Introduction to Human-centric Mobile Computing

Minho Shin
A graduate course in Fall, 2012
Computer Engineering Dept.
Myongji University

Course Information (1)

- Instructor
  - ***Minho Shin*** *(call by name!)*
  - Room 5742, 5th Engineering Bldg.
  - Phone: 031-330-6786
  - Email: shinminho@gmail.com
  - Office Hour: appointment by email
  - Research Domain
    - Wireless Networks and Mobile Computing

Course Information (2)

- Goal
  - Introduce research topics in Human-centric Mobile Computing
  - In particular, *mobile privacy*
  - Improve communication skill (in English)
  - Train with developing research idea

Course Information (3)

- Lectures
  - Introduction to the class
  - Introduction to topics
  - Misc: paper reading, presentation
- Presentation
  - Each student picks 3 papers and present 3 times
    - Each presentation takes 20~30 min.
  - Three student brings a non-obvious question
    - Discussion takes 20 min.
  - Another student becomes a note-taker
    - Upload the meeting note to Wiki

Course Information (4)

- Evaluation
  - Involvement: 20%
  - Presentation: 20% x 3
  - Note-taking: 20%
- Peer evaluation
  - Students evaluate other students

Presentation Structure

- Examples structure
  - Motivation
  - Problem
  - Existing solution
  - Approach & Solution
  - Evaluation
  - Contribution
  - Limitation
  - Suggestions or future work

Presentation Evaluation

- Presentation skill
  - Talk & slides *understandable*?
- In-depth understanding of the selected paper
  - Technical correctness
  - Knowledge on the topic: Q&A
  - Evaluation of the paper: pros/cons, future direction

Any question?

VIDEO

Human-centric Mobile Computing

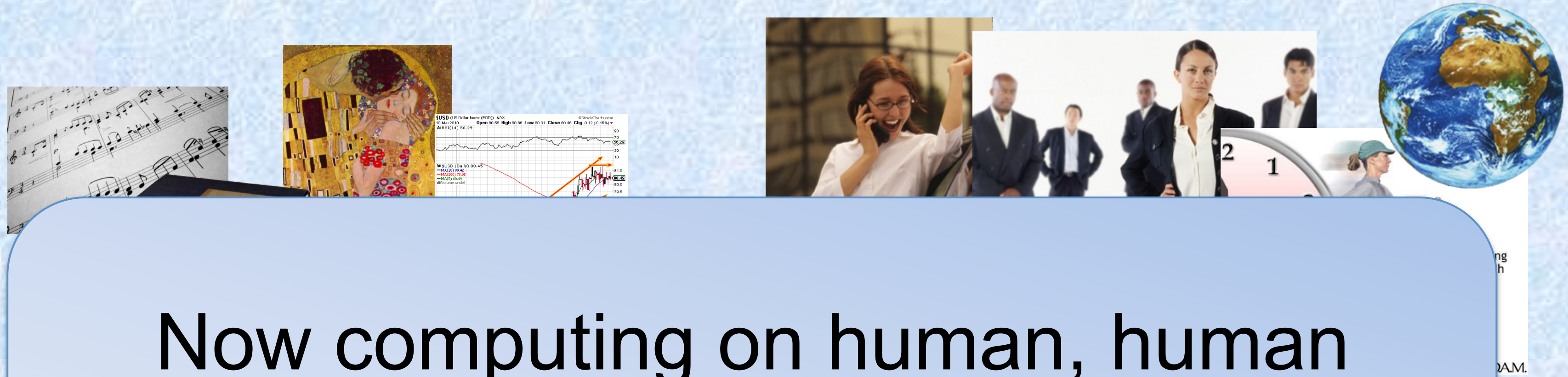
- Definition:
  - A form of computing where a computer is carried by a human, interacting with the human, maintaining network connectivity
- Example:
  - Notebook, Netbook, Tablet, PDA, Smartphone,…
- Evolution of Computing
  - Mainframe → Desktop → (HMC?) → Ubiquitous

Why Mobile?

Opportunities of HMC

- All-the-time computing
- Human behavior monitoring
- Personal assistant
- Wide-scale sensing
- Medical applications
- and….

What is Mobile Computing ?



Now computing on human, human society, human environment, health, and human life.

Challenges of HMC

- Networking with Mobility
- Energy-saving
- Privacy-risk
- Security
- Understanding human life (Semantics)
- Sensing
- Interface

Roadmap

- Areas of interest in Mobile Computing
  - Mobility-aware networking
  - Mobile sensing
  - Situation recognition
  - Context-aware Intelligence
  - Security & Privacy
  - App: Remote Health Monitoring, Traffic Monitoring

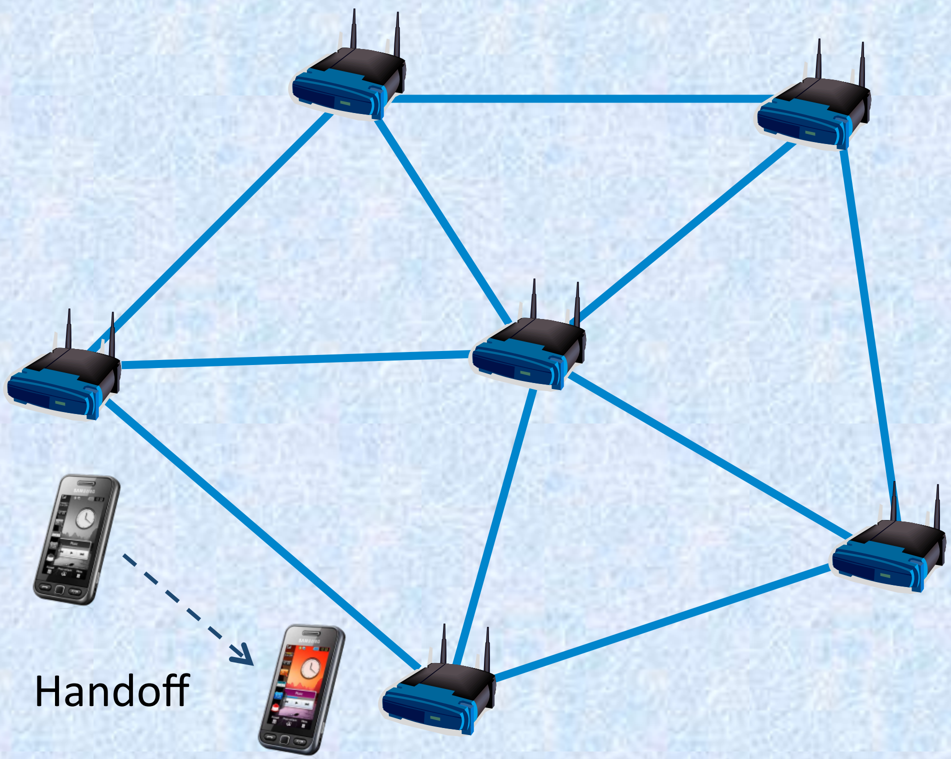
Any question?

Mobility-aware Networking

- Research question:
  - *How to provide always-on network connectivity to mobile devices?*
- *Cellular network provides low-bandwidth always-on network connectivity, already*
- *High-bandwidth networking*
  - *Wi-Fi handoff*
- *Inter-networking*
- *Traditional MANET issues*

Fast Hand-off in WiFi

- Want to move from one AP to another
- And make it fast!
- Better story-telling:
  - Why?
  - Do exactly what?
  - Is it hard?
  - Did others do?
  - How would you do?
  - How do you eval?

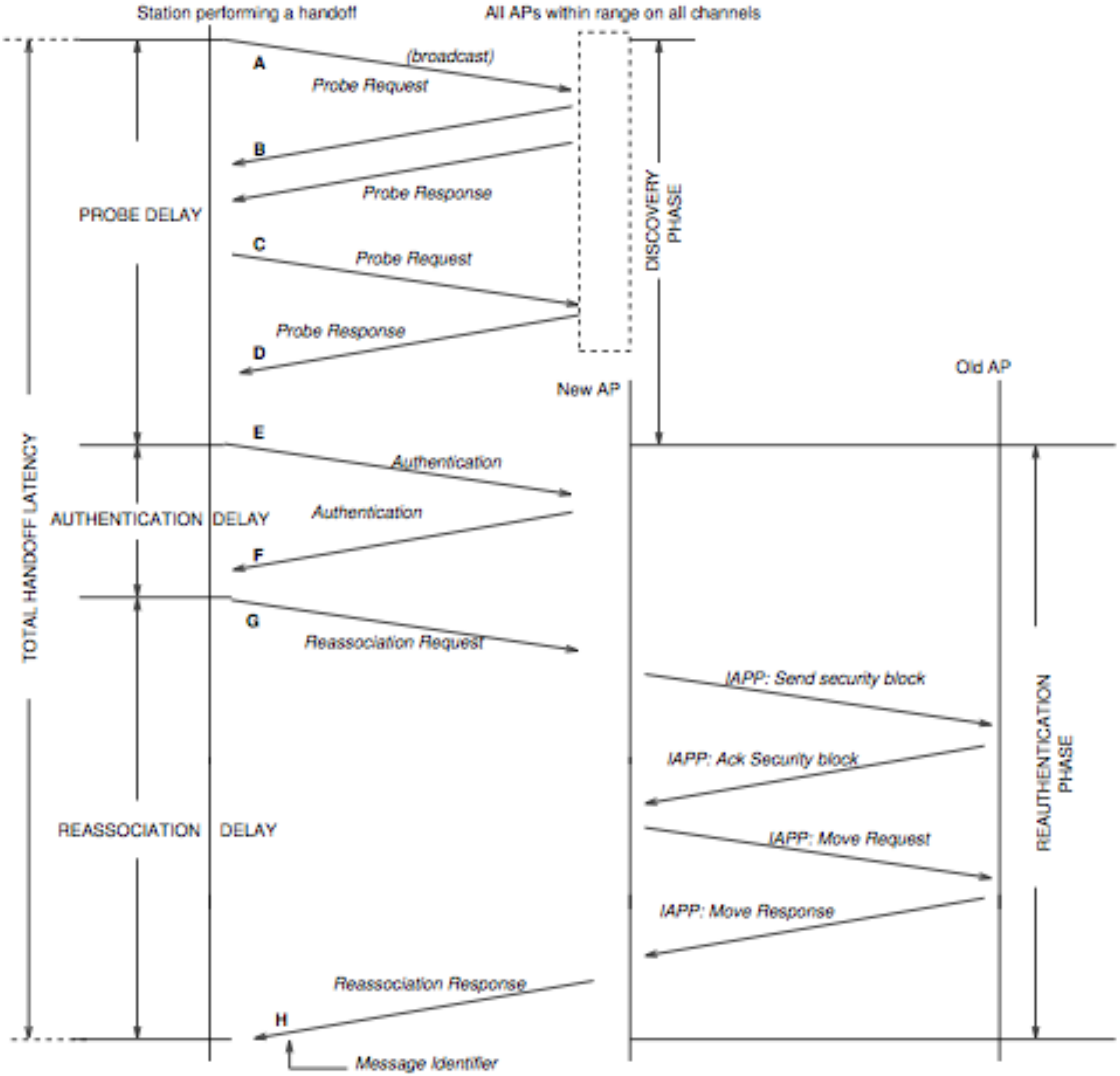


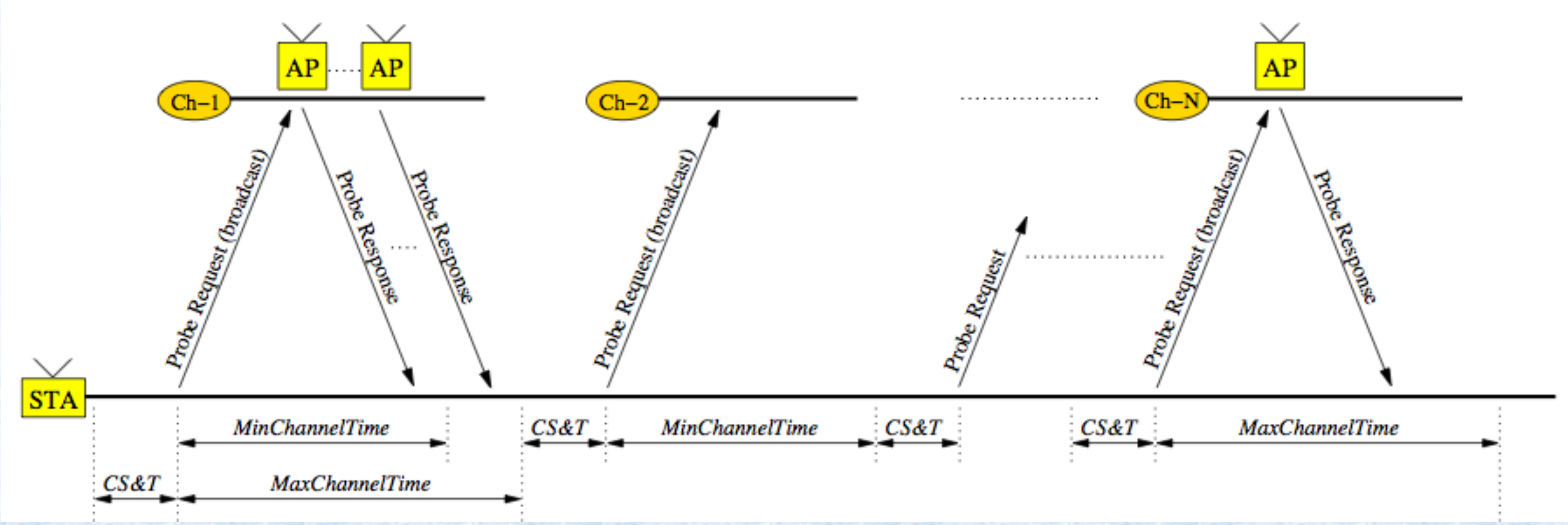
Fast Hand-off in WiFi

- Motivation (Why?)
  - Increasing mobility, Increasing bandwidth demand, Increasing security demand, …
  - But, Handoff is slow (=handoff latency is large)
- Goal/Objective/Problem def. (Do what?)
  - Provide seamless connectivity during mobility beyond one AP
  - Minimize handoff latency down to x ms to support VoIP/Video streaming apps

