Learning from Context (I)

Moshe Katz
CMSC818G
Spring 2014

Bibliography

- Context-aware system for proactive personalized service based on context history
  Jongyi Hong, Eui-Ho Suh, Junyoung Kim, SuYeon Kim
  DOI 10.1016/j.eswa.2008.09.002
- 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

By: Snigdha Chaturvedi
CMSC818G - Spring 2013
University of Maryland, College Park

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

Jongyi Hong, Eui-Ho Suh, Junyoung Kim, and SuYeon Kim. 2009. Context-aware system for proactive personalized service based on context history. Expert Syst. Appl. 36, 4 (May 2009), 7448-7457. DOI=10.1016/j.eswa.2008.09.002 http://dx.doi.org/10.1016/j.eswa.2008.09.002

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

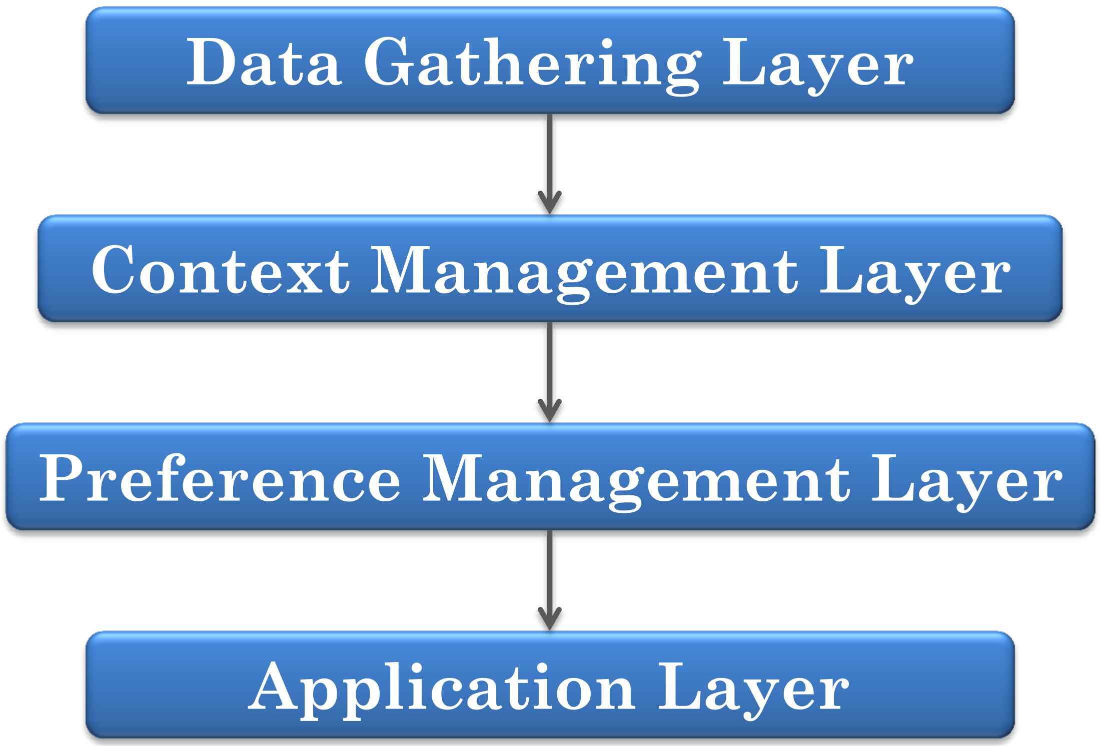
- Service Personalization
  - System to provide personalized context aware recommendations

- For the purpose of this paper, user profile is different from context

Use Case

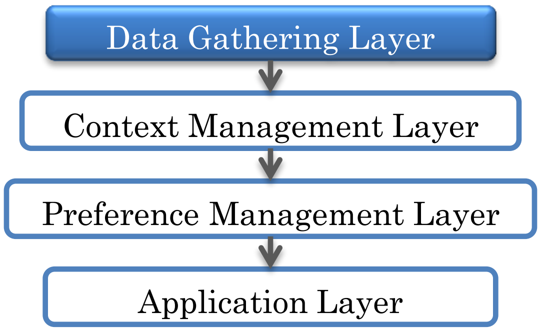
Internet Explorer
http://141.223.115.9/pms2/login.a
Preference Mining System
ID :
user1
Password :
Login
iPAQ
Internet Explorer
http://141.223.115.9/pms2/view.a
Next Destination
- shop2
- shop3
Navigation
Navigation
iPAQ
Internet Explorer
http://141.223.115.9/pms2/view.a
Navigation : shop2
Next Destination
iPAQ
Internet Explorer
http://141.223.115.9/pms2/view.a
Next Destination
- shop7
- shop6
Navigation
Navigation
iPAQ

