Internet of Mobile Things: Challenges and Opportunities

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Outline

- Motivation
  - Internet of Things (IoT)
  - Mobile Things meet Internet of Things = Internet of Mobile Things
- Challenges and opportunities
  - Data Collection
  - Data Analytics
    - Context Detection
    - Activity Detection
  - Energy Consumption
  - Software Frameworks
- Conclusions

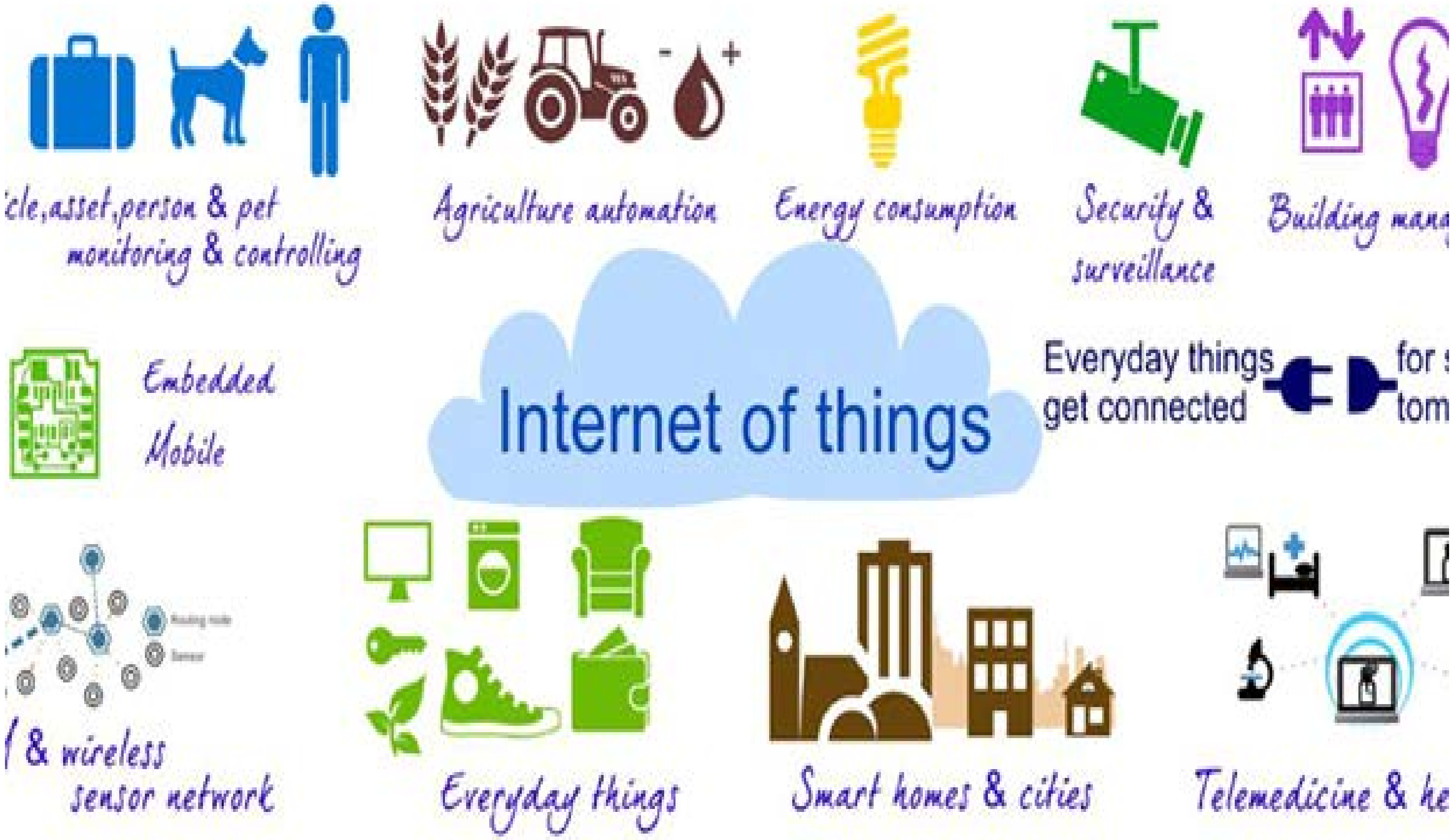
Technology Cycles Have Tended to Last Ten Years

Mainframe Computing 1960s	*Mini* Computing 1970s	*Personal* Computing 1980s	*Desktop Internet* Computing 1990s	*Mobile Internet* Computing 2000s	*Wearable / Everywhere* Computing 2014+

Reporting, Visualization, Dashboards, Analytics

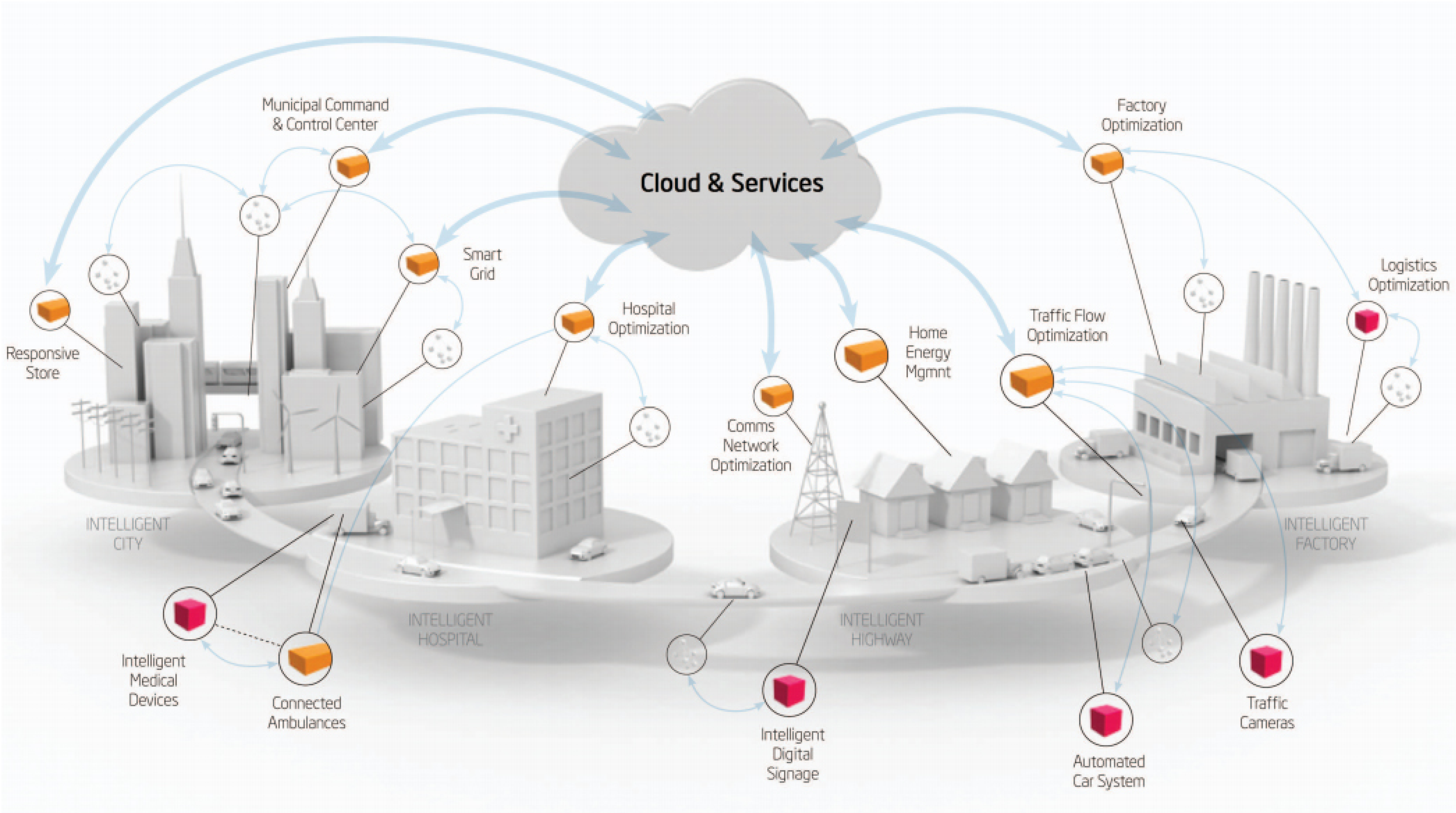
Every generation of technology created the need for new analytics capabilities and new technology platforms

Internet of Things (IoT)