Fast Hand-off in WiFi

- Challenges (Why is it hard?)
  - Need to complete necessary handoff procedures
  - Handoff = (Detection) + Scanning + Association + Security + Vertical handoff
    - (Detection: when to handoff)
    - Scanning (probe): find best AP, slow, O(#ch, #Aps)
    - Association: quick
    - Security: Auth & Key Exchange, Auth server, slow
    - Vertical handoff: Network-layer (IP assign), slow


Station performing a handoff
All APs within range on all channels
A
(broadcast)
Probe Request
B
Probe Response
C
Probe Request
Probe Response
D
DISCOVERY PHASE
PROBE DELAY
New AP
Old AP
E
Authentication
Authentication
F
AUTHENTICATION DELAY
TOTAL HANDOFF LATENCY
G
Reassociation Request
IAPP: Send security block
IAPP: Ack Security block
IAPP: Move Request
IAPP: Move Response
REASSOCIATION DELAY
REAUTHENTICATION PHASE
Reassociation Response
H
Message Identifier

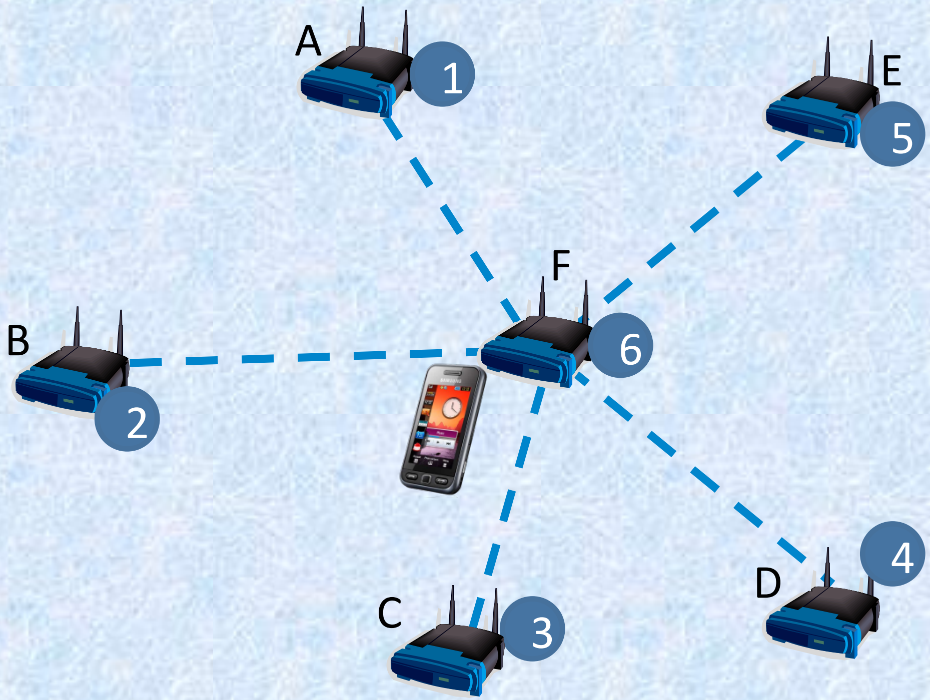

AP
AP
AP
Ch−1
Ch−2
Ch−N
Probe Request (broadcast)
Probe Response
Probe Response
Probe Request (broadcast)
Probe Request
Probe Request (broadcast)
Probe Response
STA
MinChannelTime
CS&T
MinChannelTime
CS&T
CS&T
MaxChannelTime
CS&T
MaxChannelTime

Fast Handoff in WiFi

- Related work (scanning)
  - Optimize Min/MaxChannelTime
  - Selected Scanning (Channel Masking)
  - Neighbor Graph (NG-pruning)
  - Collaboration with APs (SyncScan)
  - Multi-radio scanning (MultiScan)

Fast Scanning with NG-pruning

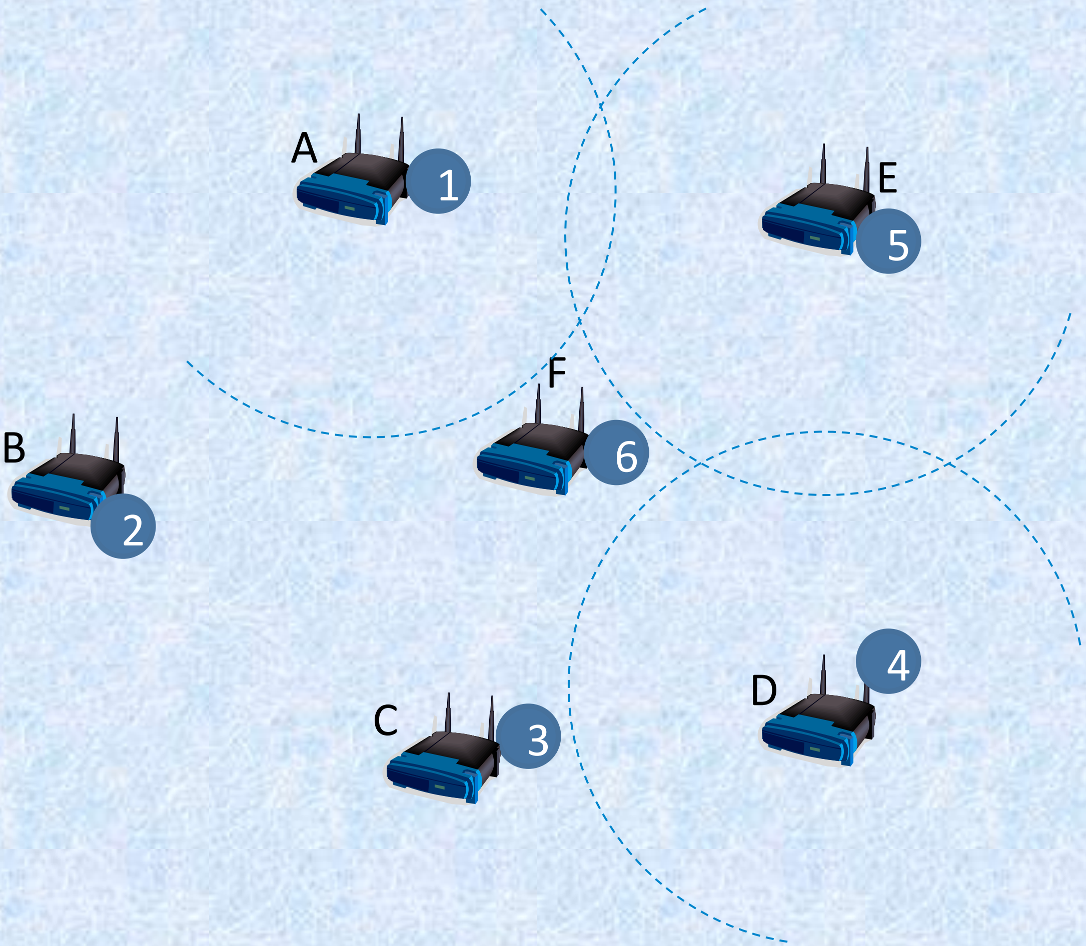
- Minimize # of channels to scan w/ NG & NOG



Neighbor Graph

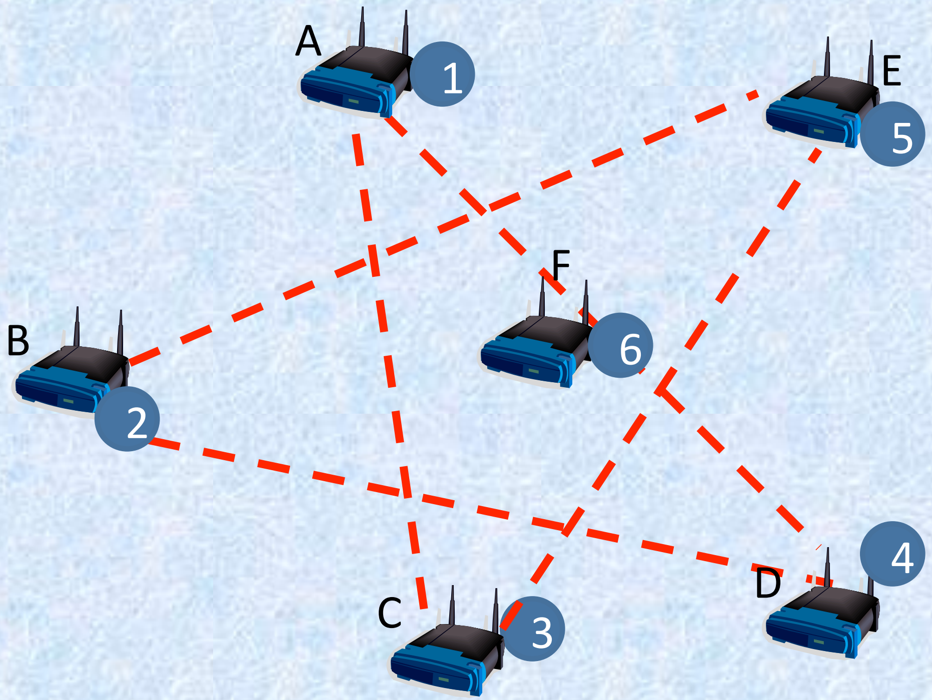
Fast Scanning with ng-pruning

- Minimize # of channels to scan w/ NG & NOG



Fast Scanning with ng-pruning

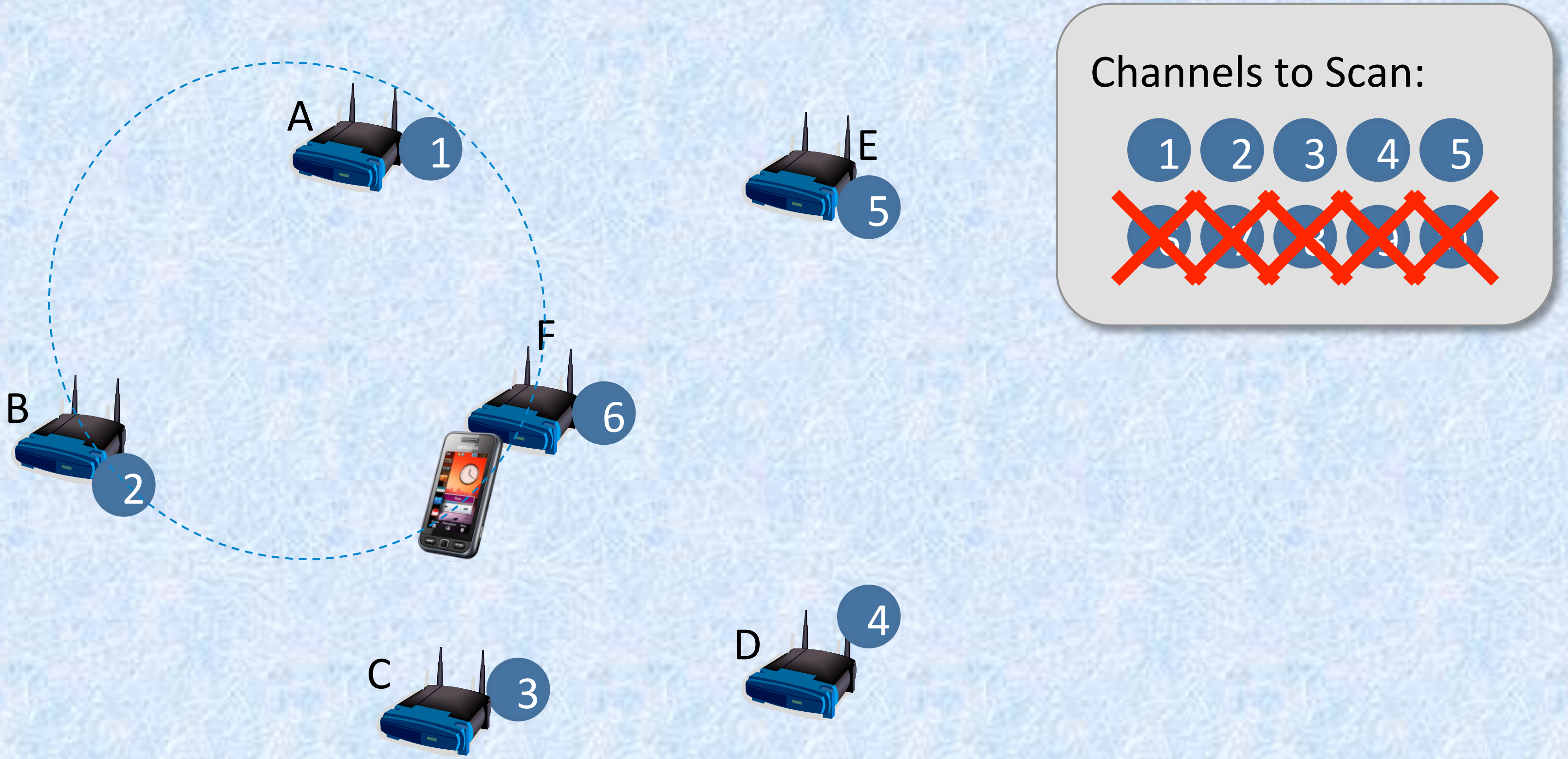
- Minimize # of channels to scan w/ NG & NOG



