future reference
- Case representation = Frame
- Similarity Calculations
  - Local Similarity a.k.a Attribute Similarity
  - Table Similarity
  - Global Similarity

Fig. 1. Representation of context in frame form
CBR

- “Solution Adaptation”
- Best Match = First Nearest Neighbor of current case
  - Good for boolean choices like On/Off
  - Need K-Nearest Neighbors for variable choices like temperature
    - Chose K=5 or K=10. Why???

- “Similar Problems have Similar Solutions”
  - Find closest solution in previous cases and adapt as necessary

- No way to mark or modify incorrect solutions!
  - Can only move forward with new ones