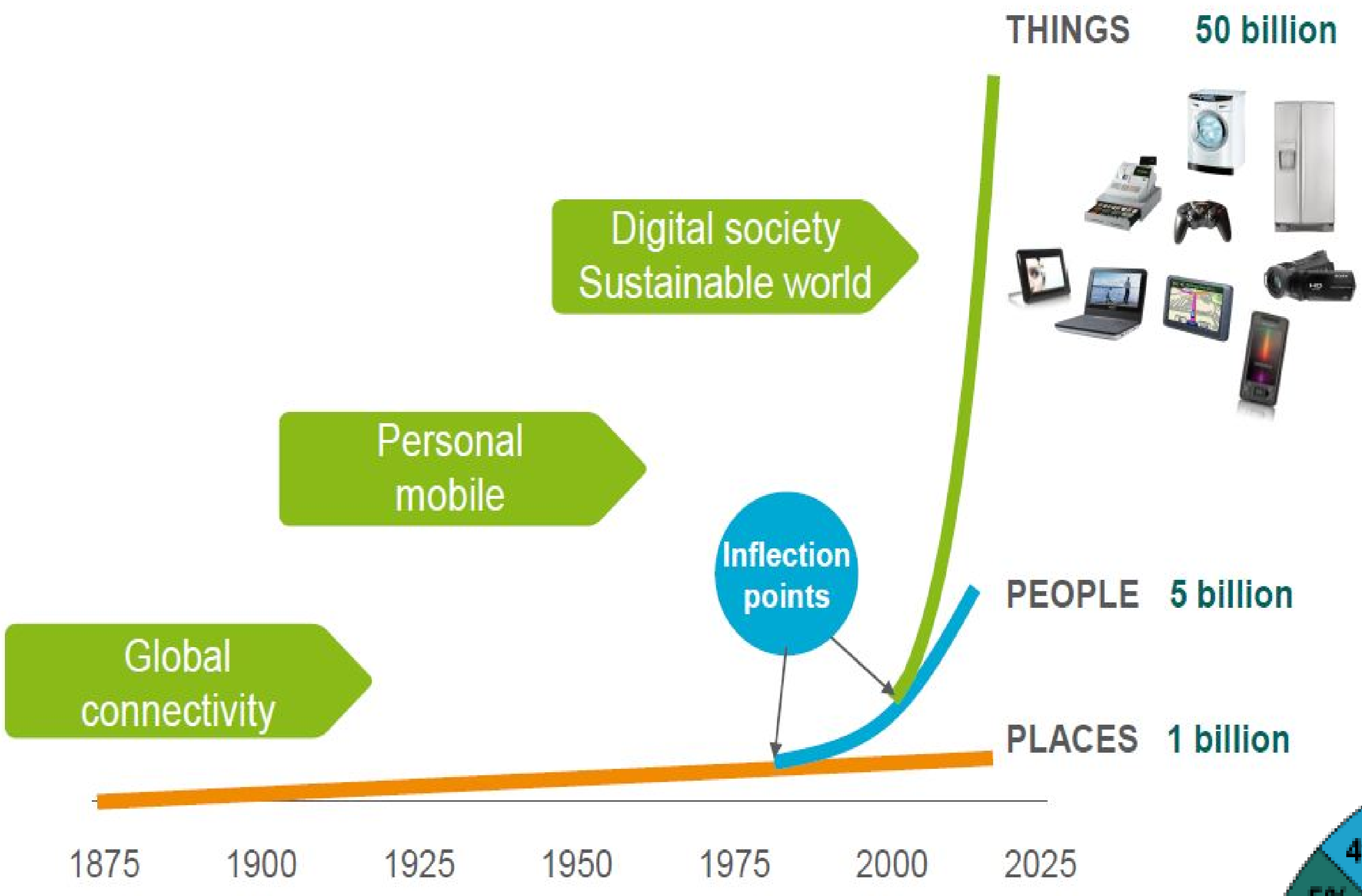


Source: http://www.satiztpm.it/internet-things/?lang=en

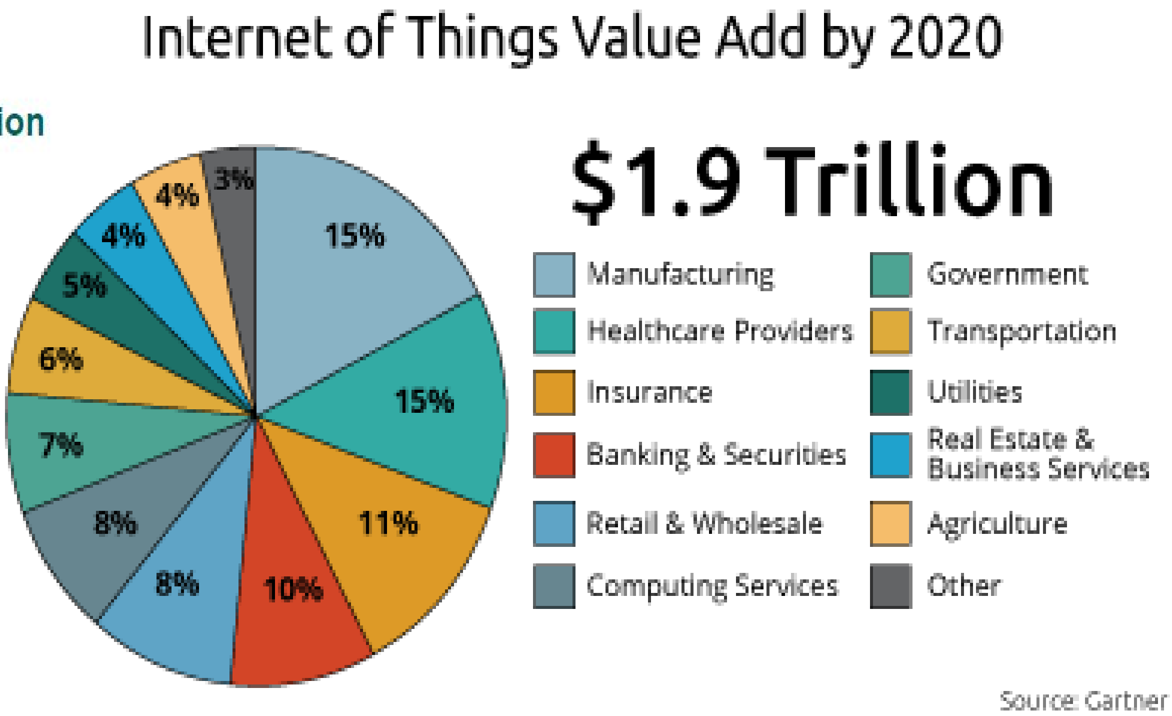
IoT Distribution and Interconnectivity



IoT Numbers

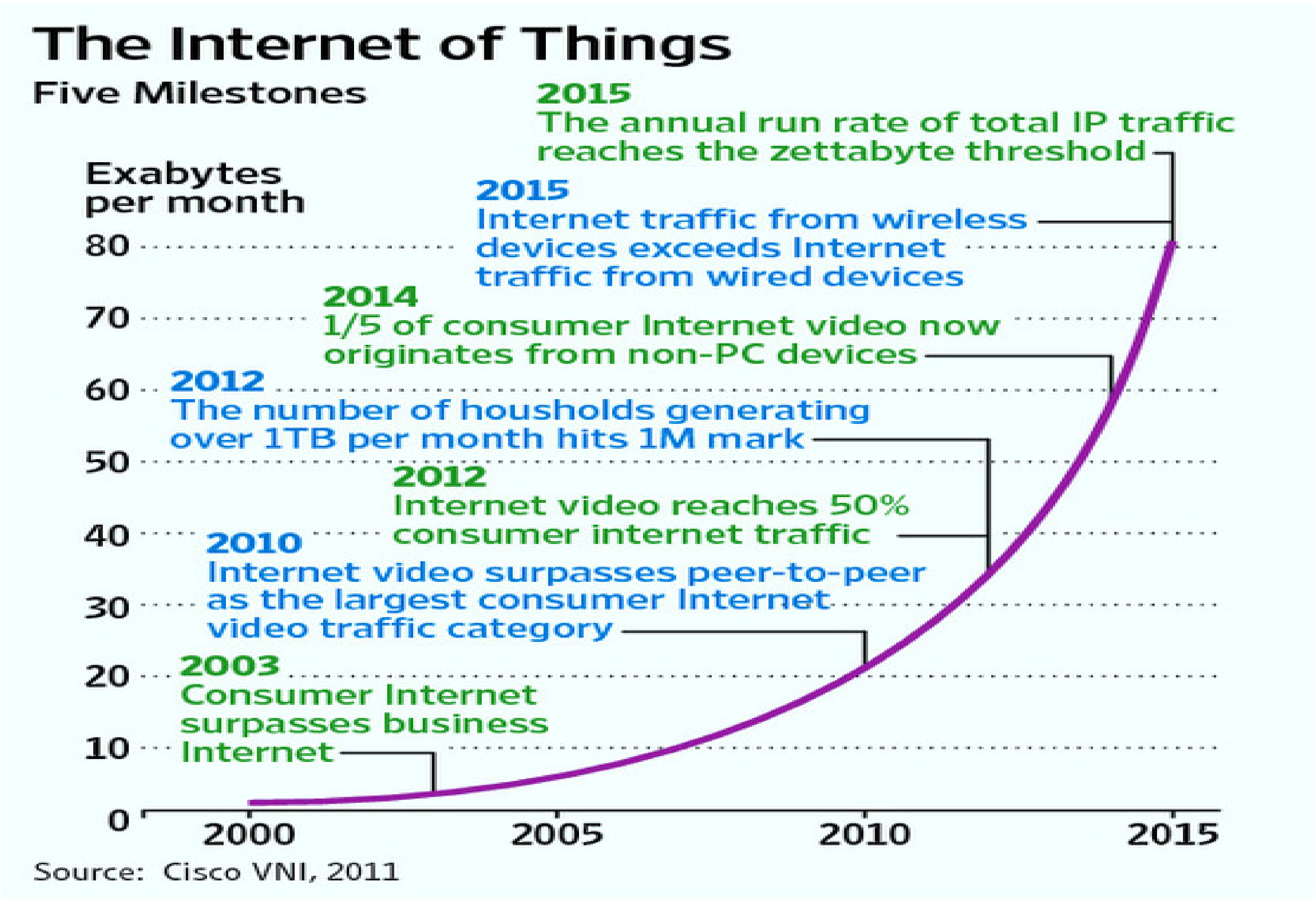


THINGS 50 billion
Digital society
Sustainable world
Personal
mobile
Inflection
points
PEOPLE 5 billion
Global
connectivity
PLACES 1 billion
1875
1900
1925
1950
1975
2000
2025



Internet of Things Value Add by 2020
$1.9 Trillion
15%
15%
11%
10%
8%
8%
7%
6%
5%
4%
4%
3%
Manufacturing
Healthcare Providers
Insurance
Banking & Securities
Retail & Wholesale
Computing Services
Government
Transportation
Utilities
Real Estate &
Business Services
Agriculture
Other
Source: Gartner