Non-Overlap Graph

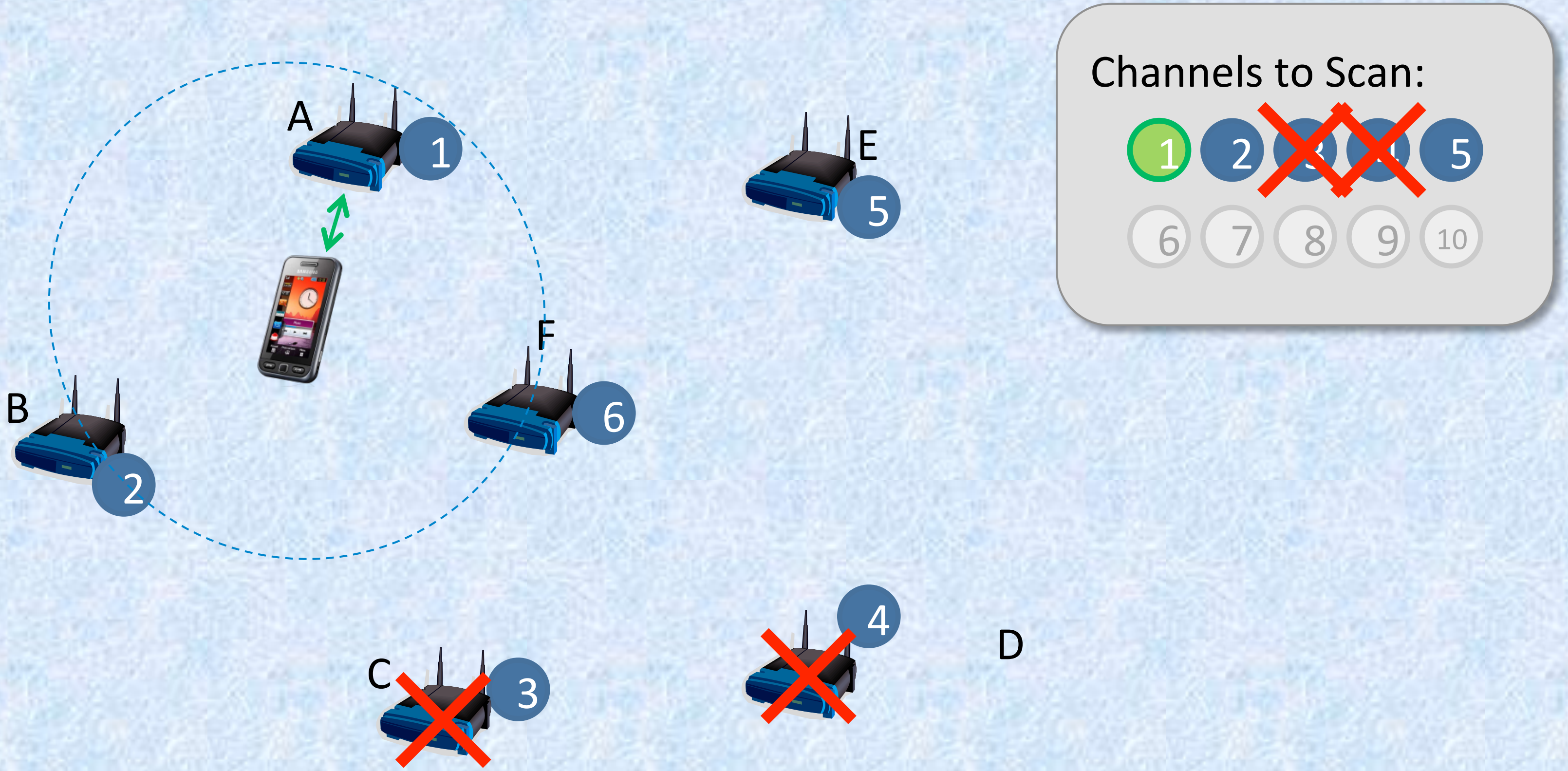
Fast Scanning with ng-pruning

- Minimize # of channels to scan w/ NG & NOG



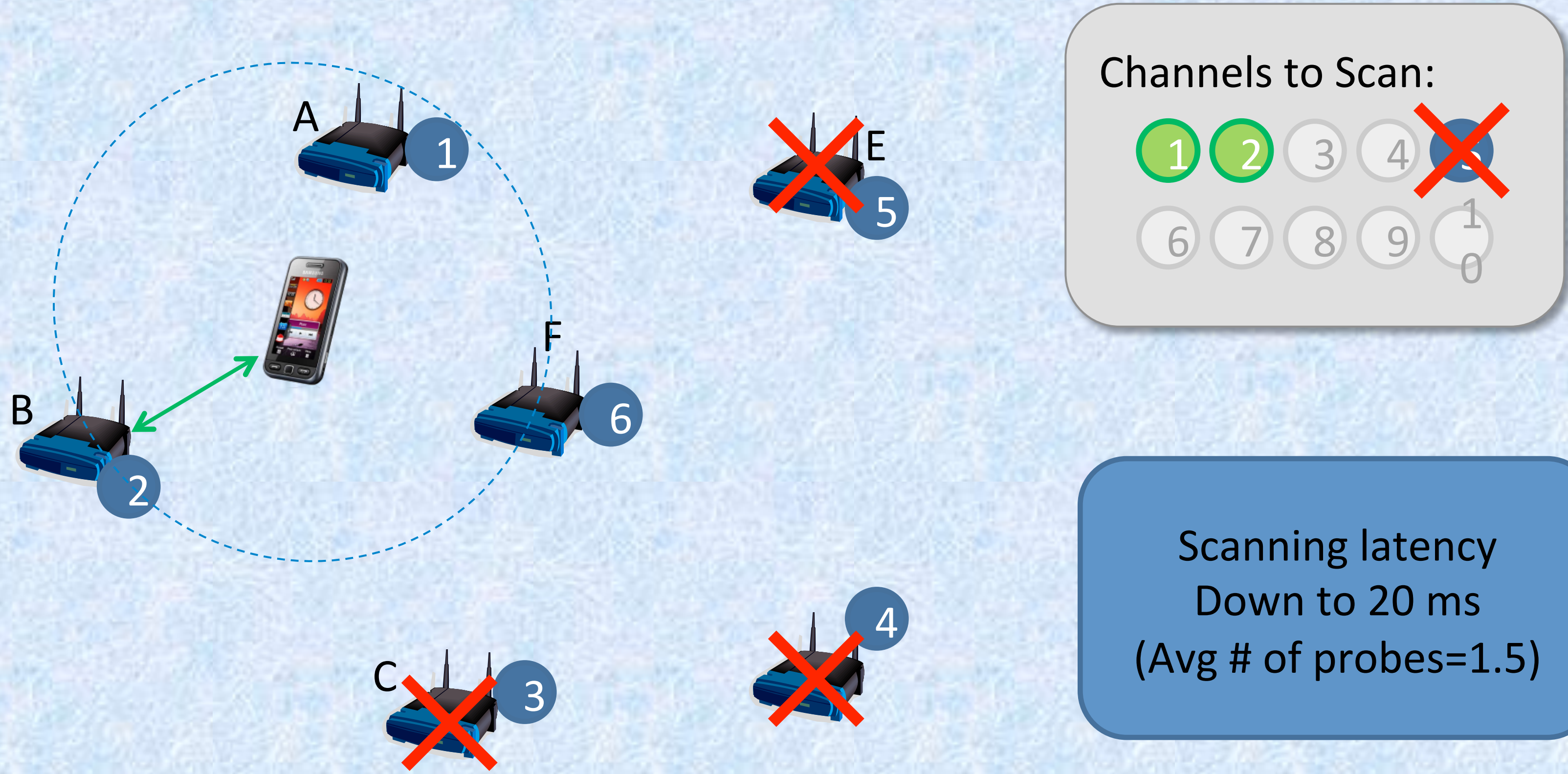
Fast Scanning with ng-pruning

- Minimize # of channels to scan w/ NG & NOG



Fast Scanning with ng-pruning

- Minimize # of channels to scan w/ NG & NOG



Scanning latency
Down to 20 ms
(Avg # of probes=1.5)

Fast Handoff in WiFi

- Remaining topics
  - Fast AKE in WiFi handoff
  - Fast vertical handoff
  - Fast inter-network handoff

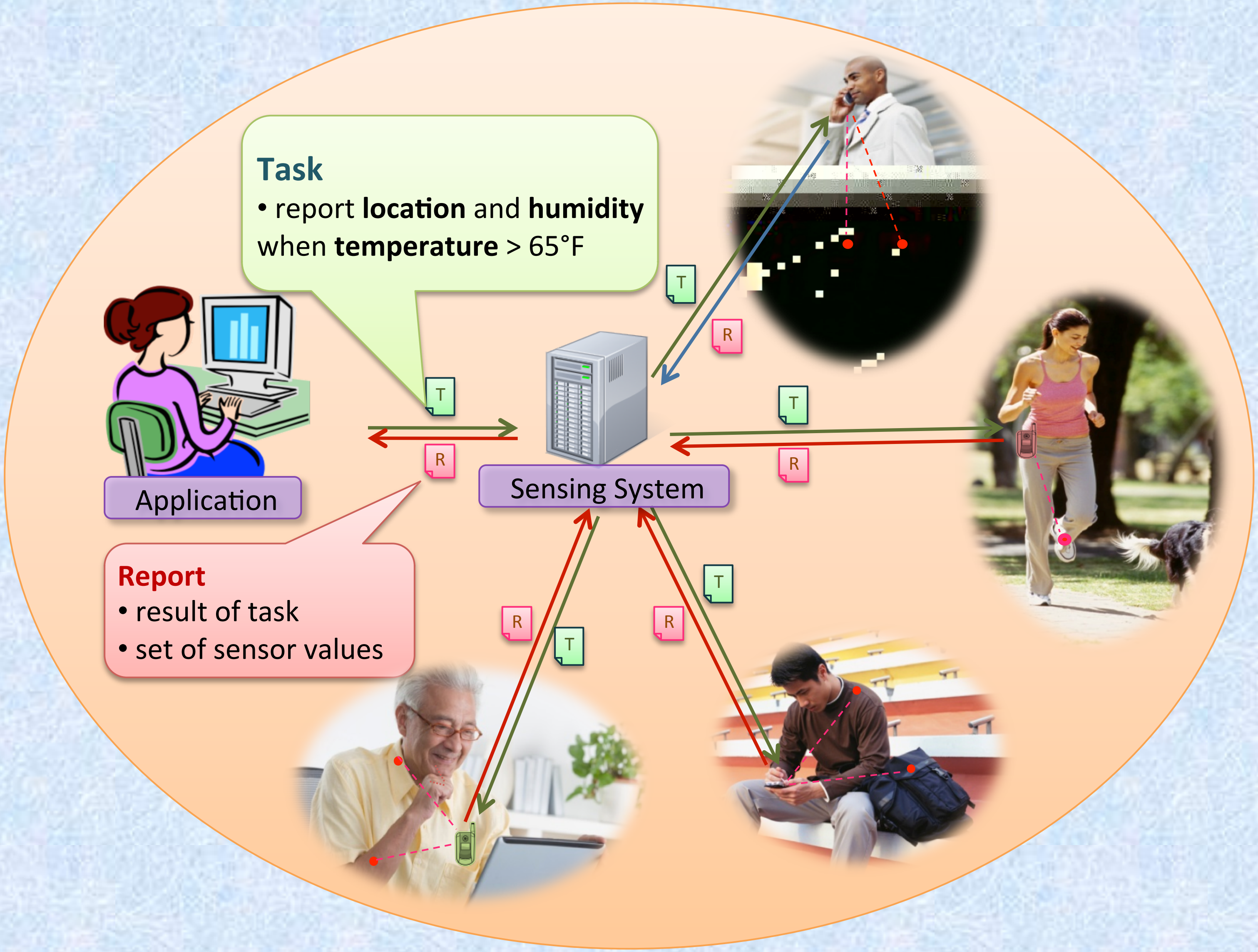
People-centric Sensing

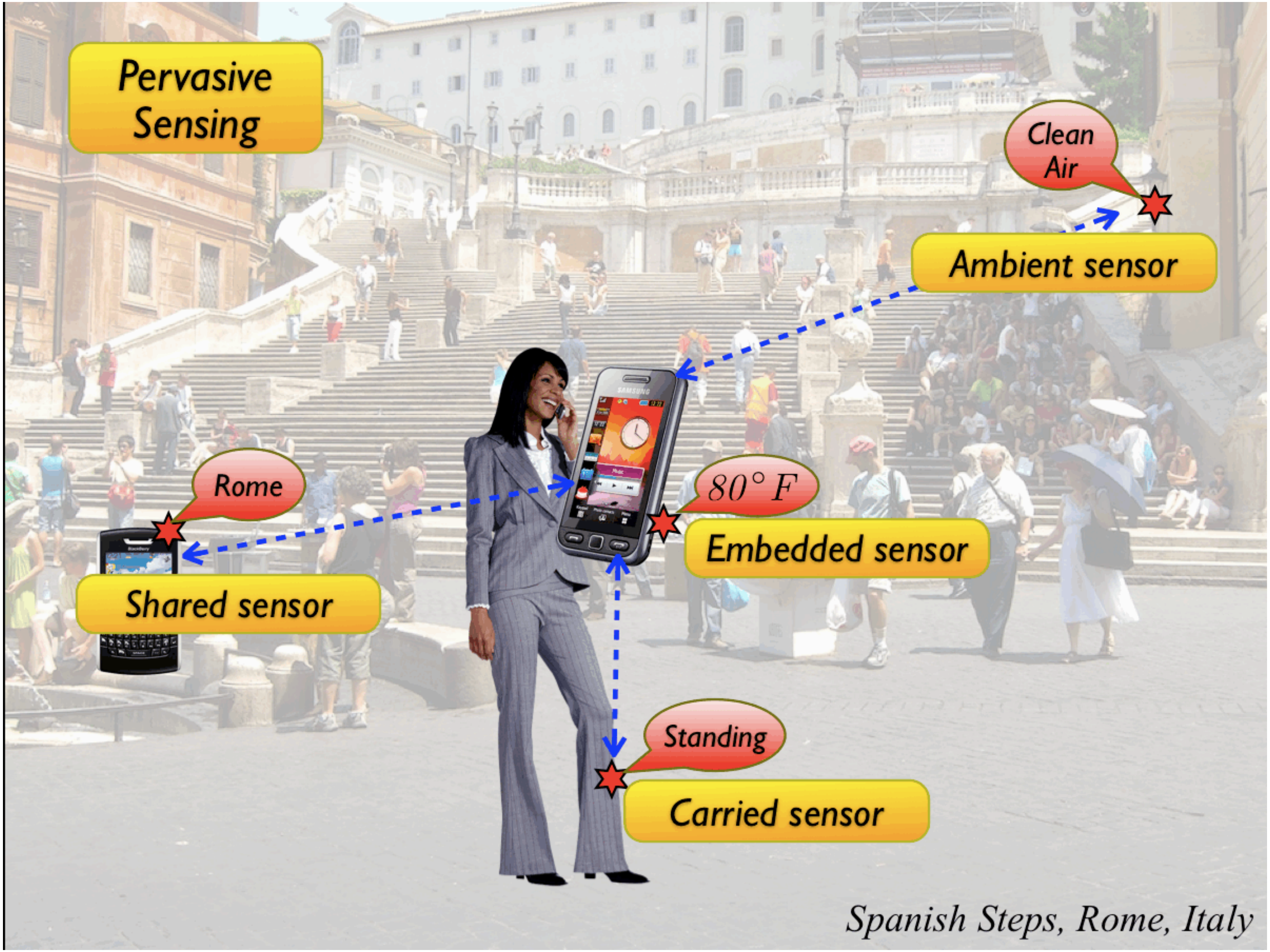
- Leverage human-carried devices for sensing
- Large-scale wide-area sensing
  - Task-based sensing
- Ambient sensing (pervasive)
  - Context-aware services
- Medical/Health sensing
  - Chronic disease
  - Emergency management
  - Lifestyle management