System Framework



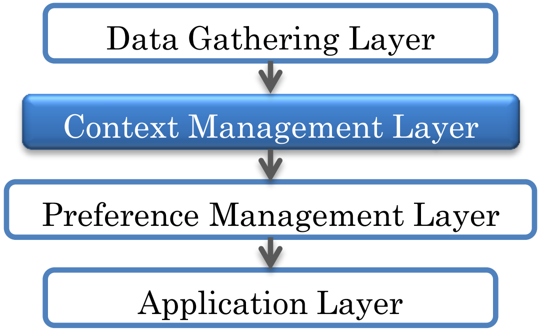
Data Gathering Layer

- 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

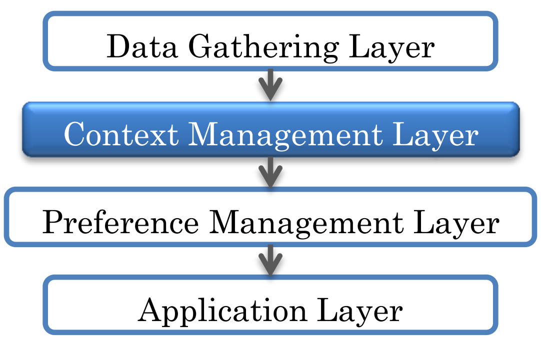
- 1: Infers the current high-level context
- 2: Manages context history
- 3: Filter the dataset



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

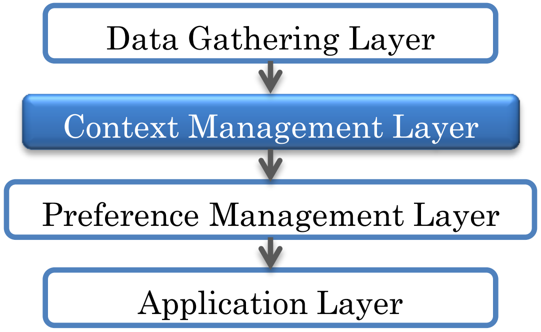
(?user rdf:type Person)^(?user locatedIn ?Bed)^(light status Off) ?
(?user status Sleeping)



Context Management Layer

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

User ID	Sex	Age	•••	High-level Context	Selected services (Destination)
Kimjy	M	25	•••	Dinner	Family restaurant
Kange	F	20	•••	Shopping	Department store
•••	•••	•••	•••	•••	•••

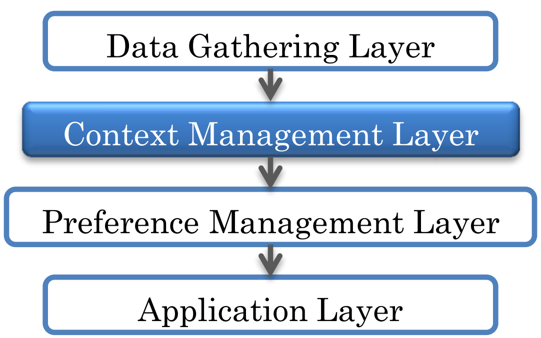


Context Management Layer

- 3: Filter the dataset

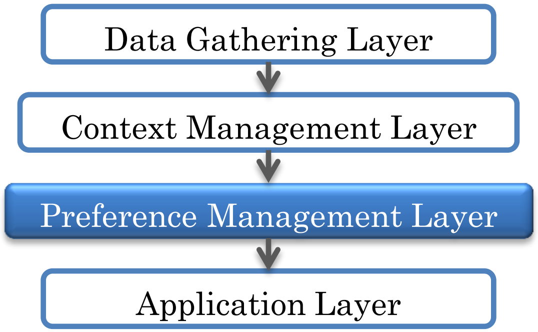
Filtered data set (Context: dinner)