IoT Data Scale



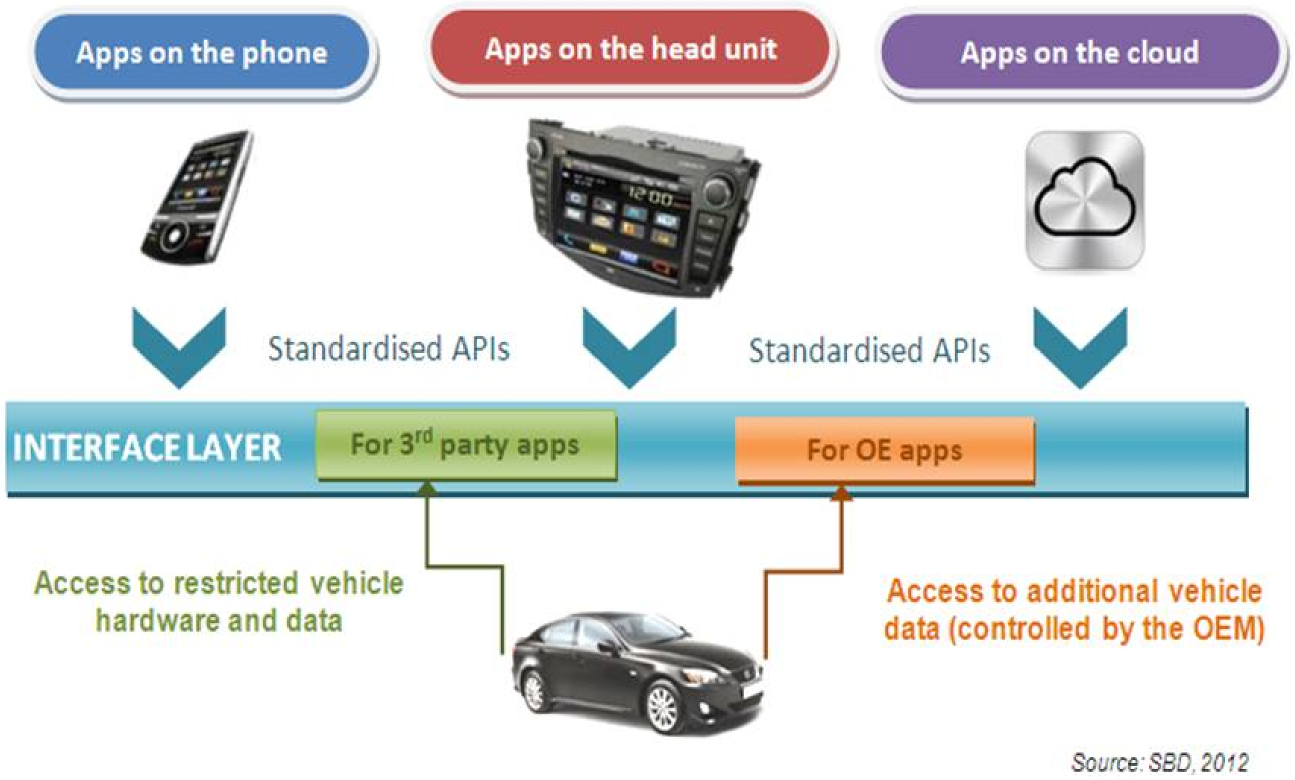
Internet of Mobile Communities



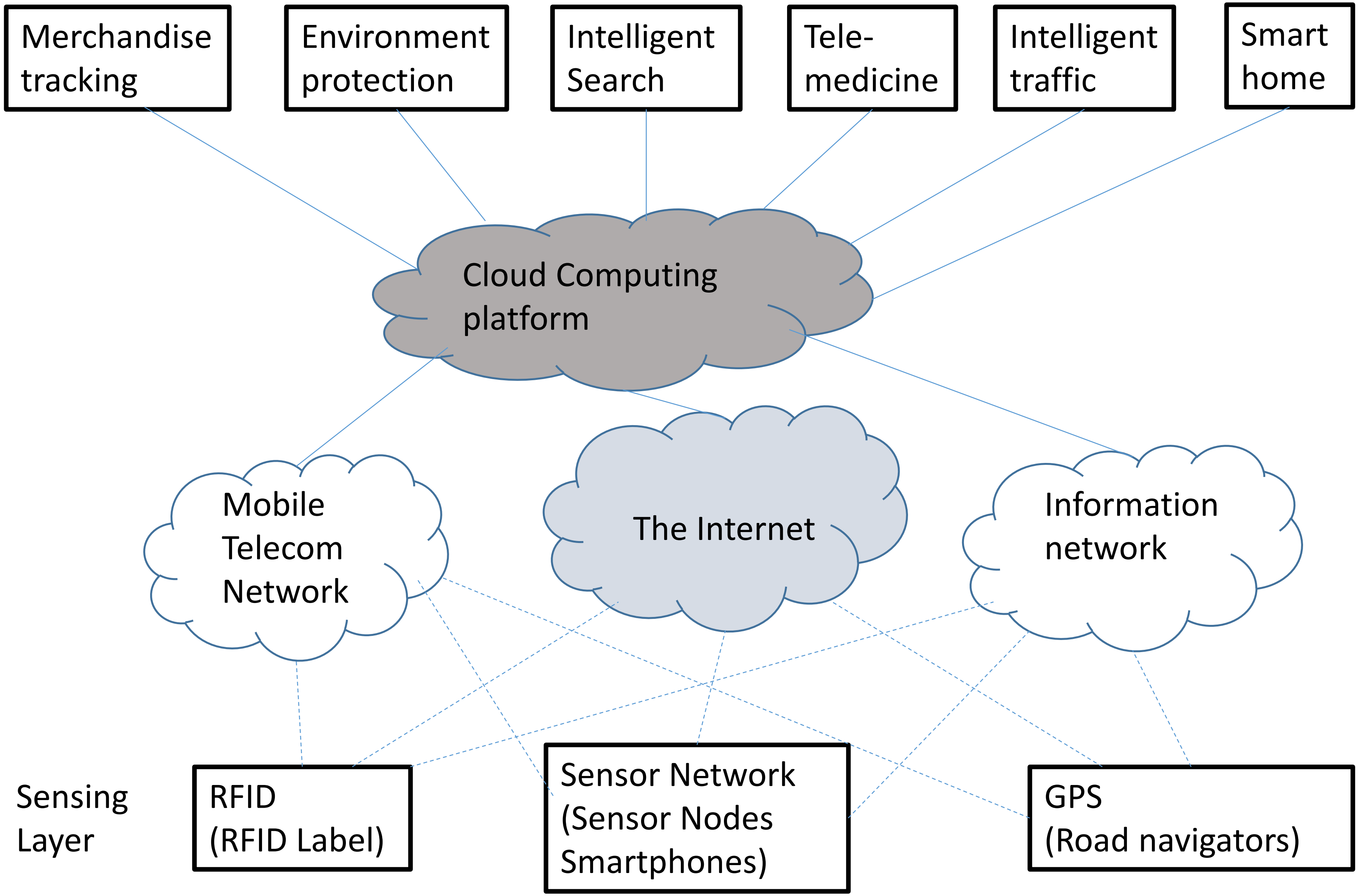




Mobile Things Meet Internet of Things

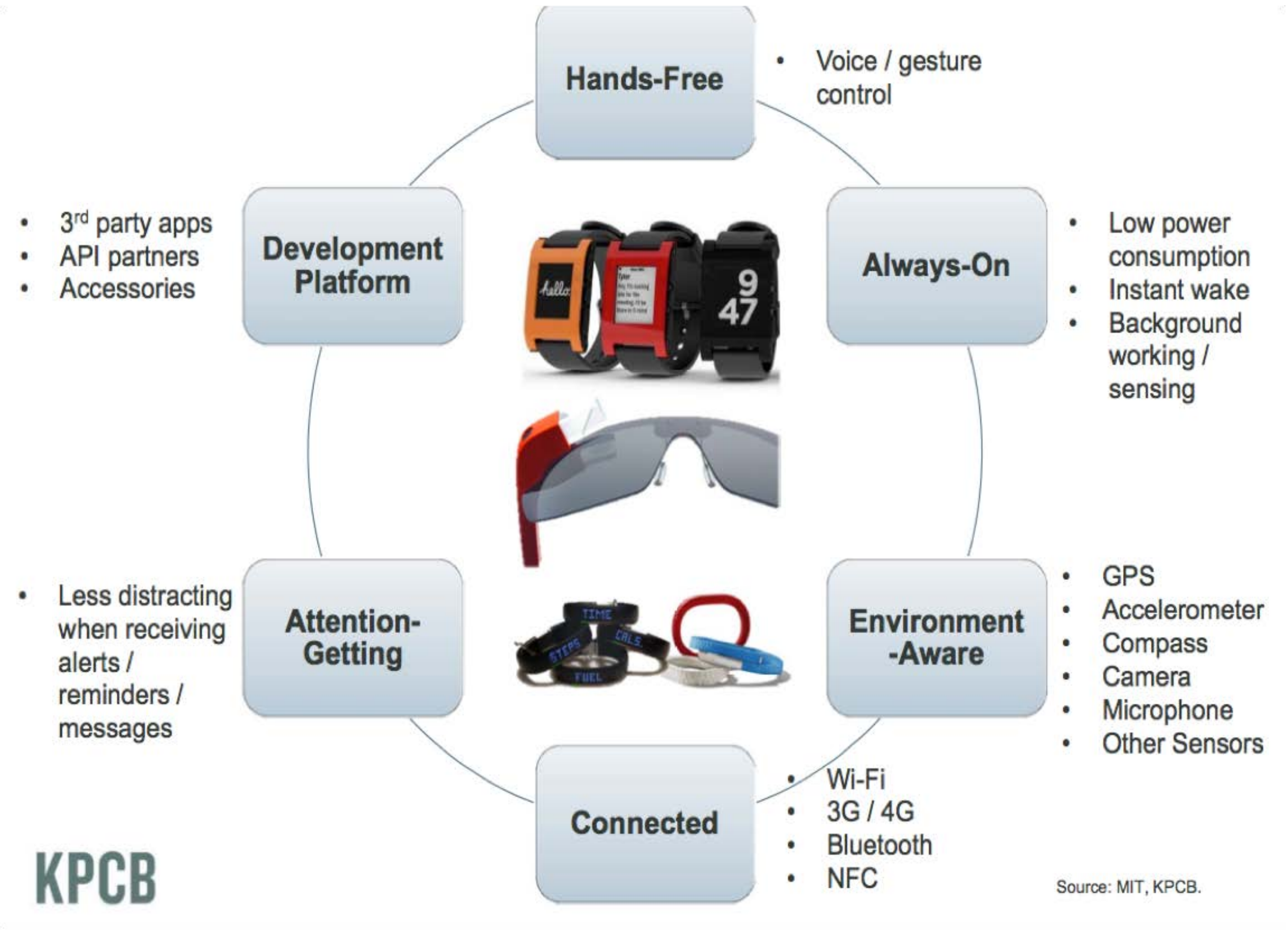


Architecture of Internet of Everything



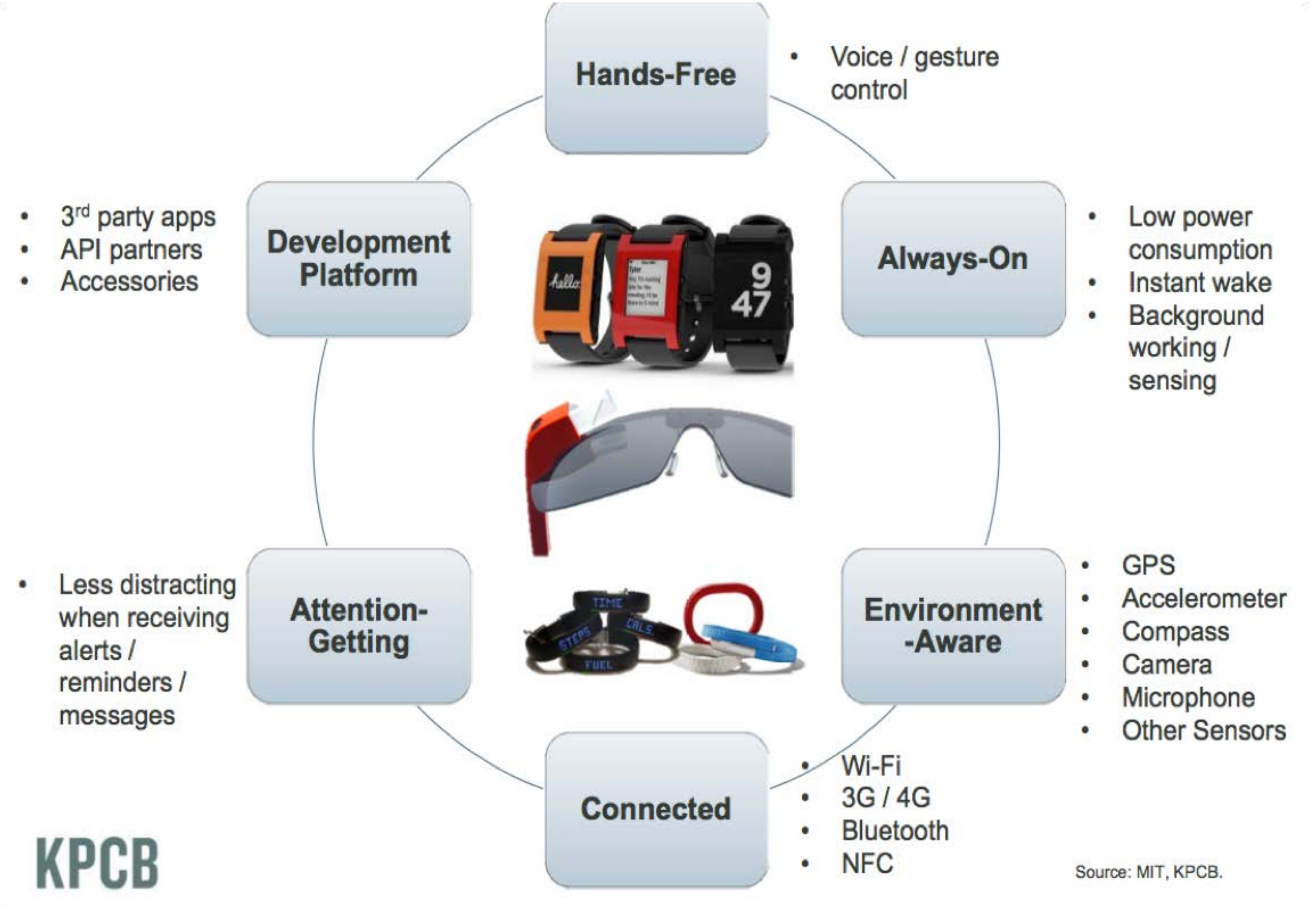
Technological Challenges

- Scalability – large scope of “things”
- Arrive and operate
- Interoperability
- Discovery
- Software Complexity
- Data Collection and Volume
- Data Analytics
- Security and Privacy
- Fault Tolerance
- Energy Consumption
- Wireless Communication



Today We Discuss: Challenges and Opportunities

- Scalability – large scope of “things
- Arrive and operate
- Interoperability
- Discovery
- Software Complexity
- Data Collection and Volume
- Data Analytics (related to Mobility
    - Context Detection
    - Activity Detection
- Security and Privacy
- Fault Tolerance
- Energy Consumption
- Wireless Communication



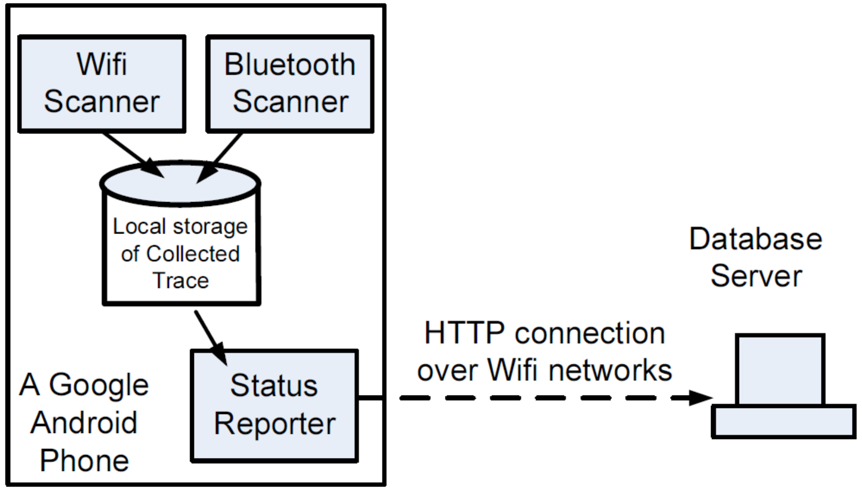
Data Collection

Data Collection Selection of Parameters

- **Sensors**
  - WiFi, Bluetooth, GPS, Accelerometer, Sound, Images
- **Contact Parameters**
  - Probability of contact
  - Duration of contact
  - Frequency of contact
- **Environment Parameters**
  - Number of days
  - Period of scanning (accuracy of tracked data)