People-centric Sensing

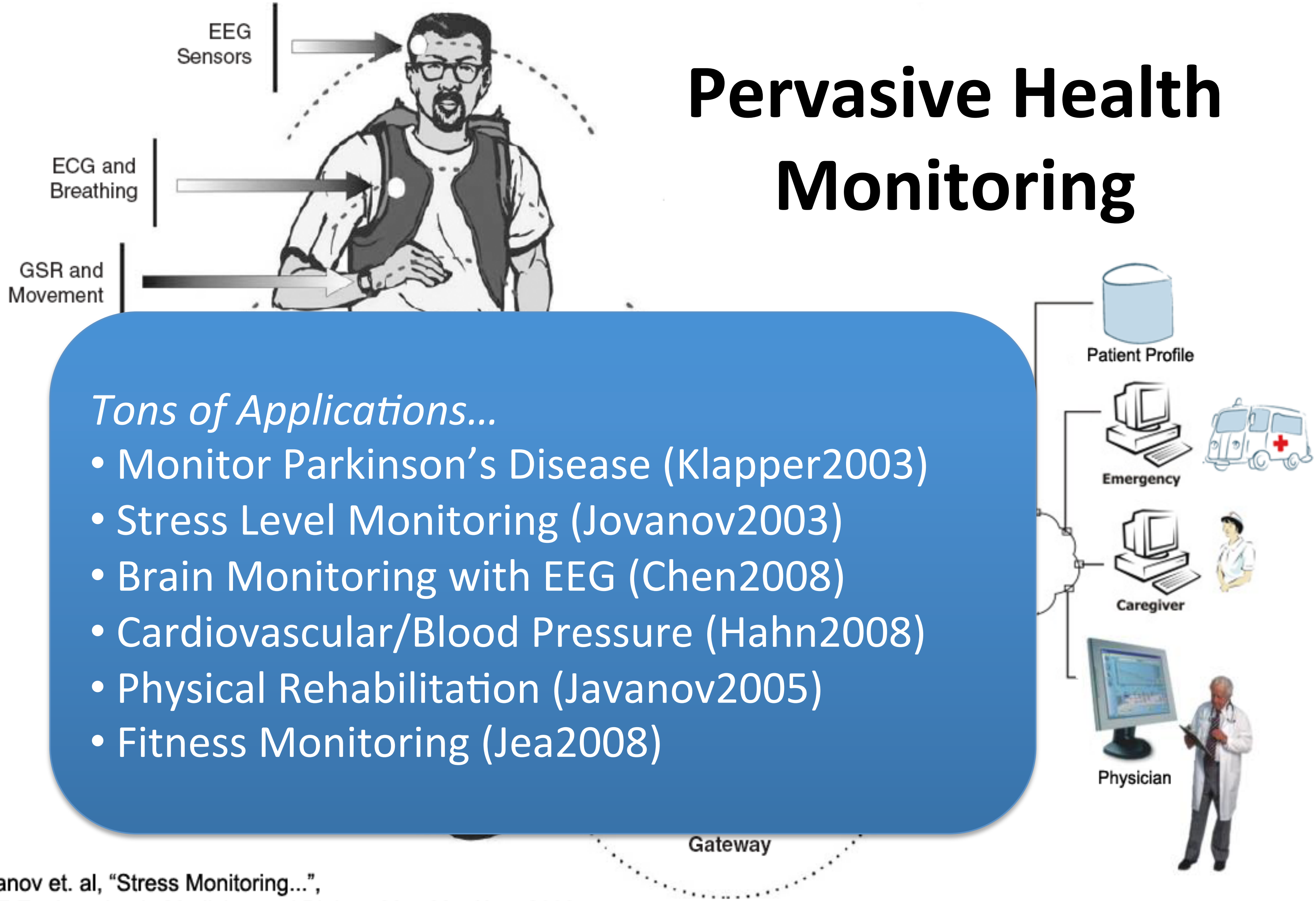
- Large-scale wide-area sensing
  - How to monitor environmental/human/social phenomena in an efficient, correct, and secure way?
  - Examples:
    - CarTel
    - Mobiscopes
    - SenseWeb
    - Urbannet
    - Metrosense
    - Millennium Project

Large-scale Task-based Sensing




Pervasive Sensing
Clean Air
Ambient sensor
Rome
80° F
Embedded sensor
Shared sensor
Standing
Carried sensor
Spanish Steps, Rome, Italy

Pervasive Health Monitoring



Tons of Applications…

- Monitor Parkinson's Disease (Klapper2003)
- Stress Level Monitoring (Jovanov2003)
- Brain Monitoring with EEG (Chen2008)
- Cardiovascular/Blood Pressure (Hahn2008)
- Physical Rehabilitation (Javanov2005)
- Fitness Monitoring (Jea2008)

Jovanov et. al, "Stress Monitoring...",
IEEE Engineering in Medicine and Biology Mag.May/June2003

Challenges

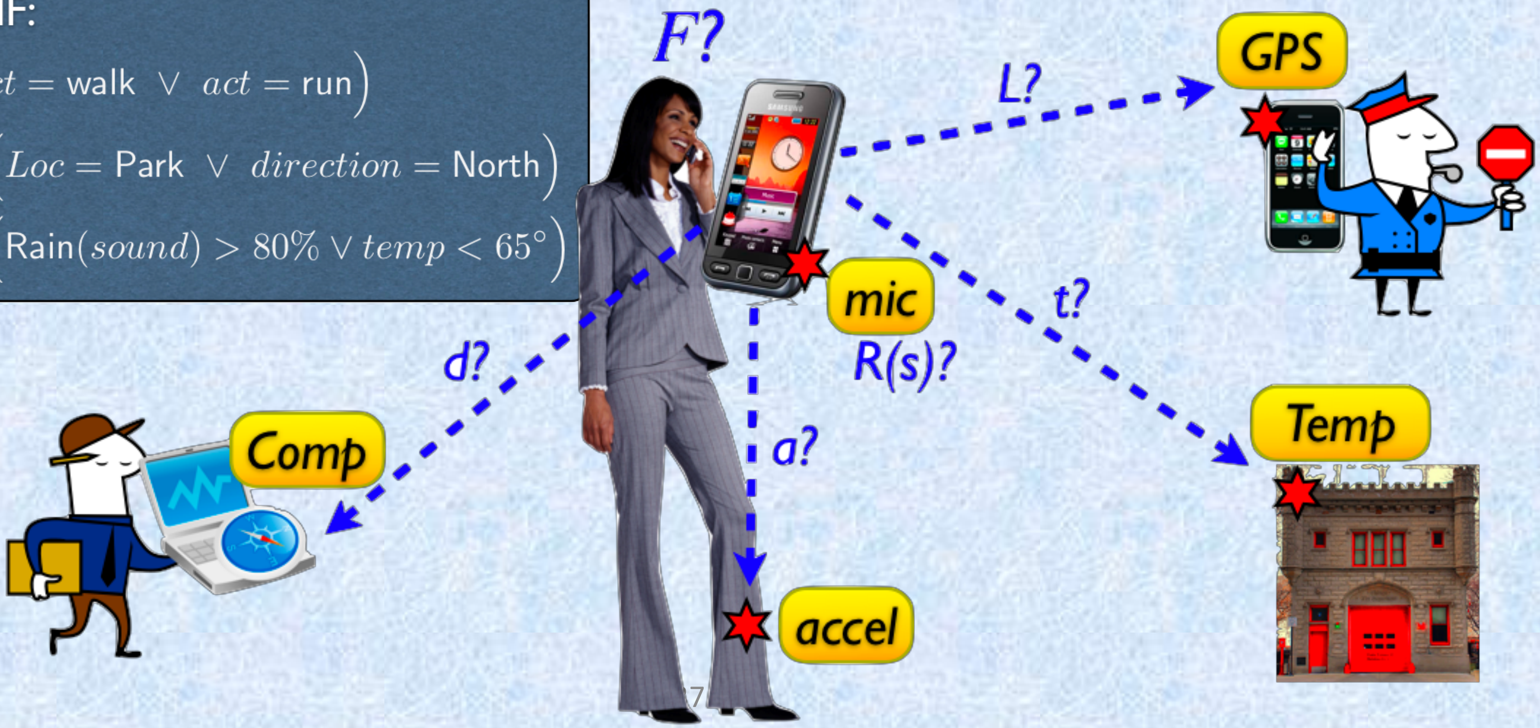
- System design
  - Architecture
  - Scalability
  - Performance
- Energy-aware sensing
- Data integrity
- Privacy
- Authentication
- Etc…

Energy-aware context monitoring

- Problem:
  - Context monitoring requires continuous (wireless) communication with sensors (internal & external)

Event in CNF:

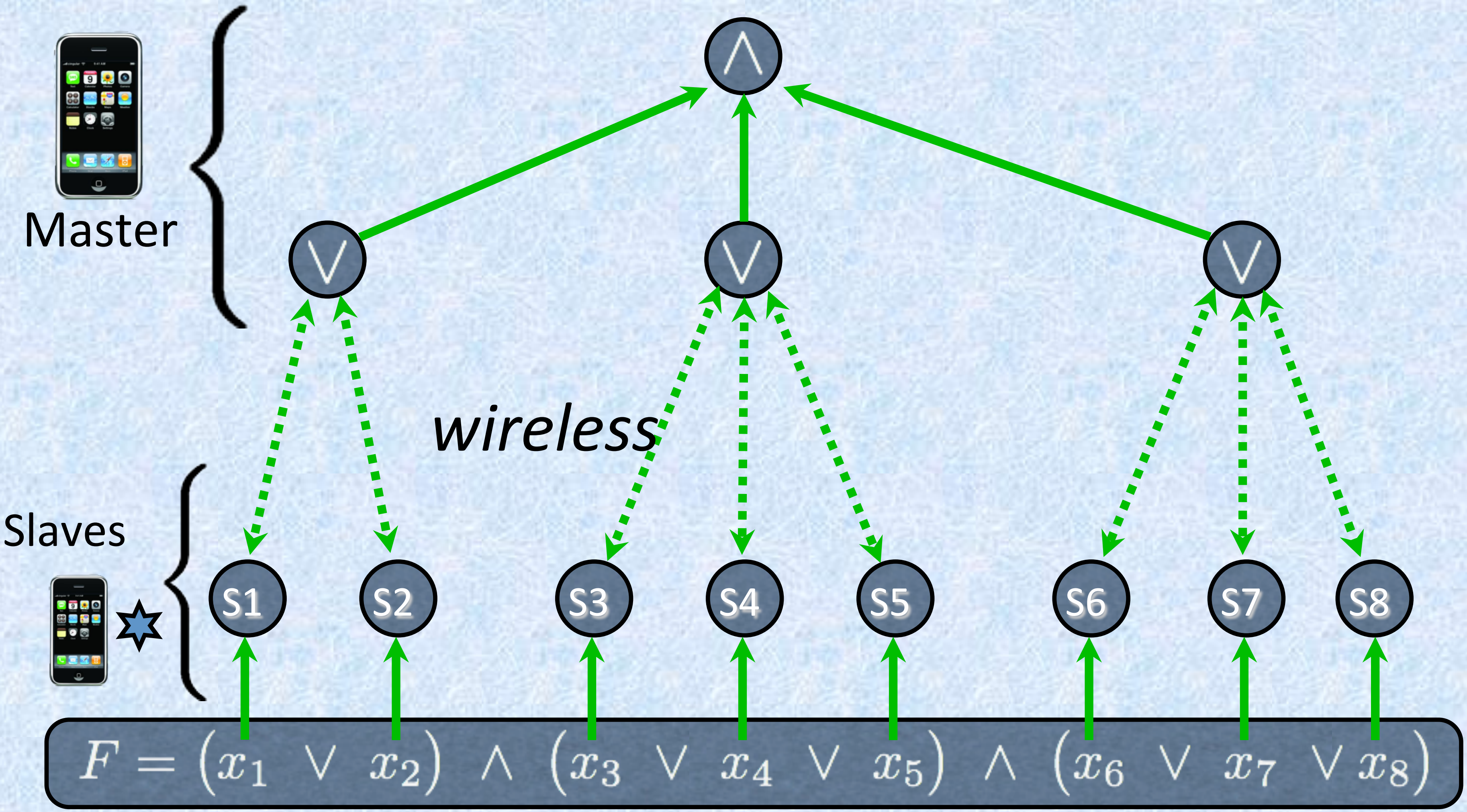
$$
\begin{aligned}
F \;=\; & \big(act = \text{walk} \;\vee\; act = \text{run}\big) \\
& \wedge \big(Loc = \text{Park} \;\vee\; direction = \text{North}\big) \\
& \wedge \big(\text{Rain}(sound) > 80\% \vee temp < 65^{\circ}\big)
\end{aligned}
$$