User ID	Sex	Age	●●●	High-level Context	Selected services (Destination)
Kimjy	M	25	●●●	Dinner	Family restaurant
Kange	F	20	●●●	Dinner	Chinese restaurant
●●●	●●●	●●●	●●●	Dinner	●●●



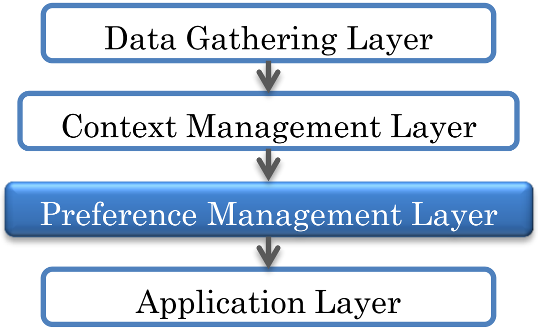
Preference Management Layer

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

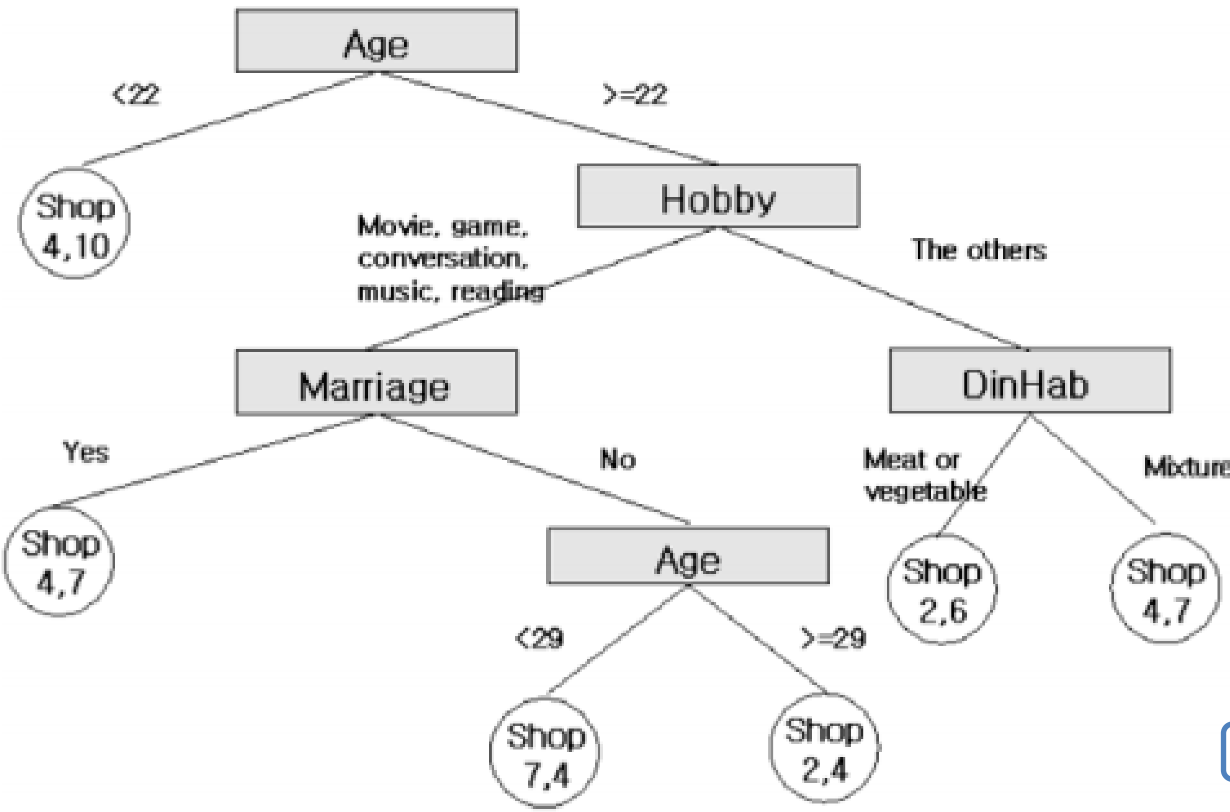


Preference Management Layer

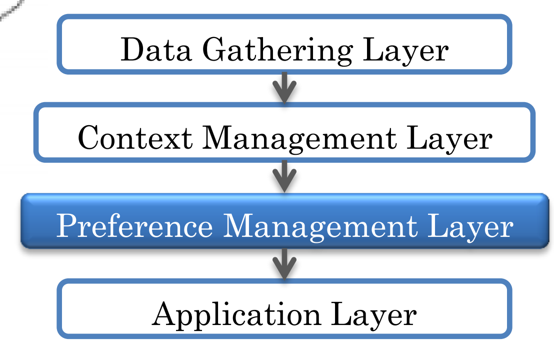
- 1: Determine user preference from filtered dataset for a given context
  - Learn a DT on filtered data
    - Fast
    - Easy to understand
    - Handles categorical and numerical data
    - Easily handles missing value