- **Mobile Device Parameters**
  - Speed of person carrying mobile device
  - Density of mobile devices

Data Collection

UIM System



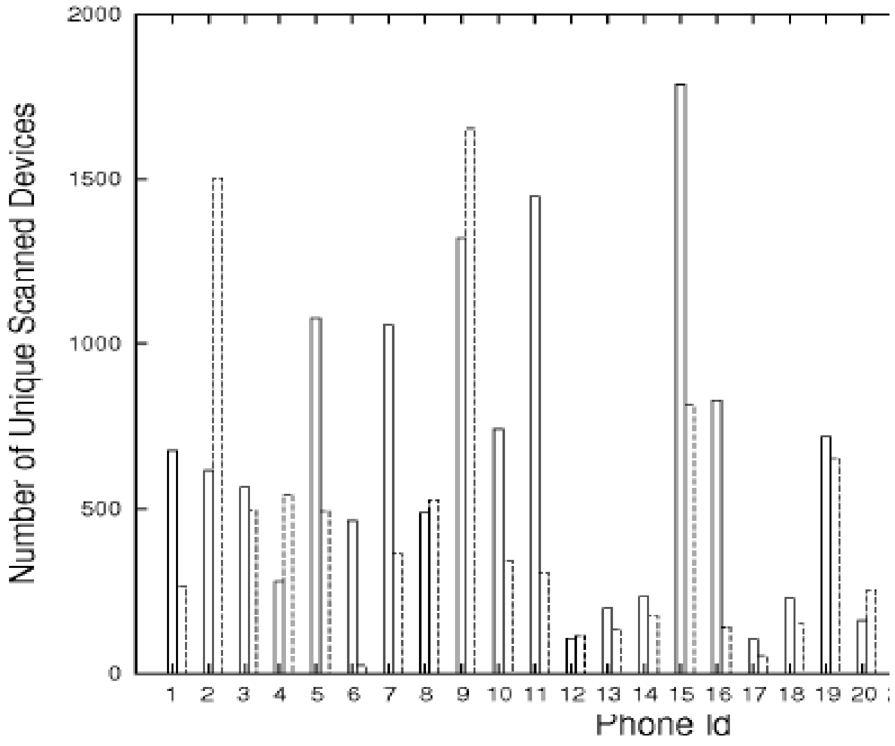
- Collects MAC addresses of Wifi Access Points (AP) and Bluetooth-enabled devices
  - Wifi AP MACs are used to infer location information
  - Bluetooth MACs are used to infer social contact
- Important: Data Collection must
  - Take very little CPU (computational overhead)
  - Be very energy-efficient (energy overhead)

L. Vu, K. Nahrstedt, S. Retika, I. Gupta "Joint Bluetooth/Wifi Scanning Framework for Characterizing and Leveraging People Movement in University Campus" *MSWiM 2010*

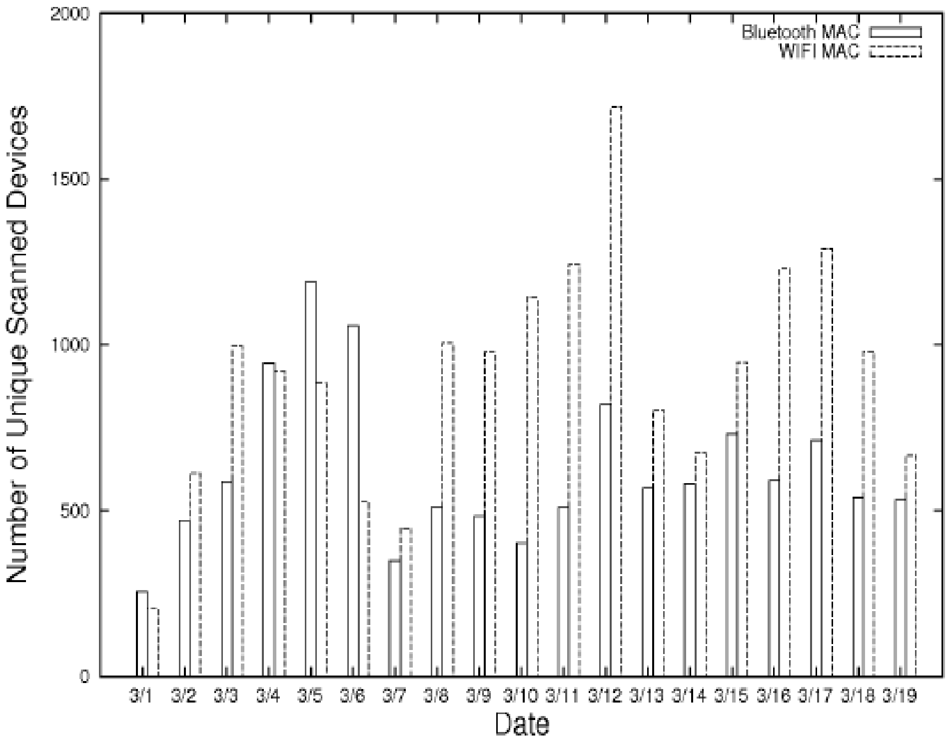
UIM Collected Mobility Trace

Overall Characteristics			
Name of Data Set	D_1	D_2	D_3
Number of Internal Devices (participants)	28	79	14
Experiment Period	03/01-03/20	04/08-05/15	05/24-08/16
Number of Days	19	38	85
Bluetooth Scanning Period (sec, δ_B)	60	60	60
Wifi Scanning Period (min, δ_W)	30	20	30
Number of External Scanned BT MACs	8508	17080	4834
Number of Scanned Wifi AP MACs	7004	29324	4340
Participant Information			
Number of CS faculties	2	2	0
Number of CS staff	1	1	0
Number of CS grads	14	30	12
Number of CS undergrads	8	43	1
Number of ECE grads	2	2	2
Number of ABE grad	1	1	1