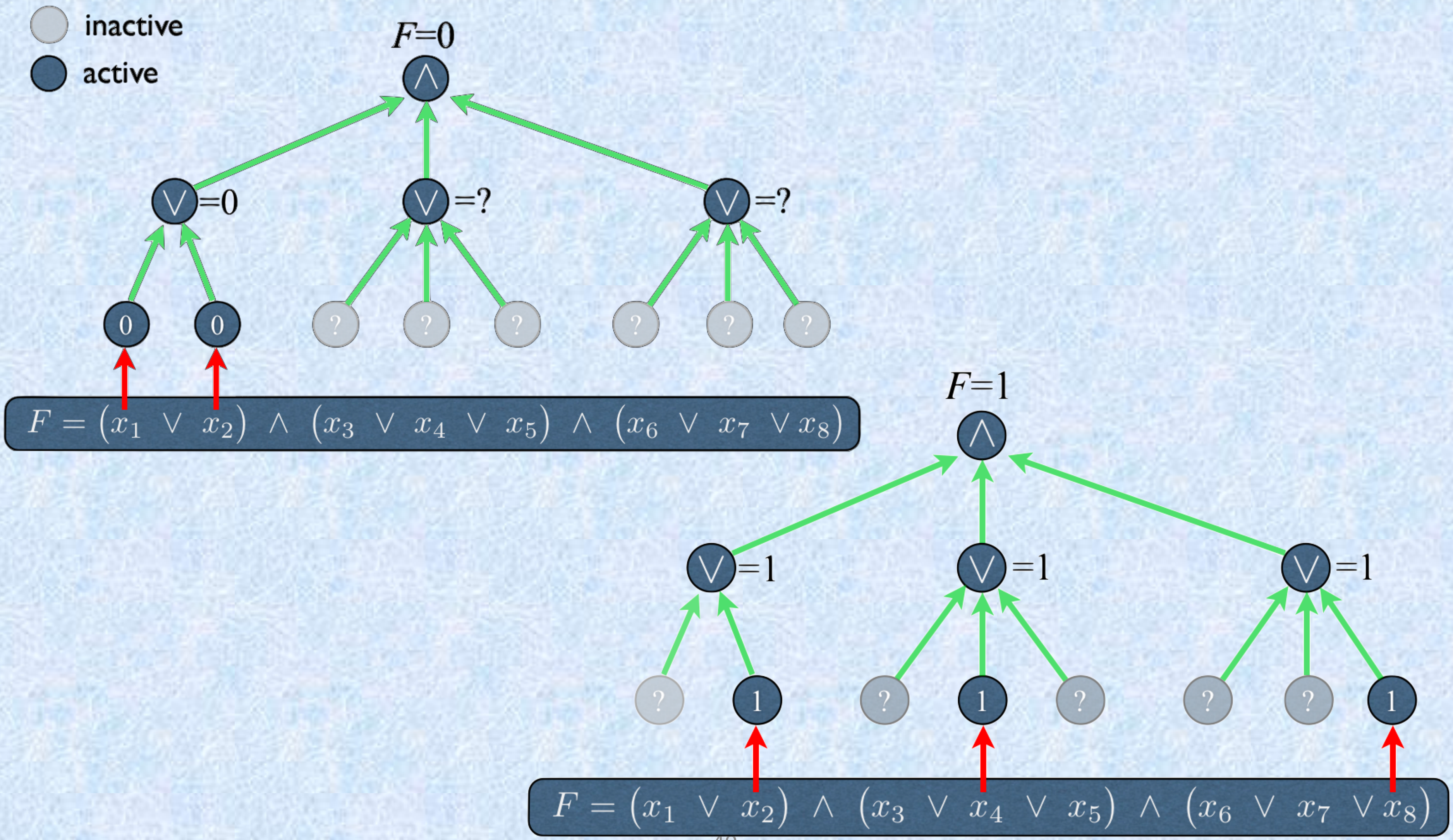
Deamon: energy efficient monitoring

- Goal:
  - Given a Boolean expression F defined on sensor values, a set of helping nodes, detect when F becomes true
  - Save energy: less communication and sampling
- Method:
  - DEAMON (Distributed Energy-Aware sensor Monitoring)
  - F is either in CNF or DNF
  - Assign sensors to helping nodes: weighted set cover prob.
  - Monitor only sensors that determine value of F

CNF Evaluation Tree



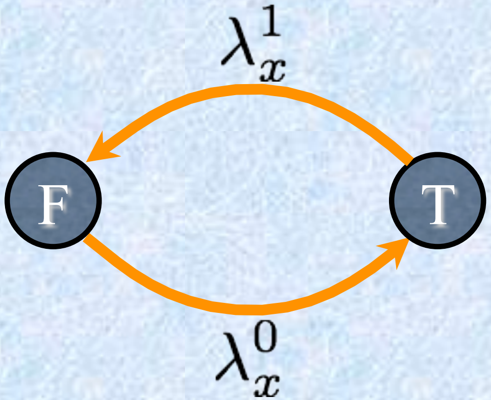
Deamon: idea



inactive
active
F=0
=0
=?
=?
0
0
?
?
?
?
?
?
$F = (x_1 \vee x_2) \wedge (x_3 \vee x_4 \vee x_5) \wedge (x_6 \vee x_7 \vee x_8)$
F=1
=1
=1
=1
?
1
?
1
?
?
?
1
$F = (x_1 \vee x_2) \wedge (x_3 \vee x_4 \vee x_5) \wedge (x_6 \vee x_7 \vee x_8)$

Model for analysis

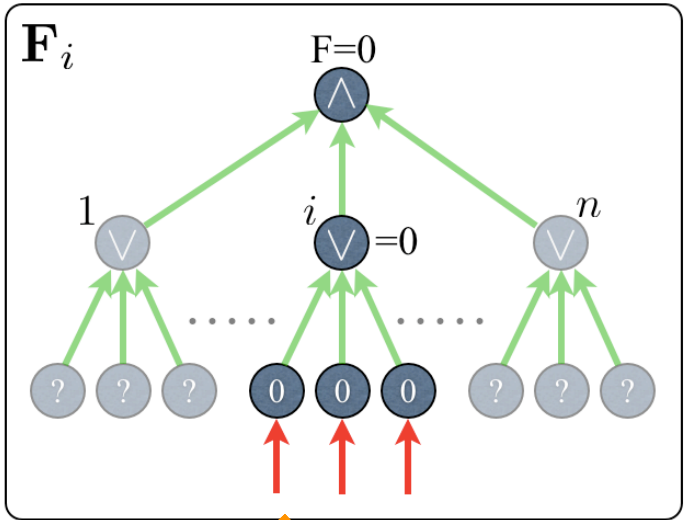
- Dynamics of atom x in CNF
- alternating renewal process (p_x, λ_x)
- $p_x := \Pr(x = \mathrm{F})$ stationary probability
- λ_x : change rate



$$\lambda_x = \frac{2\lambda_x^0 \lambda_x^1}{\lambda_x^0 + \lambda_x^1}$$

$$p_x = \frac{\lambda_x}{2\lambda_x^0}$$

Markov Chain: Transition

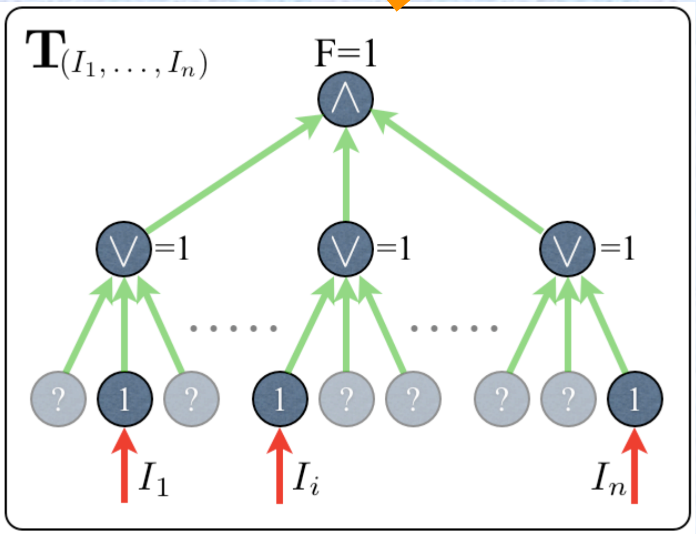


$$\lambda^1_{x_{I_{i*}}} (1 - p_{x_{J_{i*}}}) \prod_{\substack{x_l \in f \\ l \neq I_{i*}}} p_{x_l} \prod_{\substack{x_n \notin f \\ n < J_{i*}}} p_{x_n}$$

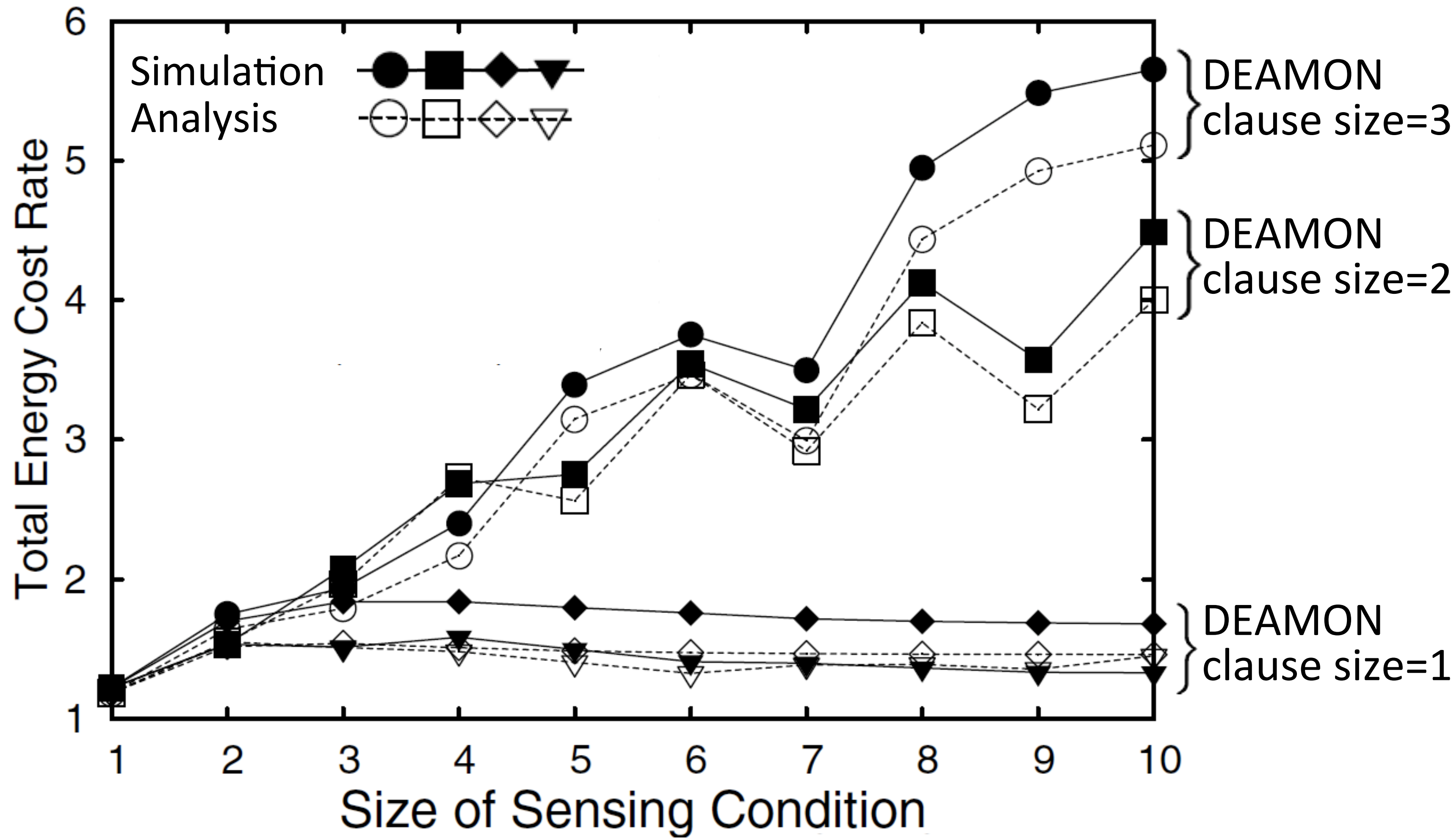
$$\lambda^1_{x_{I_i}} \prod_{\substack{x_l \in C_i \\ l < I_i}} p_{x_l}$$

$$\lambda^0_{x_{I_i}} \prod \left\{ (1 - p_{x_{I_j}}) \prod_{\substack{x_l \in C_j \\ l < I_j}} p_{x_l} \right\}$$