    - Scalable
    - Not sensitive to outliers
  - Suggest top K services



Preference Management Layer



Decision Tree for Dinner

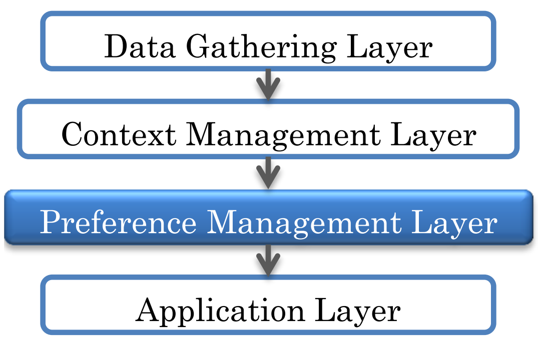


Preference Management Layer

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

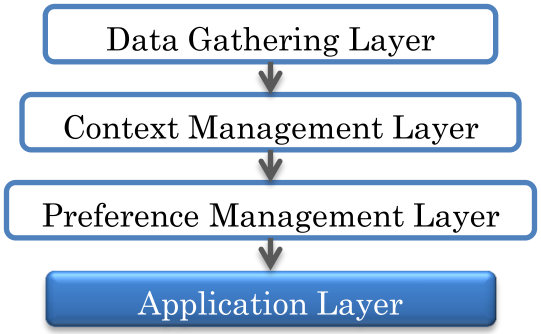
Association rule (Context: dinner)

Rule ID	Rule	Support	Confidence
R1	Chinese restaurant → Beverage store	11.0	41.0
R2	Snack bar → Ice-cream store	10.0	30.0
•••	•••	•••	•••



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!

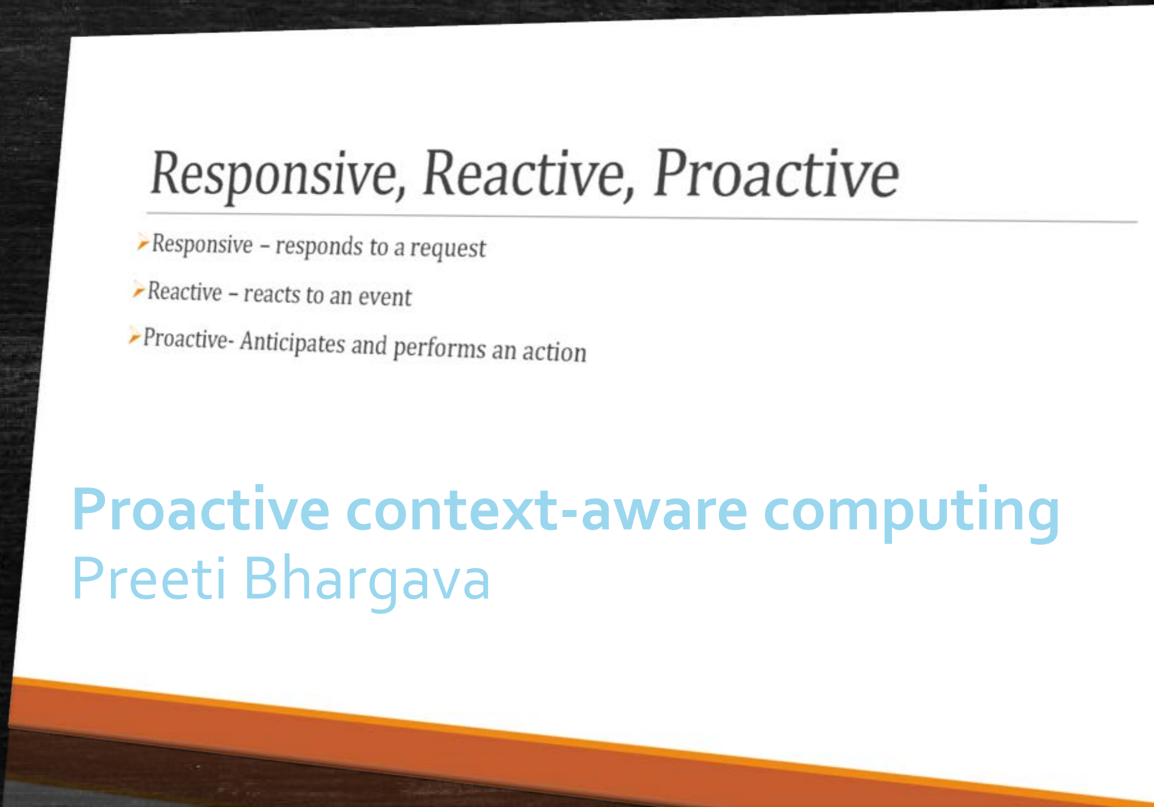
Its user manual is 257 pages long!