Scanned devices by Phones and Time



Scanned Device Distribution



Scanned Device Distribution Over Time

- Number of scanned devices varies significantly
- Number of devices scanned increases for the weekdays and decreases at the weekends

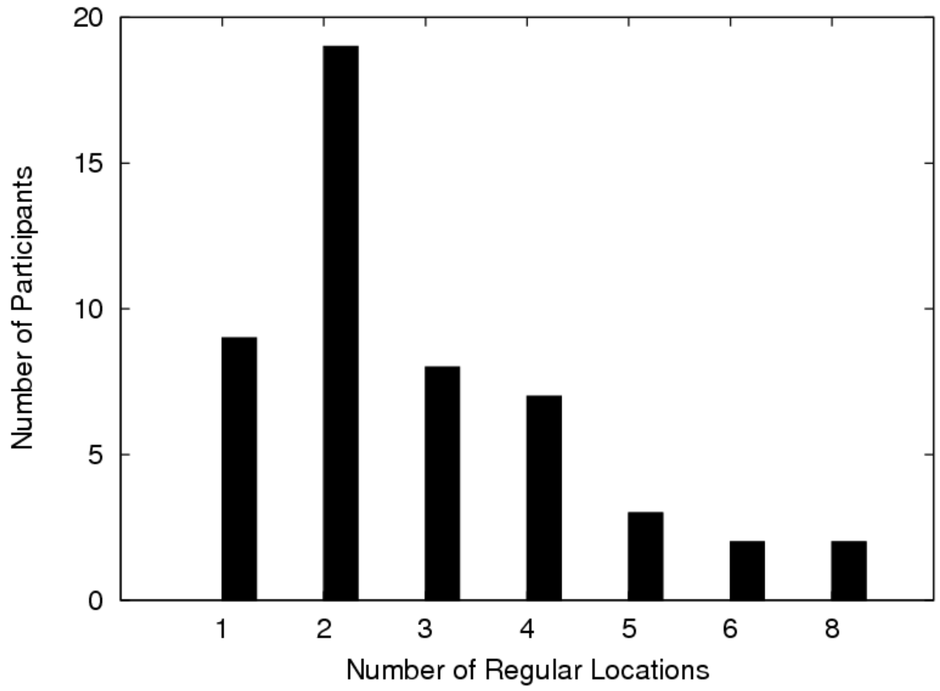
Comparison between UIM and Other Data

	PMTR	Intel	Cambridge City	Infocom	UIM
Environment	Workplace	Corp.	City	Conf.	U of I Campus
Duration (day)	19	3	10	3	19
# of Devices	49	8	36	41	28
δ_B(second)	1	120	600	120	60
Ad hoc Trace	Yes	Yes	Yes	Yes	Yes
Location Trace	No	No	No	No	Yes
Device Type	PMTR	iMote	iMote	iMote	Phone
# of In- contact	11895	1091	8545	22459	30385
# of Ex- device	N/A	92	3586	197	8508
# of Ex- contact	N/A	1173	10469	5791	82091

Comparison of UIM trace with other traces collected in City, Workplace, Corporation

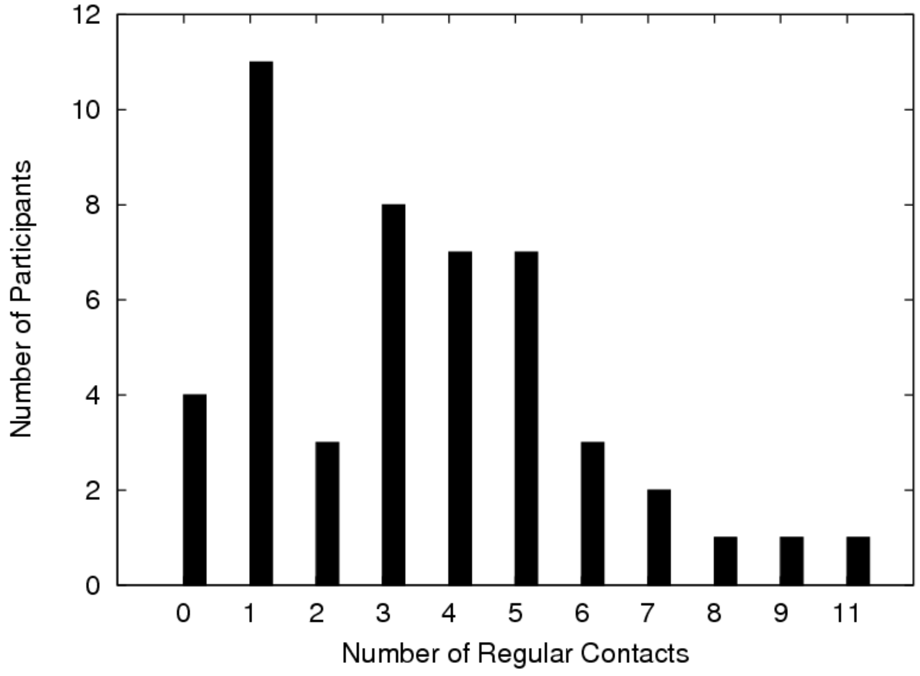
Characterizing People Movement Found in Data

- Location is regular if person visits location at the same time slot for at least half number of days
- People visit regular locations (plot is from 50 participants)



Characterizing People Movement Found in Data (2)

- Contact is regular if person makes contact at the same time slot for at least half number of days
- People make regular contact (plot is from 50 participants)



Sources: ttp://www.streamsministries.com/resources/dreams-visions/context-context-context

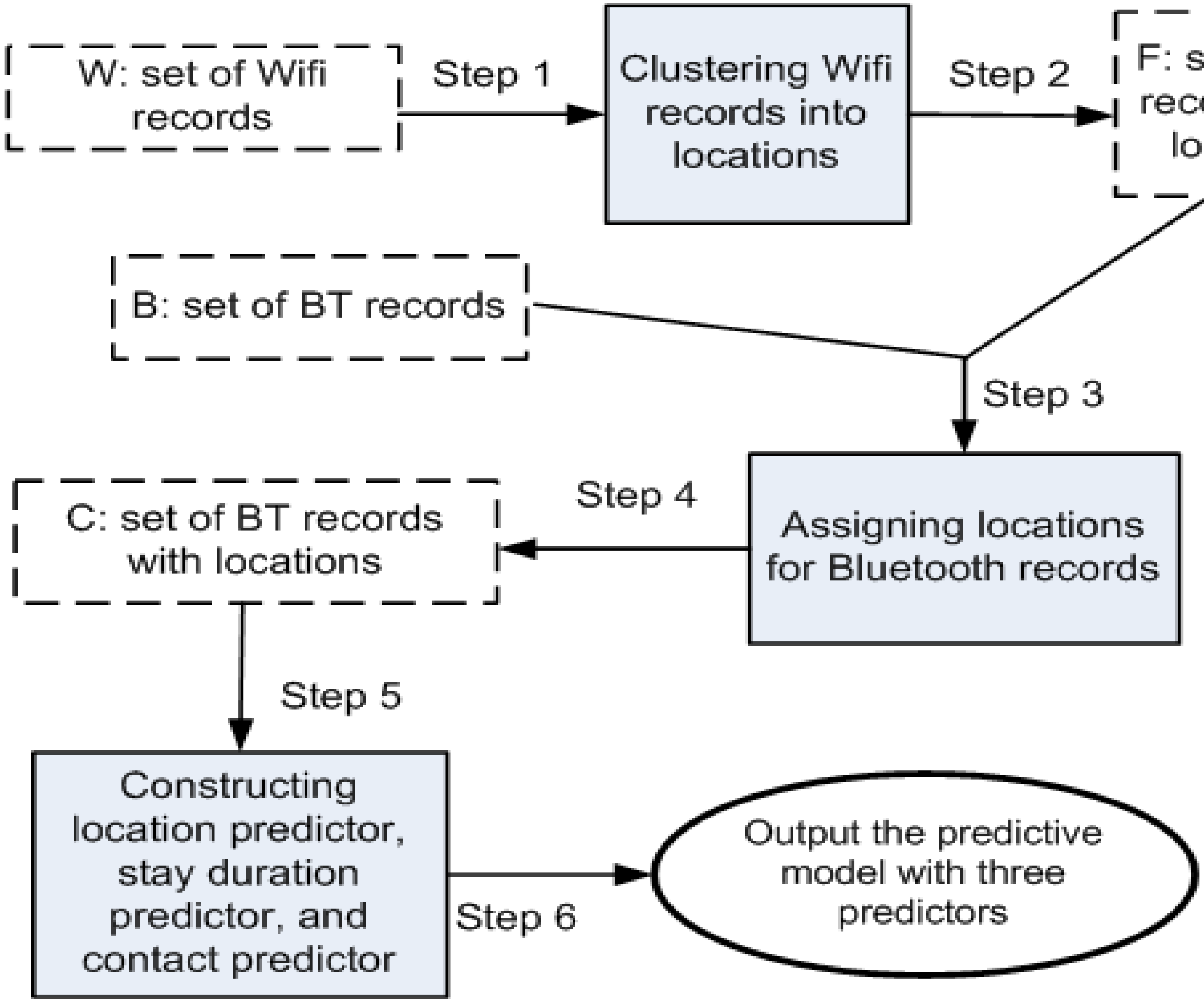
Data Analytics

Context (Location, Contact) Detection

Construction of Predictive Models

- Analysis of Mobile Sensory Data (e.g., WiFi, Bluetooth) to determine CONTEXT
  - Answer Questions about Future Movement
    - Where will the person be (location) ?
    - How long will she stay there (stay duration) ?
    - Who will she meet (social contact) ?
    - …
  - Discover New Mobility Patterns
    - For individuals
    - For crowds
    - For specific groups of interest