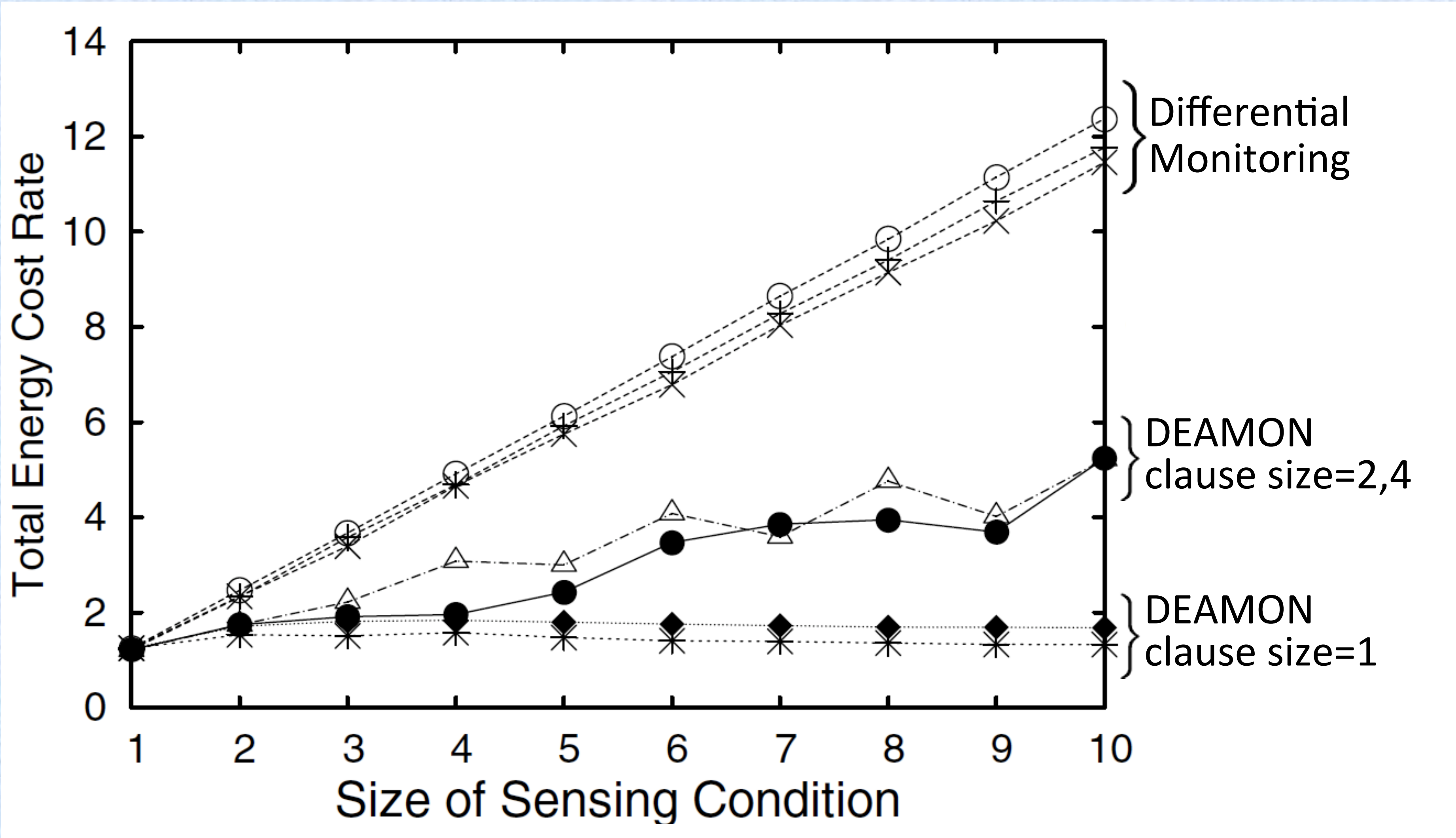
$$\Big(\sum_{x \in C_i} \lambda^0_x \Big) \Big(\prod_{x \in C_j} p_x \Big) \prod_{\substack{l=1 \\ l \neq i}}^{j-1} \Big(1 - \prod_{x \in C_l} p_x \Big)$$



Analysis vs. Simulations



DEAMON saves energy

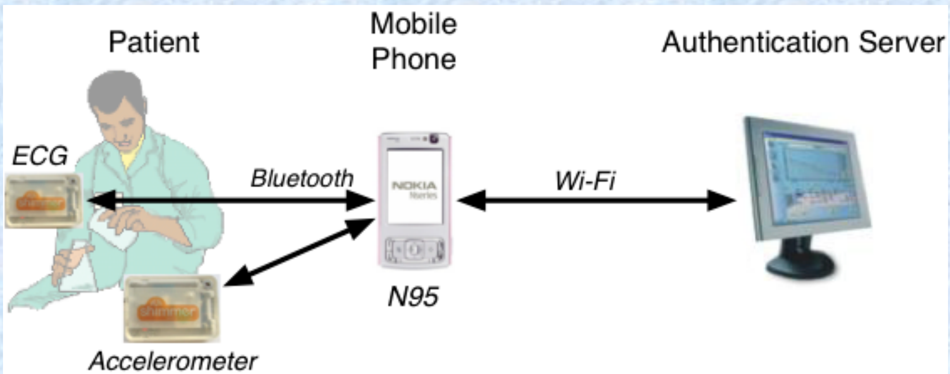


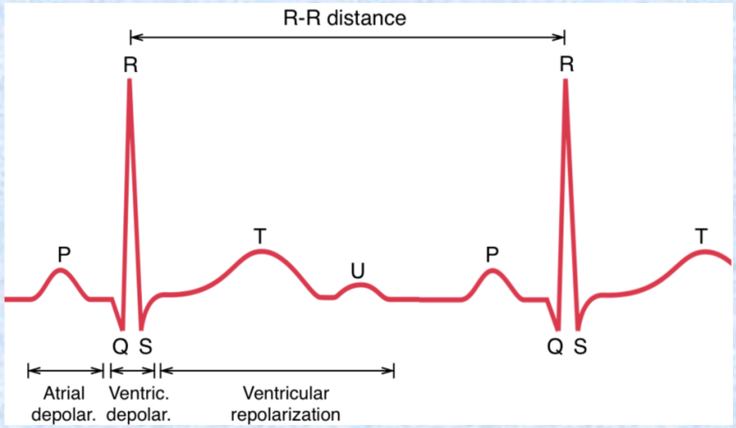
Patient verification in Remote H. M.

- Goal
  - Verify if the sensor data belongs to the right person
  - Continuous verification
  - Non-permanent identification
- ECG-based activity-aware patient authentication
  - *[ICMI-MLMI'09]*
  - Wearable ECG sensor & activity sensor
  - Classification by Machine Learning

Feature extraction

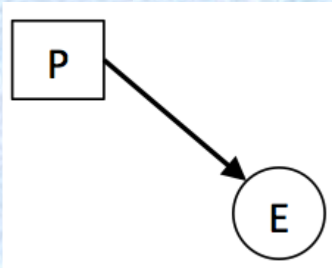
- Features:
  - Fiducial: R-R, QR-slope, RS-slope,
  - Non-fiducial: Auto-Correlation
  - Accelerometer means/variations

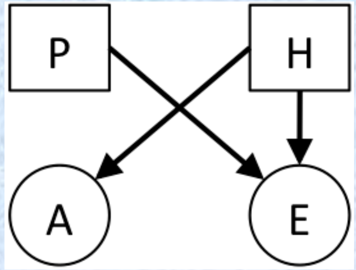




Classification and decision

- Classification methods
  - K-Nearest Neighbor (KNN)
  - Bayesian Network





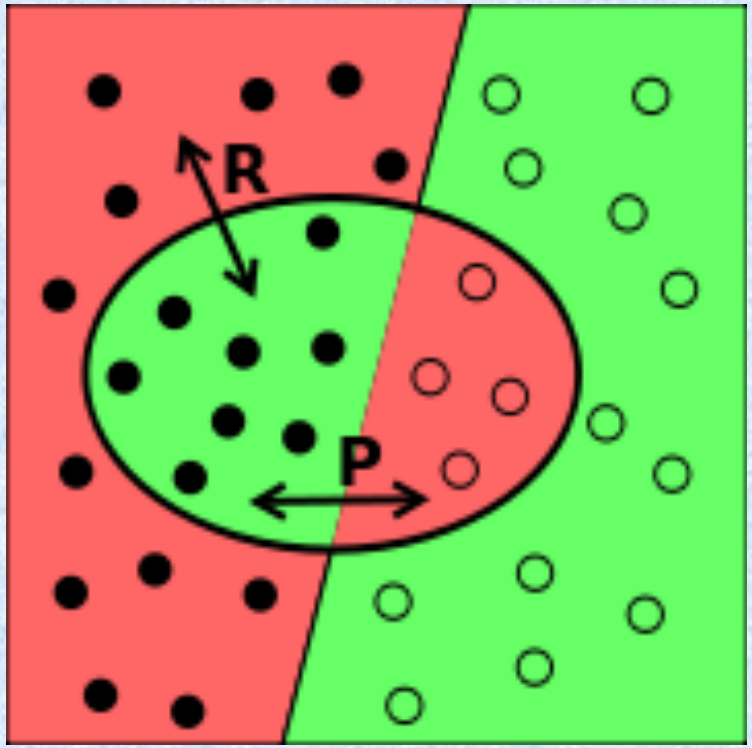
- Patient verification
  - Binary classification using imposter model

	Activity-Aware				Activity-Unaware		
	KNN	xKNN	BN		KNN	xKNN	BN
			$\|h\| = 2$	$\|h\| = 3$			
Precision	0.8243	0.8278	0.8488	0.8252	0.7855	0.7677	0.8139
Recall	0.8039	0.7925	0.8326	0.8174	0.8035	0.7987	0.8140

Precision and Recall

- Left: relevant
- Right: irrelevant
- Circle: guessed relevent

- Precision:
  - Right retrieval / Retrievals
- Recall:
  - Right retrieval / Relevants



Architecture for People-cent. Sensing

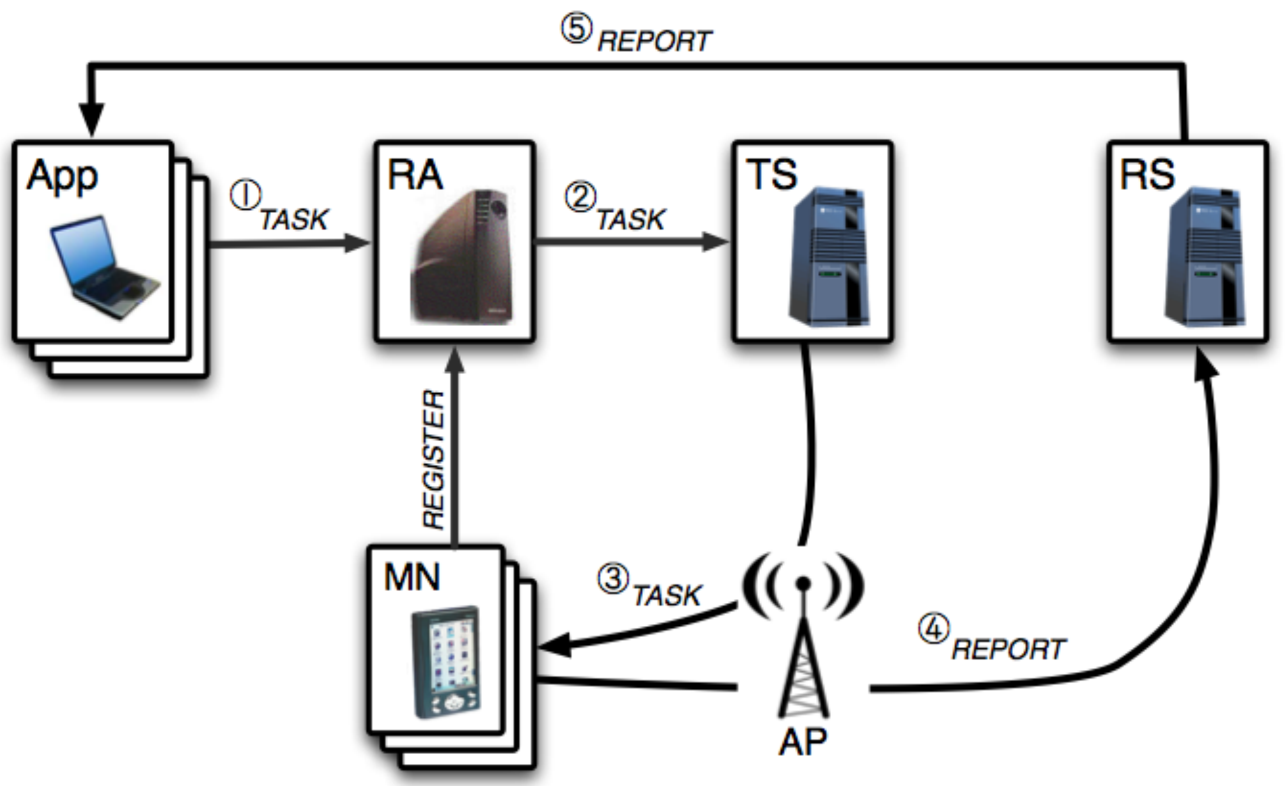


Fig. 1. Base architecture for large-scale people-centric sensing

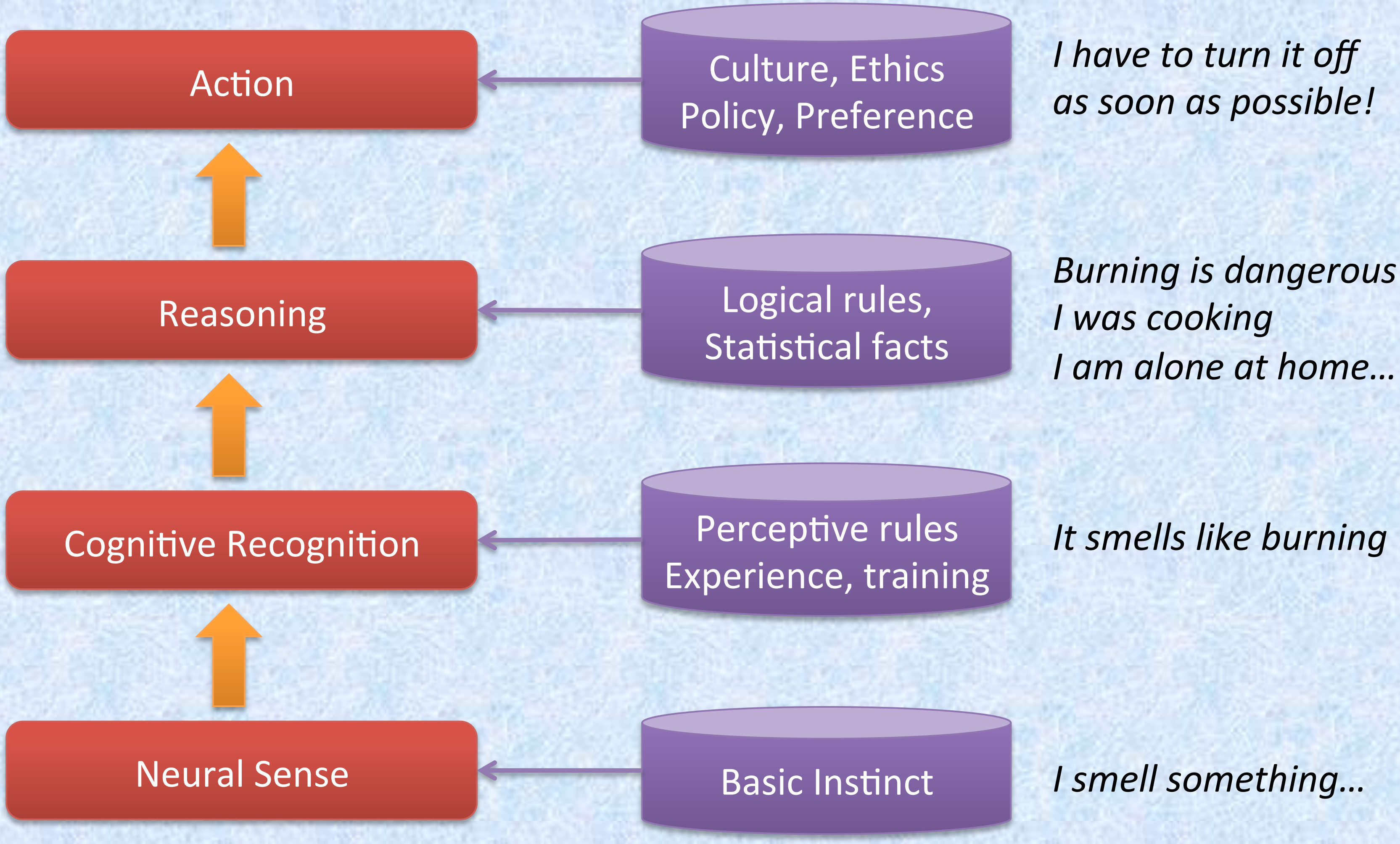
What can HMC offer?