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 [illegible] at.
  - This should sound familiar…

How?

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



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:

$$b_t = \lambda\langle \bar{q}_t, \bar{q}_{t+1,} \bar{q}_{t+2,} \dots, \bar{q}_{t+m} \rangle$$

  where $\bar{q}$ future states are predicted based on any/all previous states.

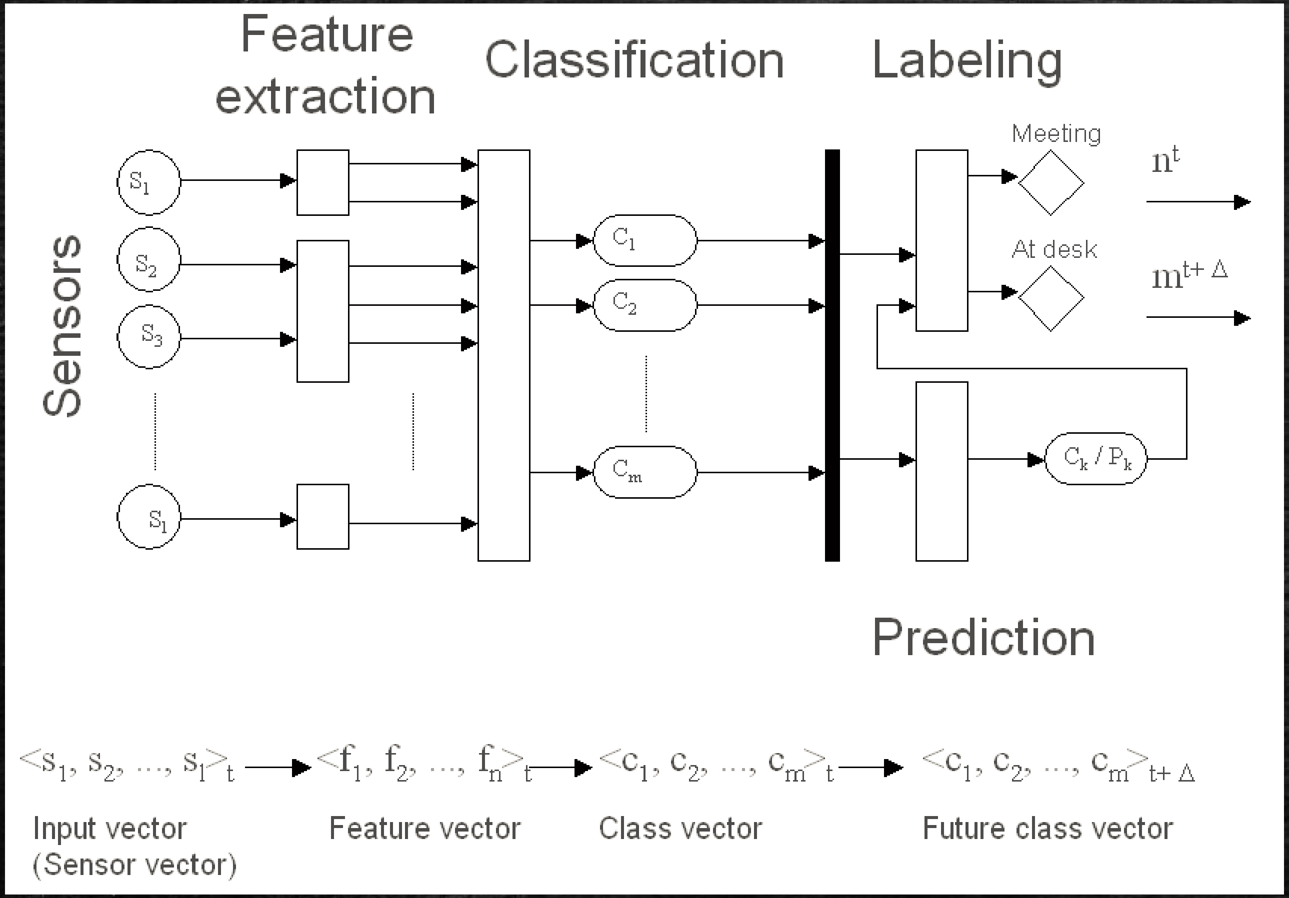
What kind of Context?