Jyotish - Predictive Data Analytics

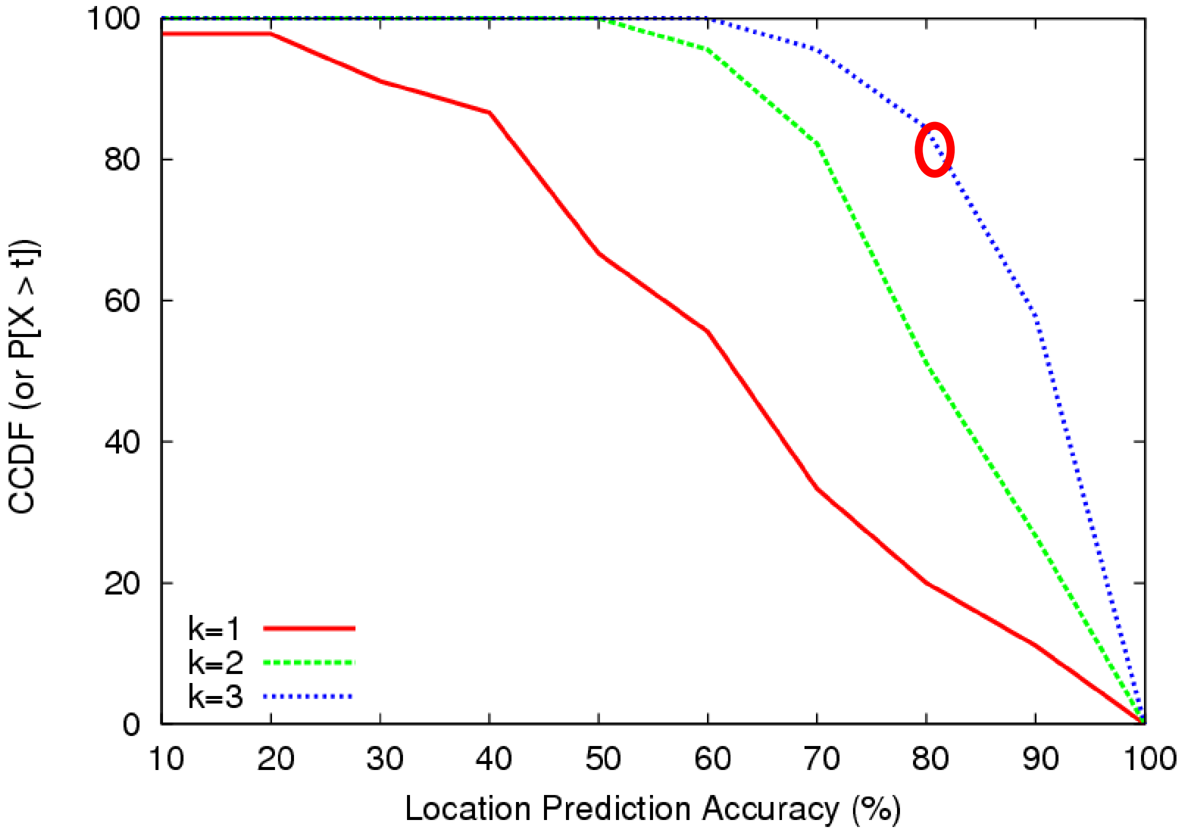


Long Vu, Quang Do, Klara Nahrstedt, " Jyotish: A Novel Framework for Constructing Predictive Model of People Movement from Joint Wifi/Bluetooth Trace", IEEE Percom 2011, Seattle, WA, March 2011 (**Mark Weiser Best Paper** Award)

Evaluation of Jyotish Predictive Model

- Settings
  - 50 Joint Wifi/Bluetooth traces from 50 participants
    - Each is from 20 to 50 days
  - Divide the Bluetooth trace (with location) into training (80%) and testing (20%) sets
    - Training set is used to train predictors
    - Testing set is used to evaluate these predictors
  - Input for all predictors: $X=\{v_1,\tau_1\}$

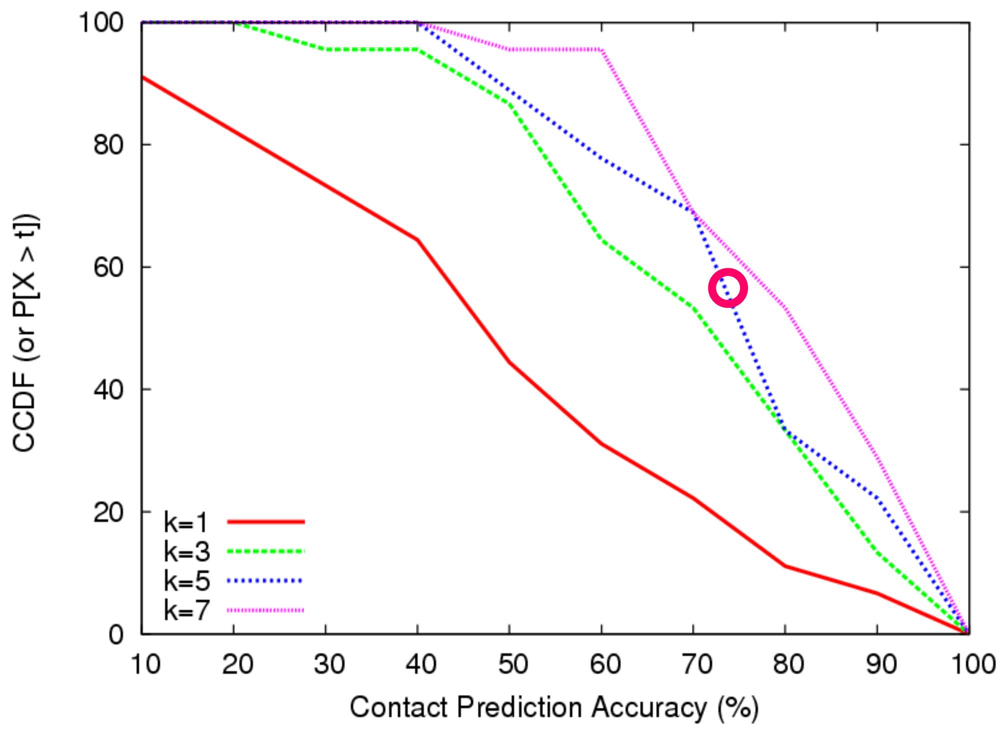
Performance of top-k Location Predictor



- With *k*=3, 85% of participants have more than 80% correct location prediction

Performance of top-k Contact Predictor

- If at least one contact is predicted correctly, top-k contact predictor is correct



- With *k*=5, 60% of participants have more than 75% of correct contact predictions

AREA SEARCH
ECONAVI detects human movements and reduces the waste of cooling the unoccupied area.

ACTIVITY DETECTION
ECONAVI detects changes in activity levels and reduces the waste of cooling with unnecessary power.

ABSENCE DETECTION
ECONAVI detects human absence in the room and reduces the waste of cooling an empty room.

Source: http://www.airforceaircon.com/panasonic.php

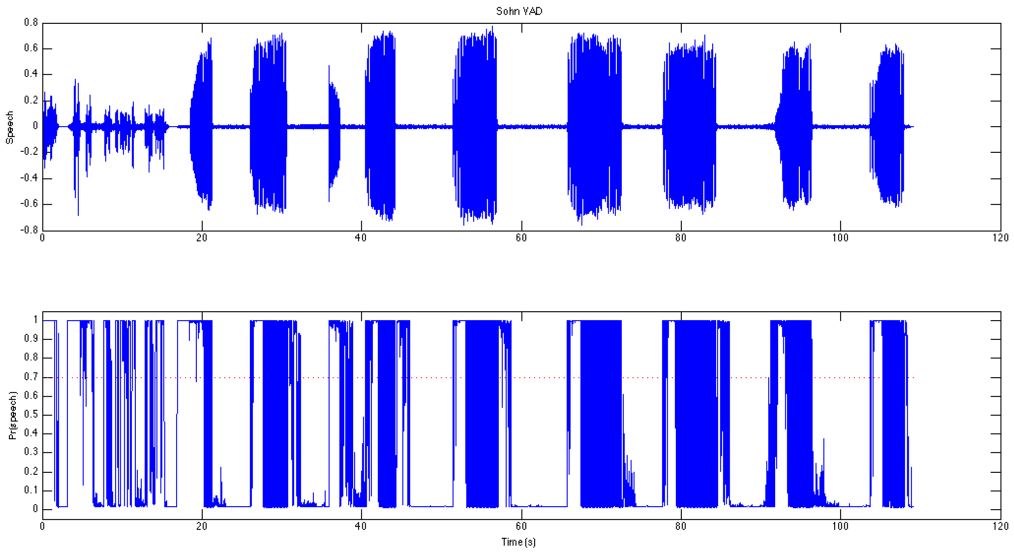
Data Analytics

Activity Detection and Recognition

Different Approaches to Detect Activities

- New Activity Recognition via IoT
  - Cell Phone Accelerometer
  - RFID-Based Sensors
- Traditional approaches: via cameras and speaker voice recognition