- Human-centric mobile computing
  - Everyone has one
  - Always carried by the user
  - Always interacts with the user
  - Always connected
  - Improving computation power
  - Sensing capability
- What can mobile device learn about the user?
- What can we do with such information?

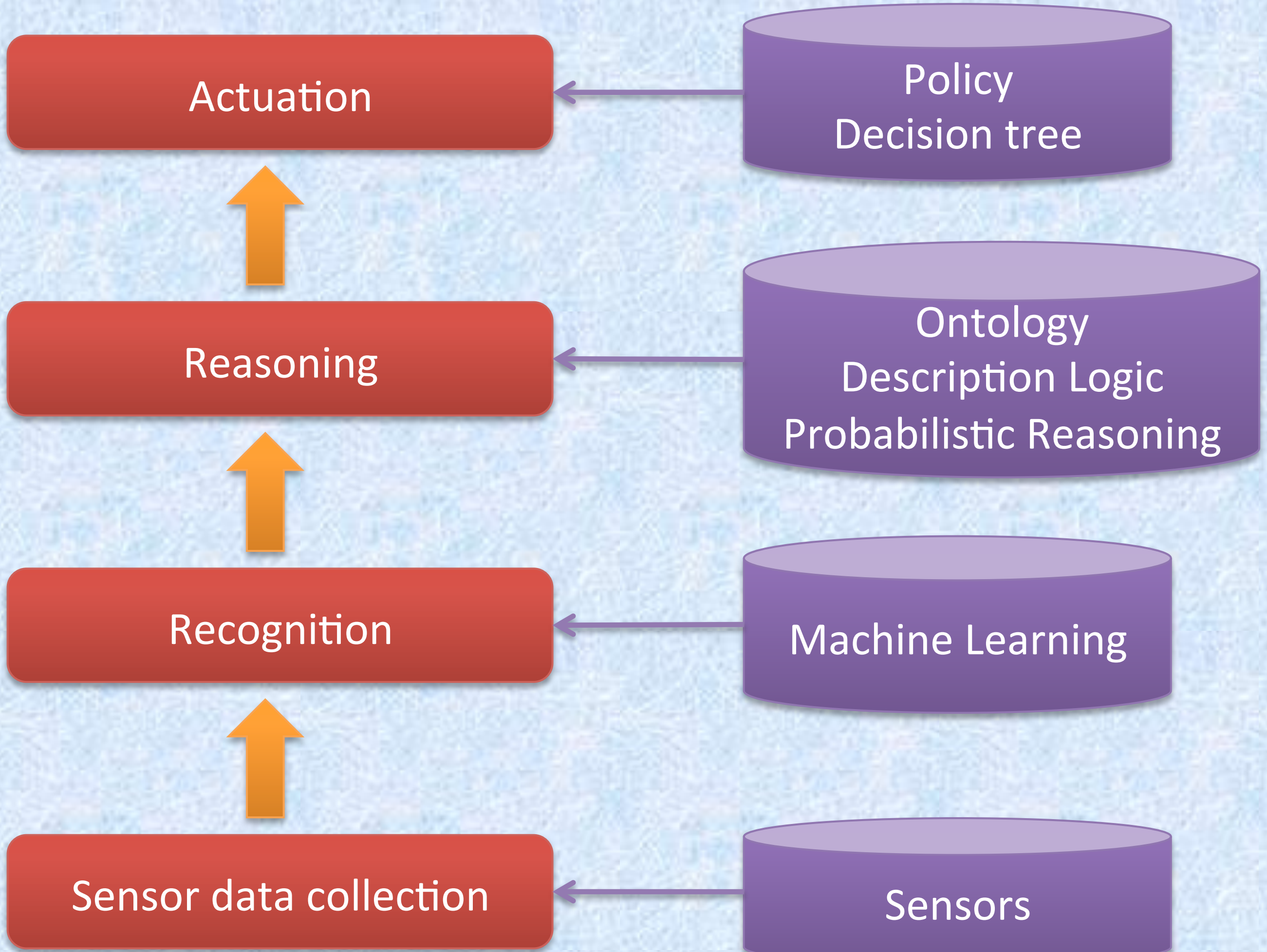
Available Data about the User

- Hard sensor
  - Location: GPS, Cell tower (Google), WiFi (Skyhook)
  - Motion: accelerometer
  - Proximity, Light, Audio, Video
- Soft sensor
  - Explicit: schedule, todo list, contacts
  - Implicit: web browsing, email, chat, app usage, resource usage, …

Data processing of Human



Data processing of HMC



Context-aware computing

- The mobile device “knows” the “context” of the user and “adapts” to the context
- ***Context*** *is any information that can be used to characterize the situation of an entity. (by A. K. Dey)*
  - *An entity is a person, place, or object that is considered relevant to the interaction between the user and application, including the user and applications themselves.*

Context

- Characteristics of Context
  - Context is Dynamic
  - Context is Relational
  - Context is Imperfect
  - Low-level context ←→ High-level context
    - Abstraction
  - Hard sensor ←→ soft sensor

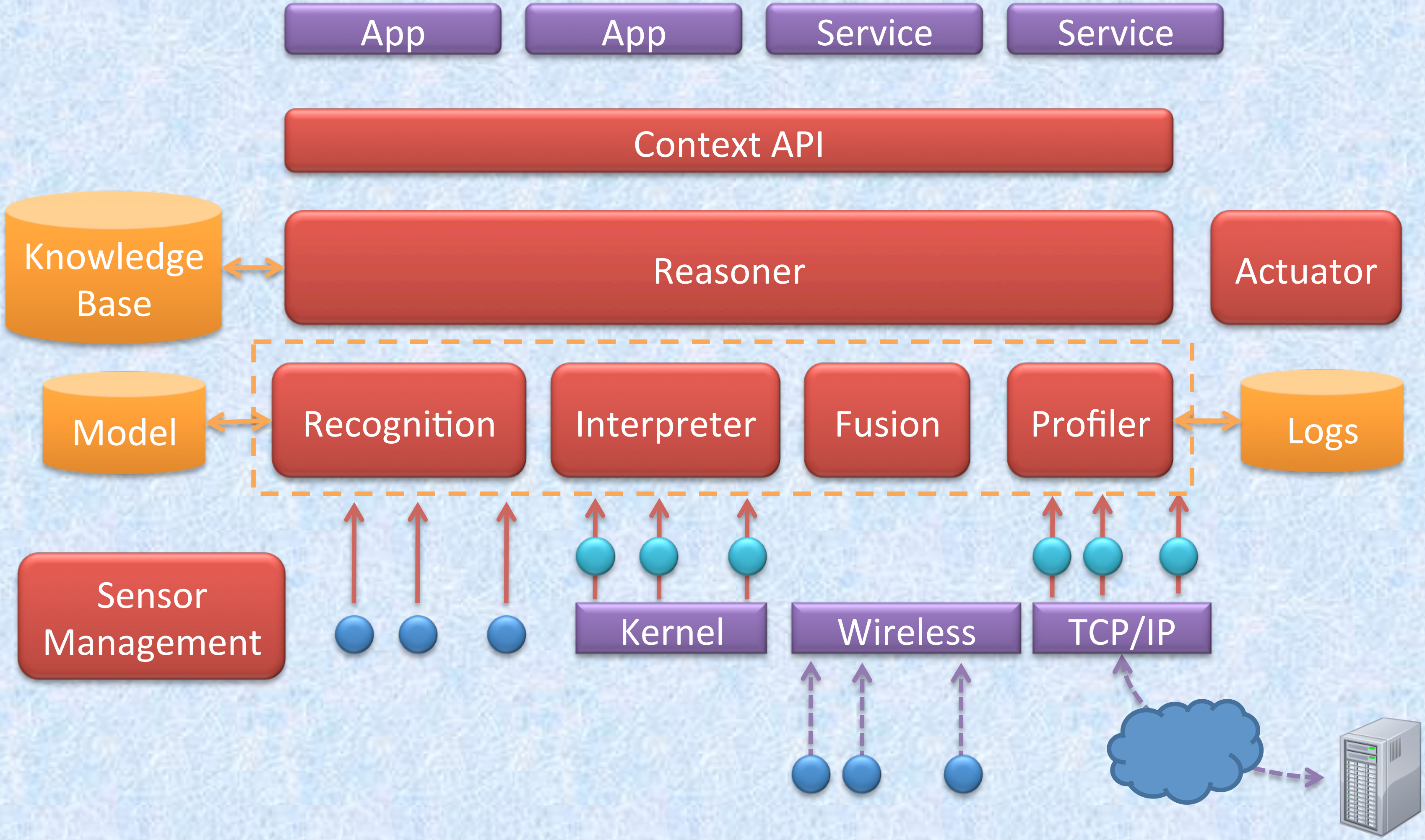
Categorization of Context

- By [Soylu2009]
  - User context
    - External/ Internal
  - Device context
    - Hard/ Soft
  - Application context
    - Target platform, memory requirement, etc…
  - Information context
    - Properties of information pieces available
  - Environmental context
    - Physical/ Digital
  - Time context
  - Historical context
  - Relational context

Applications of Context-Aware Comp.

- *Adaptation of system behavior depending on the current, past, or the future context*
- Information filtering and recommendation
- Context-adaptive user interface/presentation
- Context-aware search
- Context-dependent application configuration
- Context-based action
- Context-based resource allocation
- Collaborative filtering
- Case-based reasoning

System Architecture



Challenges

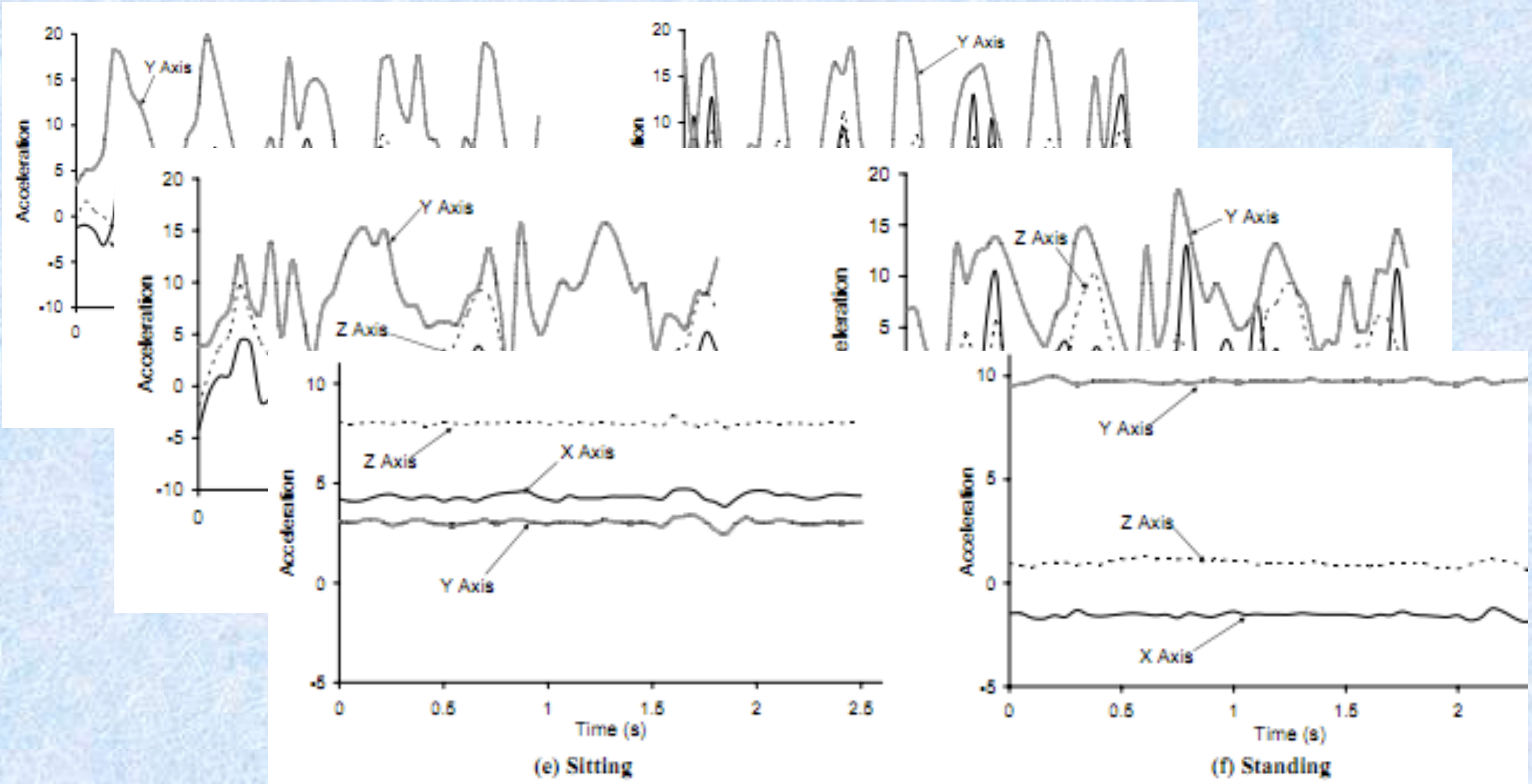
- Context acquisition
  - Given a set of contexts, provide appropriate and best low-data
  - Identify, find, and obtain context data from various context source
- Context refinement
  - Convert sensor-data into mid-level context
  - Movement → activity type
  - Sound → activity or surrounding situation
  - Image → place/ situation
- Profiling
  - Derive personalized context pattern based on history data
  - Movement profiling for significant-place learning, location prediction
  - Behavior profiling for behavior prediction/recommendation
  - Social profiling for social-activity prediction, relationship learning
  - Preference profiling