> 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 ”

- Can include:
  - 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

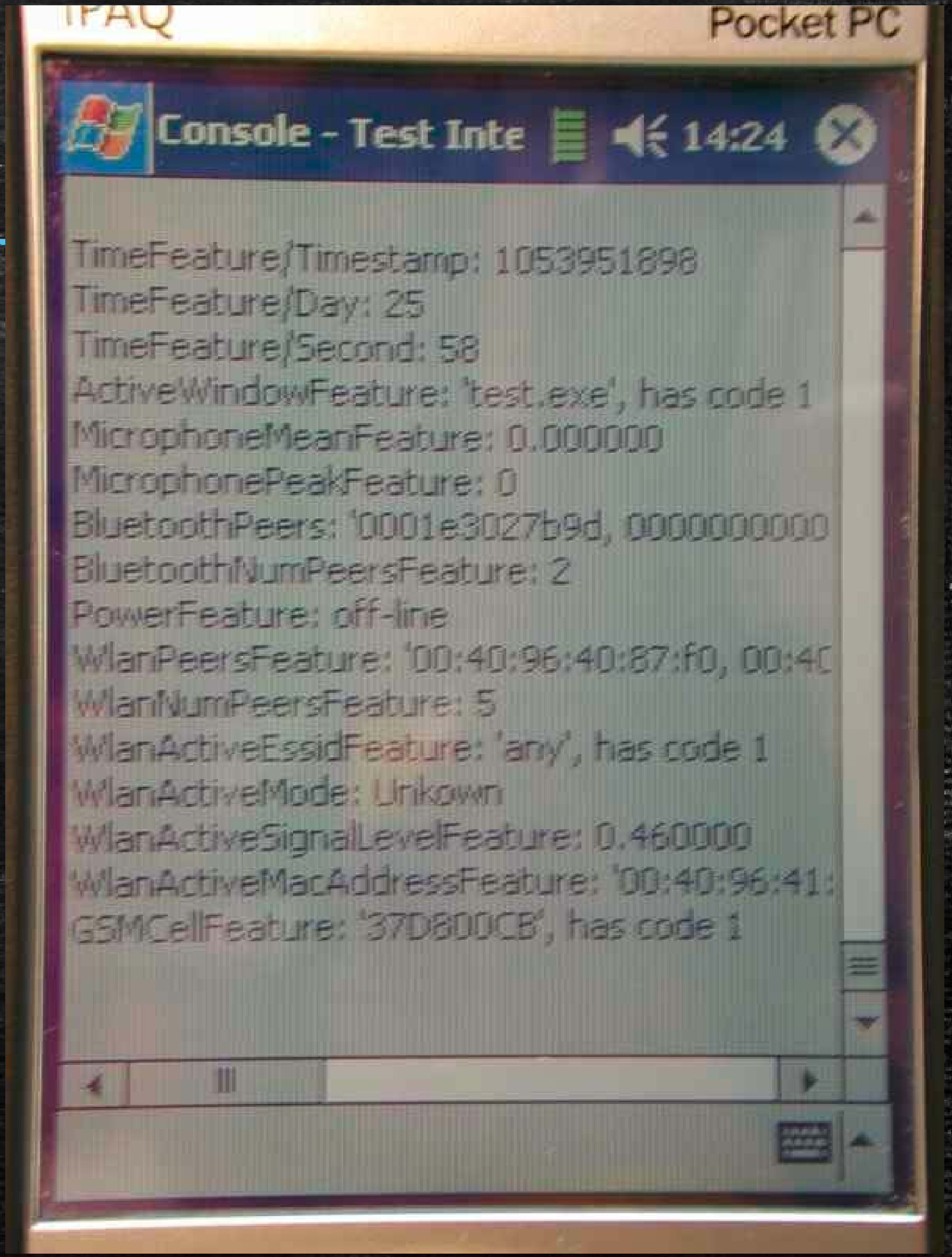
- We don't really care about the data itself!
  - Unlike most other sensing applications
  - So sensors don't have to be as intrusive
    - We can't wire your whole body to detect your context!
- Variety and Events are much more useful
- **Data remains local**