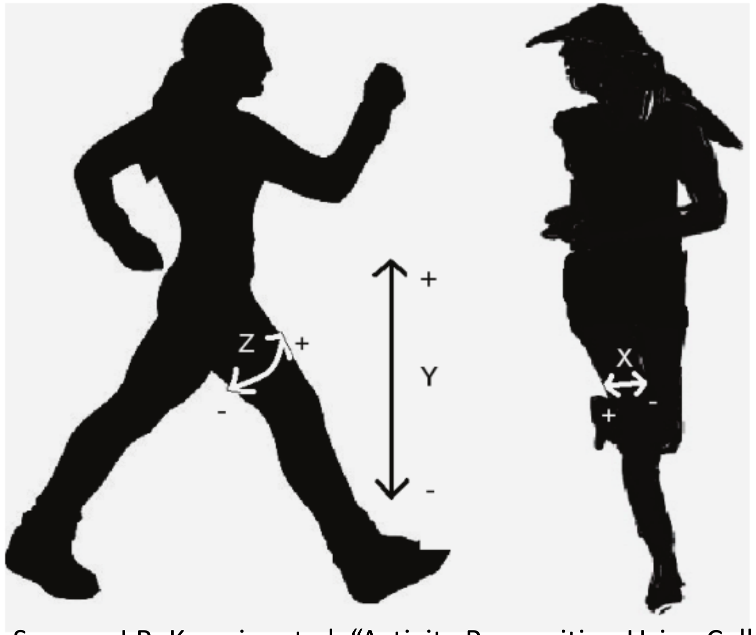
http://www.ips-analytics.com/en/products/ips-videoanalytics-new/camera-based/ips-motion-detection-axis.html



http://gbirdlab.blogspot.com/2012/12/voice-activity-detection.html

Phone Accelerometer Activity Recognition

- Sensors:
  - tree-axial accelerometer
  - X –lateral movement
  - Y – vertical movement
  - Z – forward movement
- Data Collection:
  - Sample frequency 20 Hz
  - Data stored on phone
- Feature Selection:
  - Average acceleration along each axis
  - Standard deviation for each axis
  - Time between peaks
- Classification
  - Machine-learning framework to differentiate 6 activities: walking, jogging, ascending stairs, descending stairs, sitting and standing
- Evaluation
  - High accuracy (90%) for walking, jogging, sitting, and standing.
  - Problems for detecting ascending and descending stairs



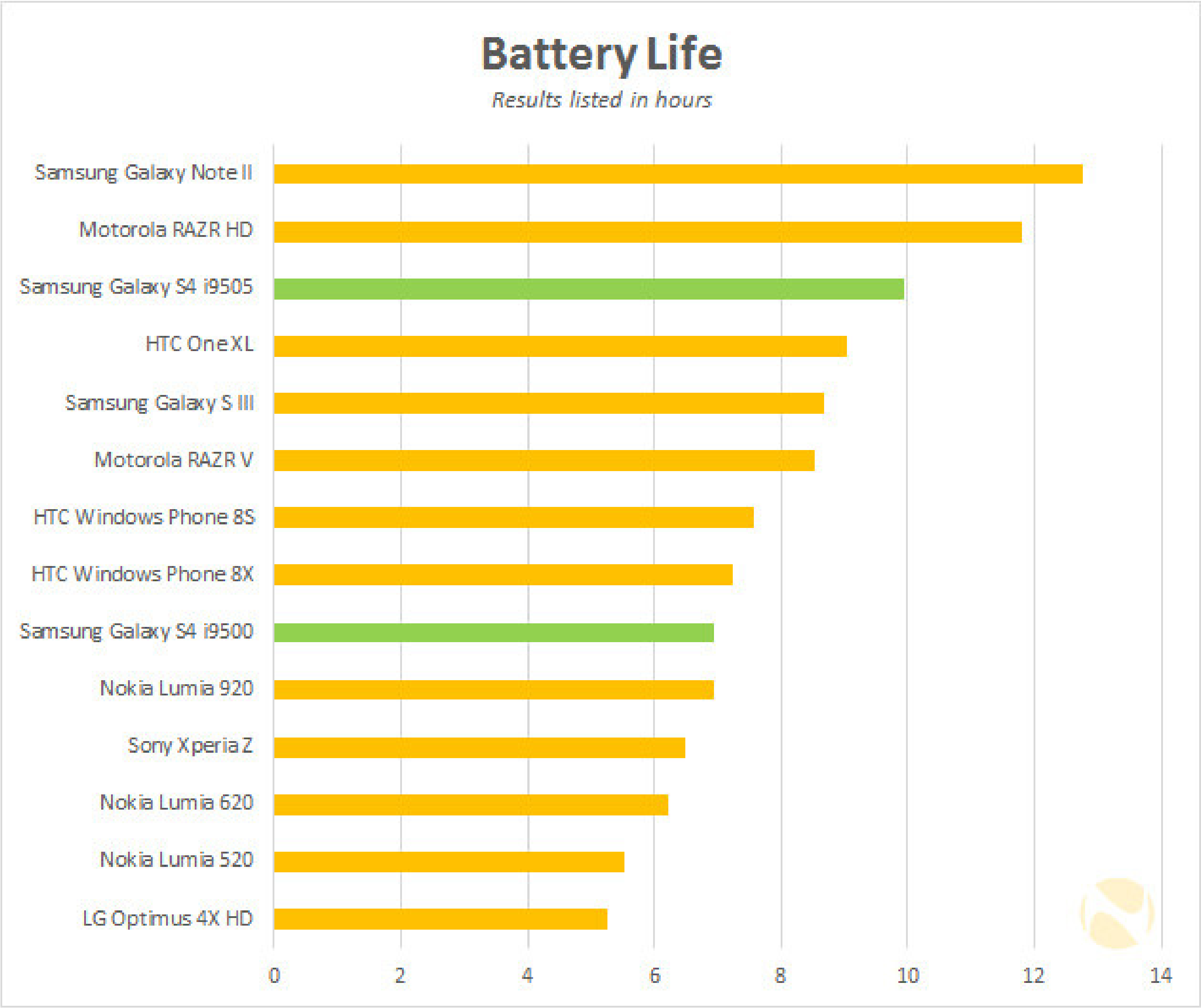
Source: J.R. Kwapisz et al, “Activity Recognition Using Cell Phone Accelerometers”, SIGKDD Newsletter, 2011

UHF RFID – WISP based Activity Recognition

- Sensor:
  - UHF RFID - WISP tag equipped with accelerometer and read by RFID reader (range 3 m)
- Data Collection
  - Sample frequency 4-20 Hz
  - Spatial density of 20 WISP
  - Orientation sensitivity – yes
  - Occlusion sensitivity – yes
- Feature Selection
  - No typical features
- Classification
  - Machine learning framework – Hidden Markov Model
  - Training done on subset of labeled data

Activity	RSN		iBracelet	
	Precision(%)	Recall(%)	Precision(%)	Recall(%)
Make Cereal	92	100	100	50
Make Sandwich	72	80	90	90
Make Coffee	92	100	100	90
Make Kool-aid	100	100	100	90
Read Book	85	100	88	90
Watch TV	83	40	100	90
Clean Windows	100	100	60	30
Tend to Plants	100	100	100	70
Use Telephone	100	100	100	20
Use Elliptical	100	100	100	30
Take Vitamins	73	80	100	30
Take Antacids	91	100	100	40
Brush Teeth	91	100	100	100
Go to Sleep	88	70	100	20
Totals	90	91	95	60

Source: M. Buettner et al, “Recognizing Daily Activities with RFID-based Sensors”, UbiComp 2009