Challenges

- Context modeling
  – Ontology (no uncertainty, heavy)
  – Bayesian networks
  – Fuzzy logic
  – Probabilistic Relational Model
  – SCM (Symbol string Clustering Map)
- Context reasoning
  – Description Logic (deterministic, deductive)
  – Machine Learning (probabilistic, inductive)
- Context imperfectness
  – Integration of Bayesian network with ontology
  – Fuzzy /PRM/ Markov Logic

Activity Recognition

- Fordham Univ. KDD 2010



Activity Recognition

Table 2: Accuracies of Activity Recognition

	% of Records Correctly Predicted			
	J48	**Logistic Regression**	**Multilayer Perceptron**	**Straw Man**
Walking	89.9	**93.6**	91.7	37.2
Jogging	96.5	98.0	**98.3**	29.2
Upstairs	59.3	27.5	**61.5**	12.2
Downstairs	**55.5**	12.3	44.3	10.0
Sitting	**95.7**	92.2	95.0	6.4
Standing	**93.3**	87.0	91.9	5.0
Overall	85.1	78.1	**91.7**	37.2

Features used

- Average[3]
  - Average acceleration (for each axis)
- Standard Deviation[3]
  - Standard deviation (for each axis)
- Average Absolute Difference[3]
  - Average absolute difference between the value of each of the 200 readings within the ED and the mean value over those 200 values (for each axis)
- Average Resultant Acceleration[1]
  - Average of the square roots of the sum of the values of each axis squared over the ED
- Time Between Peaks[3]
  - Time in milliseconds between peaks associated with most activities (for each axis)
- Binned Distribution[30]
  - The range of values for each axis (maximum – minimum), divide this range into 10 equal sized bins, and then record what fraction of the 200 values fell within each of the bins.

Jigsaw [Sensys2010]

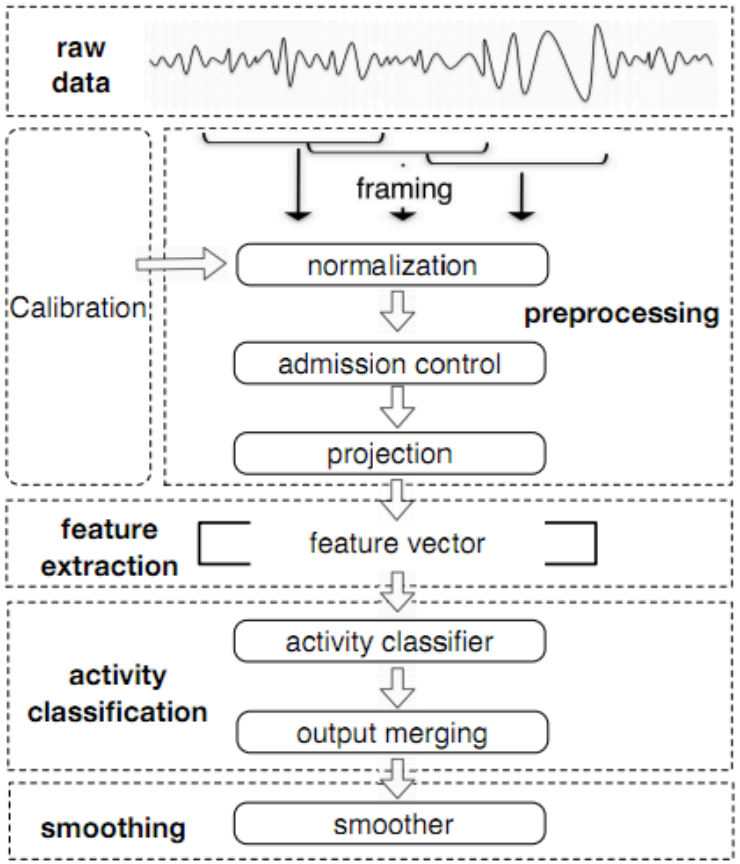


Figure 4: Jigsaw Accelerometer Pipeline

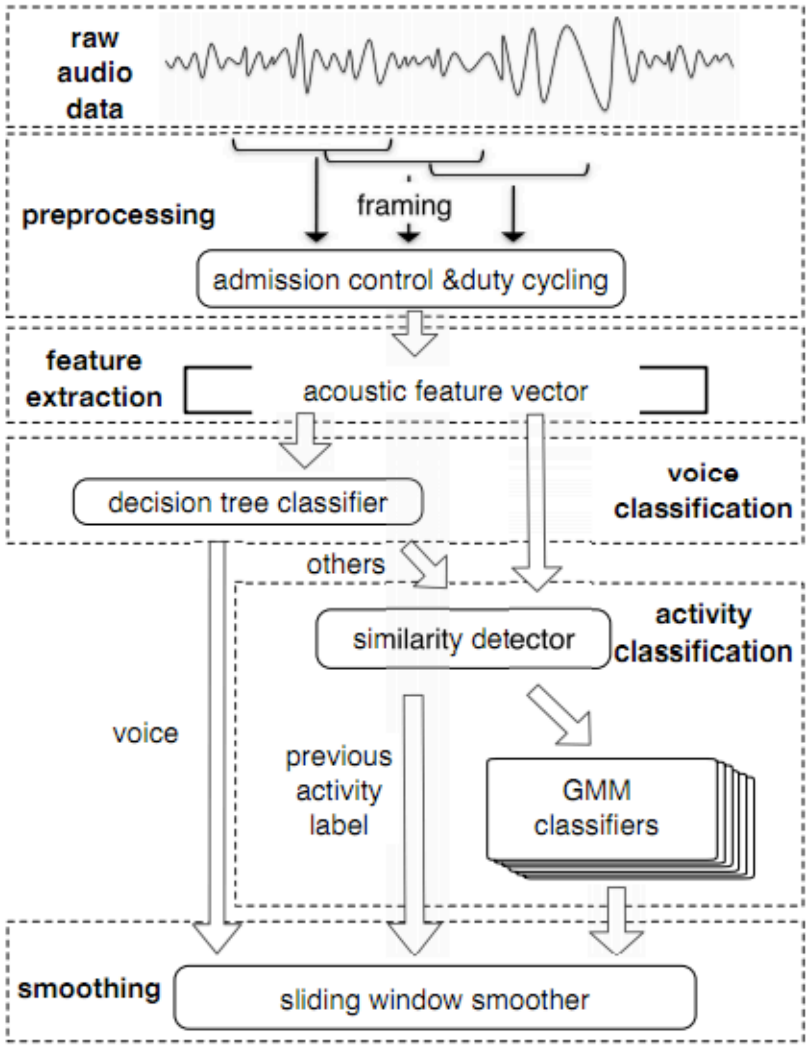


Figure 5: Jigsaw Microphone Pipeline

Features

Time domain	mean, variance, mean crossing rate
Frequency domain	spectrum peak, sub-band energy, sub-band energy ratio, spectral entropy

Table 1: Motion Feature Set

Category	Feature set
voice	Spectral Rolloff [12],Spectral Flux [25] Bandwidth [12],Spectral Centroid [12] Relative Spectral Entropy [6] Low Energy Frame Rate [25]
other activities	13 MFCC coefficient feature set [32] Spectral Centroid [12],Bandwidth [12] Relative Spectral Entropy [6] Spectral Rolloff [12]

Table 3: Acoustic Feature Set

Jigsaw Architecture

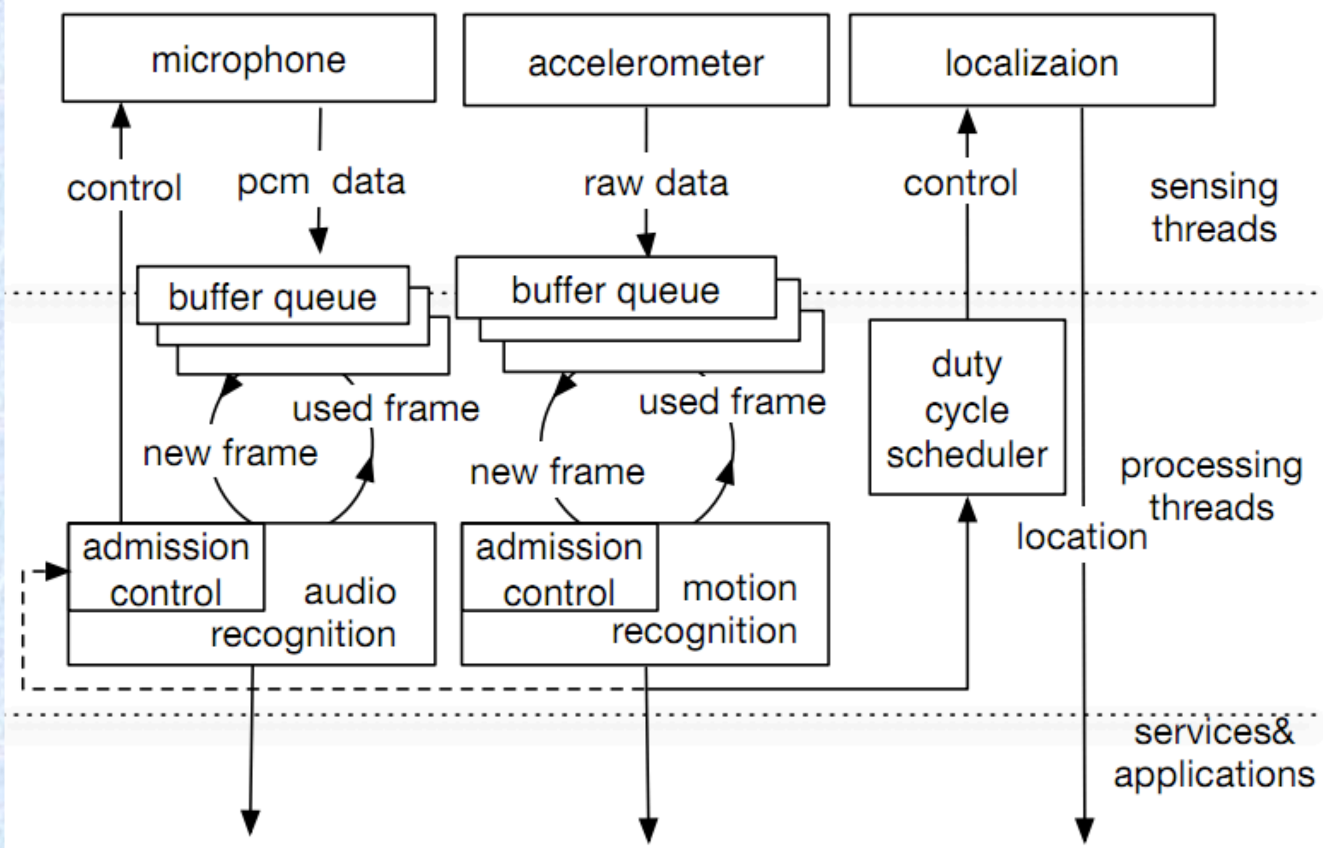


Figure 7: Jigsaw Software Architecture

Results

	Accuracy w/o Split&Merge(%) DT	MG	SVM	NB	Accuracy with Split&Merge(%) DT	MG	SVM	NB
cycling	82.62	82.41	86.60	77.45	92.05	90.07	92.88	90.87
vehicle	92.87	93.80	93.52	83.59	90.52	87.47	90.29	89.83
running	98.11	97.18	97.40	98.37	98.01	97.40	98.03	97.30
stationary	94.25	96.81	97.48	94.99	95.19	98.07	97.68	96.19
walking	90.35	91.89	93.90	88.55	96.81	97.04	96.66	95.17
Average	91.64	92.42	93.78	88.59	94.52	94.01	95.10	93.87

Table 7: Classifier Accuracy with and w/o Split and Merge

actual\output	voice	other
voice	0.8535	0.1465
other	0.0408	0.9592

Table 9: Confusion Matrix for the Voice Classifier

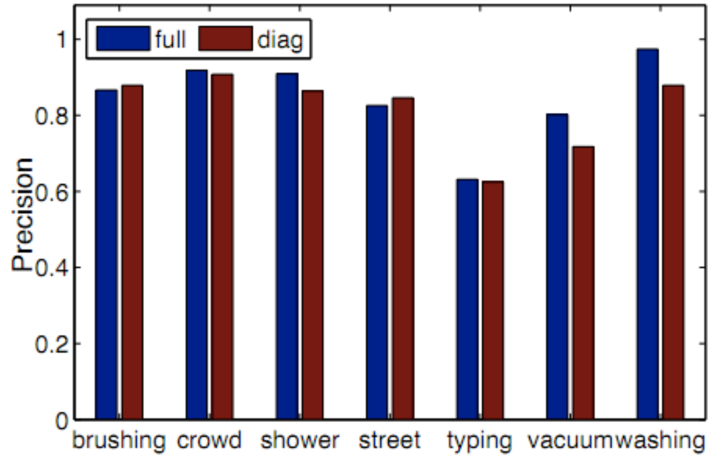


Figure 10: Precision of Two Types of GMM