Types of Sensors

NOW (2003)	**FUTURE**
Time	GPS ✓
Microphone	GSM ✓
Brightness	Compass ✓
Bluetooth	Accelerometer ✓
Wi-Fi	Tilt ✓
(un)docked	Temperature **?**
Logged in/out	Pressure ✓
Applications	Bio-medical ✓

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. ”

On-line Algorithm	Network Topology	Topology preserving	Competitive
SOM	fixed	yes	soft
RSOM	fixed	yes	soft
K-Means	fixed	no	hard
Leader	variable	no	hard
G K-Means	variable	no	hard
Neural Gas	variable	no	soft
NG+CHL	variable	yes	soft
GNG	variable	yes	soft
DBSCAN	variable	no	hard

LLGNG

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

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

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.

TABLE 1
CONTEXT CATEGORIES AND ENTITIES IN SMART HOME

Time	time	second/Minute/Hour/Day/Week/Month/Season
	Time sequences	Event occurring Sequence
Environment	location	Bedroom/Bathroom/Kitchen/Dining room/Living room
	status	Leaving/Staying/Entering
	temperature	Environment's temperature
Person	ID	Person's ID
	Profile	Name/Gender/Age
	Habit	Sports/News/Warm/…

- 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

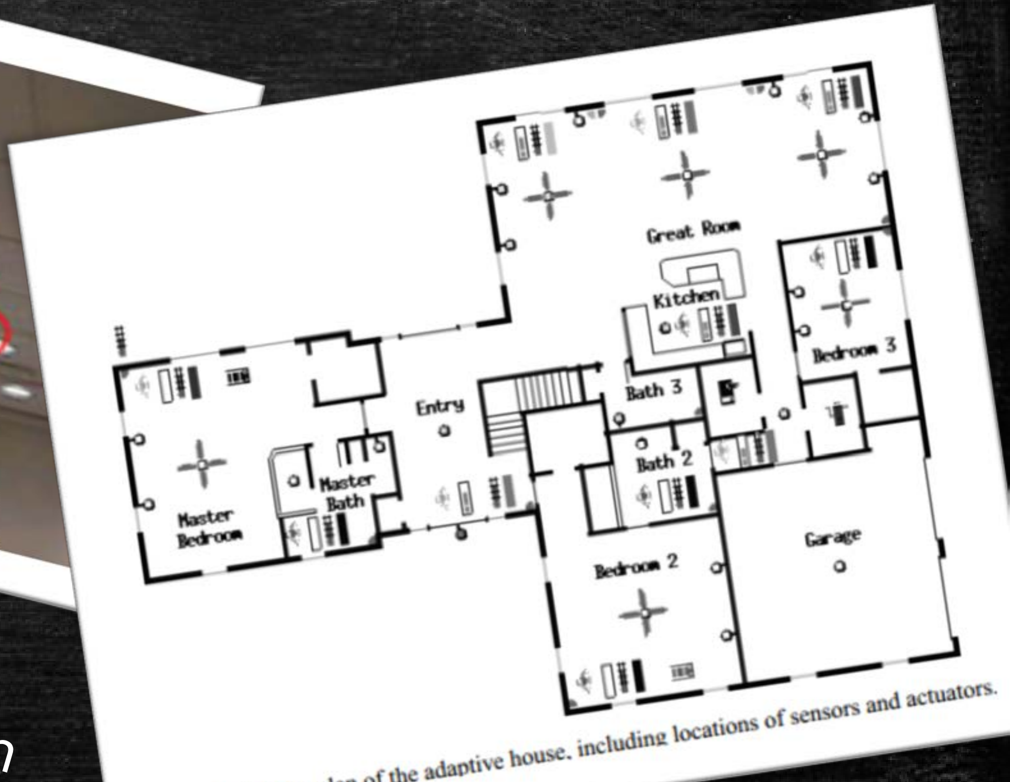


Figure 2. A floor plan of the adaptive house, including locations of sensors and actuators.

UC Boulder Neural Net. House

Use Cases

- "At noon, Mr. Lee enters the living room; the room temperature is 30C. 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

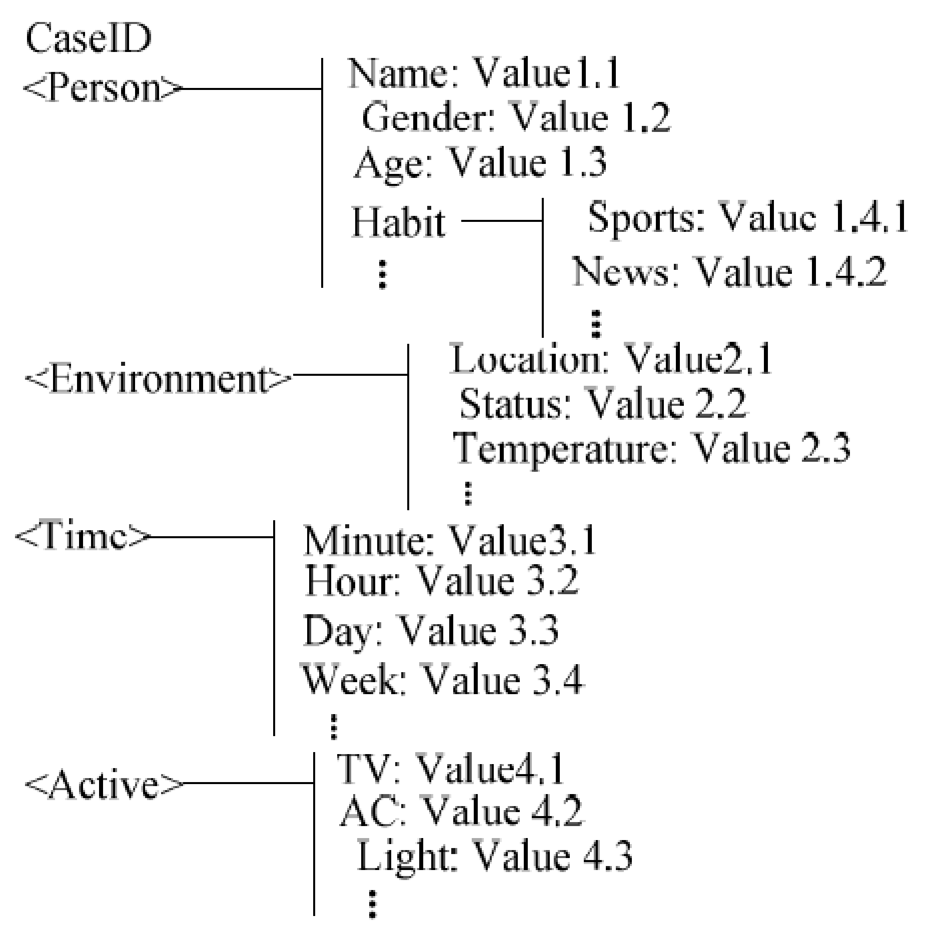


Fig. 1. Representation of context in frame form

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