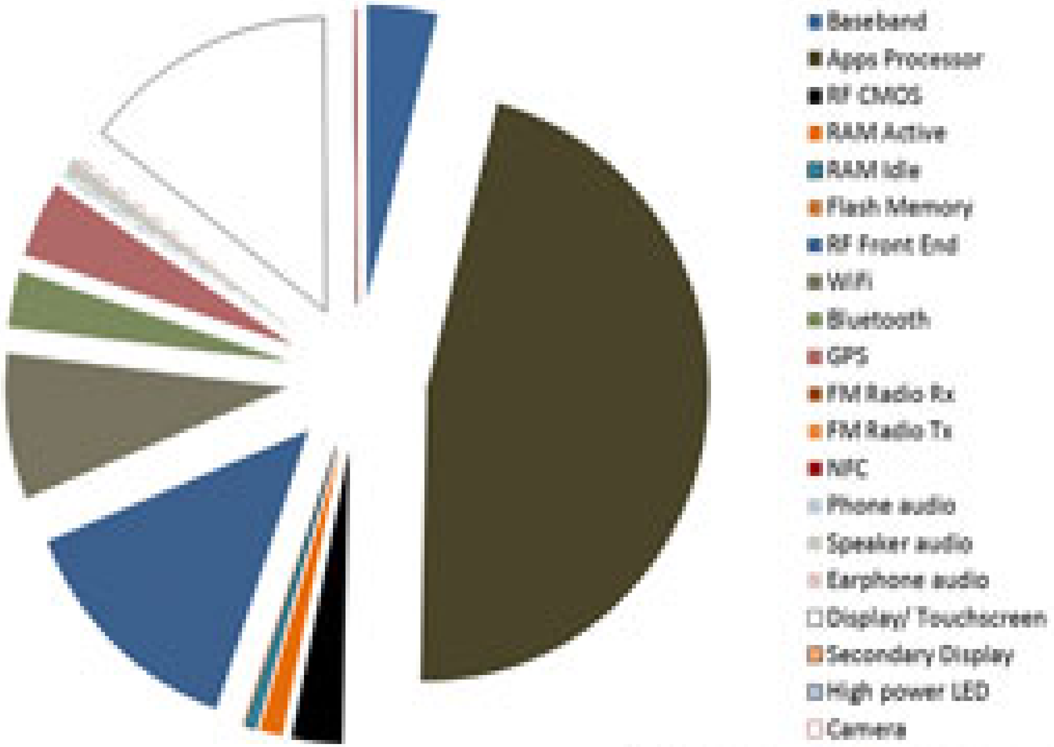


Energy Consumption

http://www.neowin.net/news/review-samsung-galaxy-s4-3g-i9500-and-4g-i9505

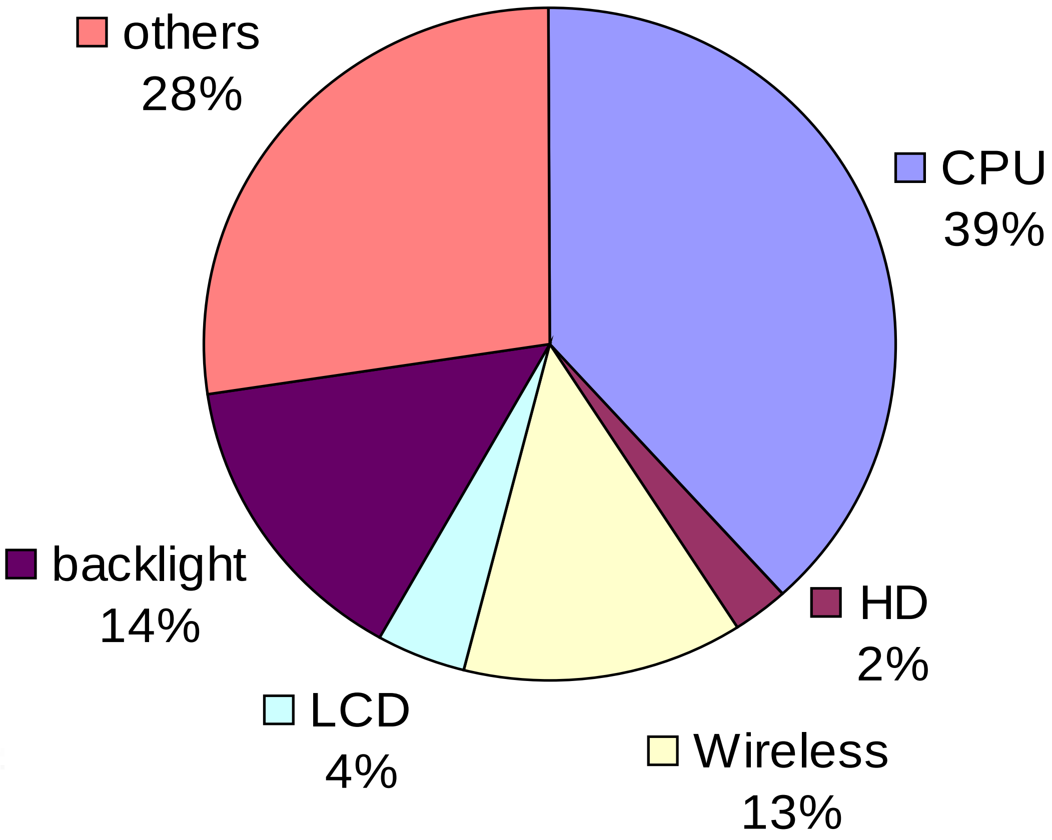
Power Distribution

Typical LTE Smartphone



Breakdown of power consumption in a typical LTE smartphone, urban case, business user

IBM ThinkPad R40

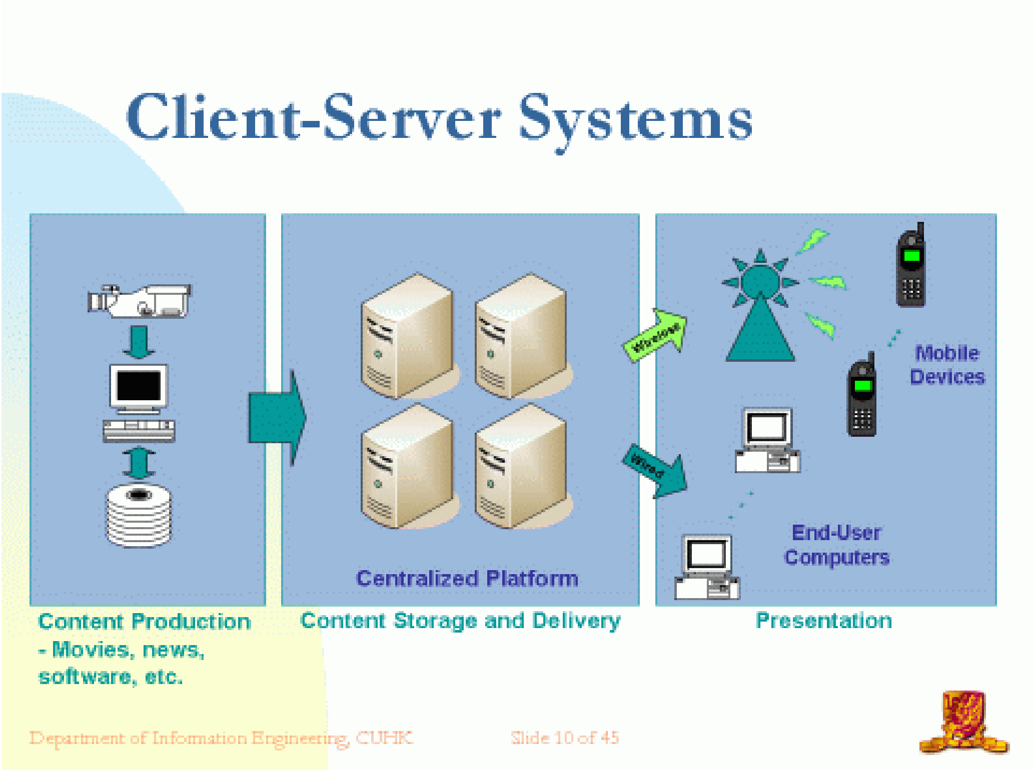


Source: http://www.microwavejournal.com/articles/print/20949-the-economics-of-gaas-and-cmos-pas-crunch-time

Video Streaming Services

- Content Production
  - Phones are content producers
  - Example: Grace System
- Content Playback
  - Diverse mobile devices receive TV and movies from streaming services

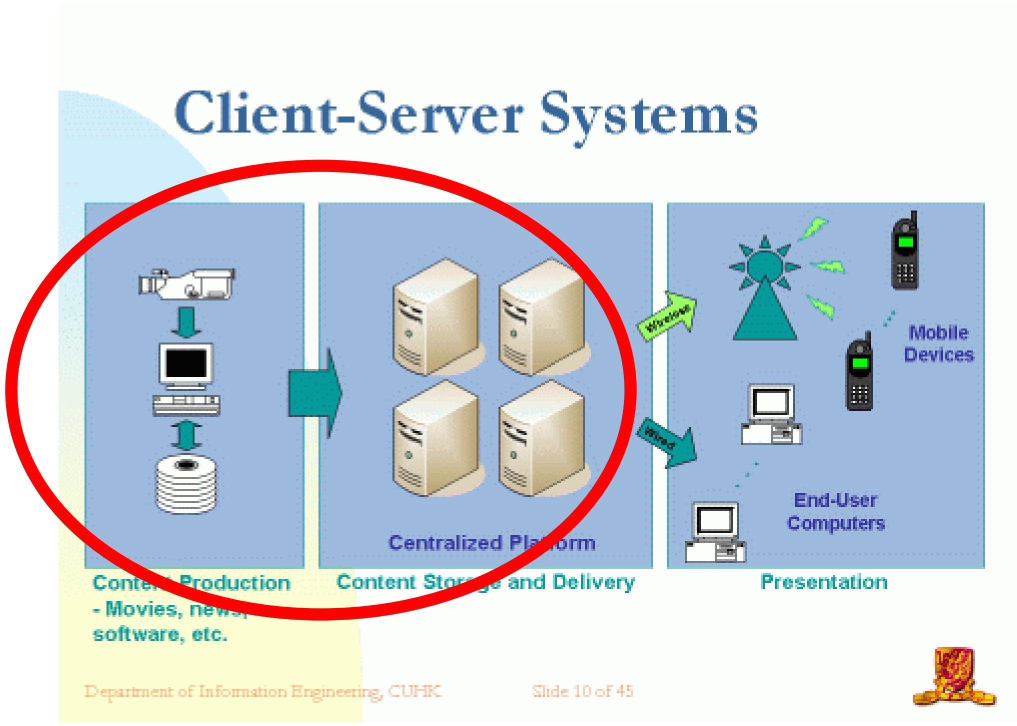
- Video streaming – biggest energy consuming service!!



Source: http://fuugo.tv/platform/solution/

Content Production – GRACE System

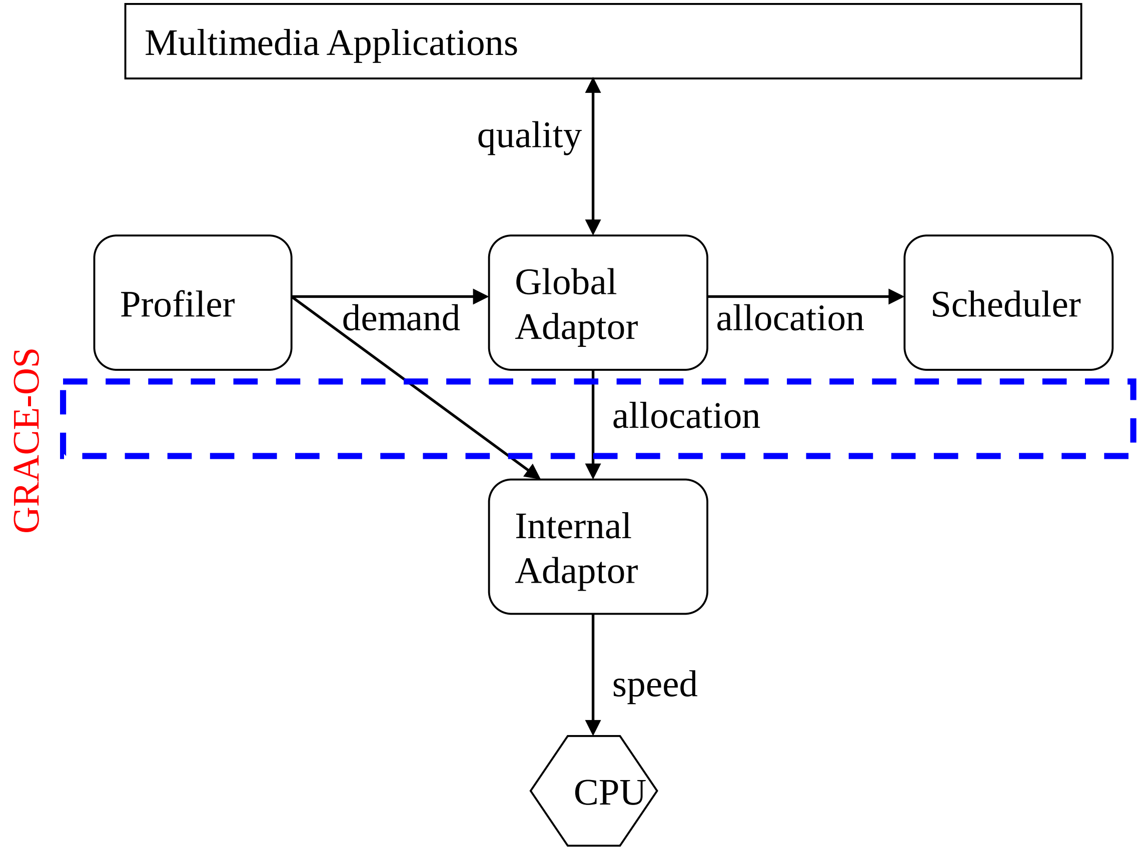
- Research Problem:
  - Want CPU Power Savings
  - When to execute what applications?
- Energy-aware real-time scheduling
  - What application quality?
- Global adaptation
  - What CPU speed and power?
- Internal CPU adaptation
  - How to predict CPU demand?
- Kernel-based profiling

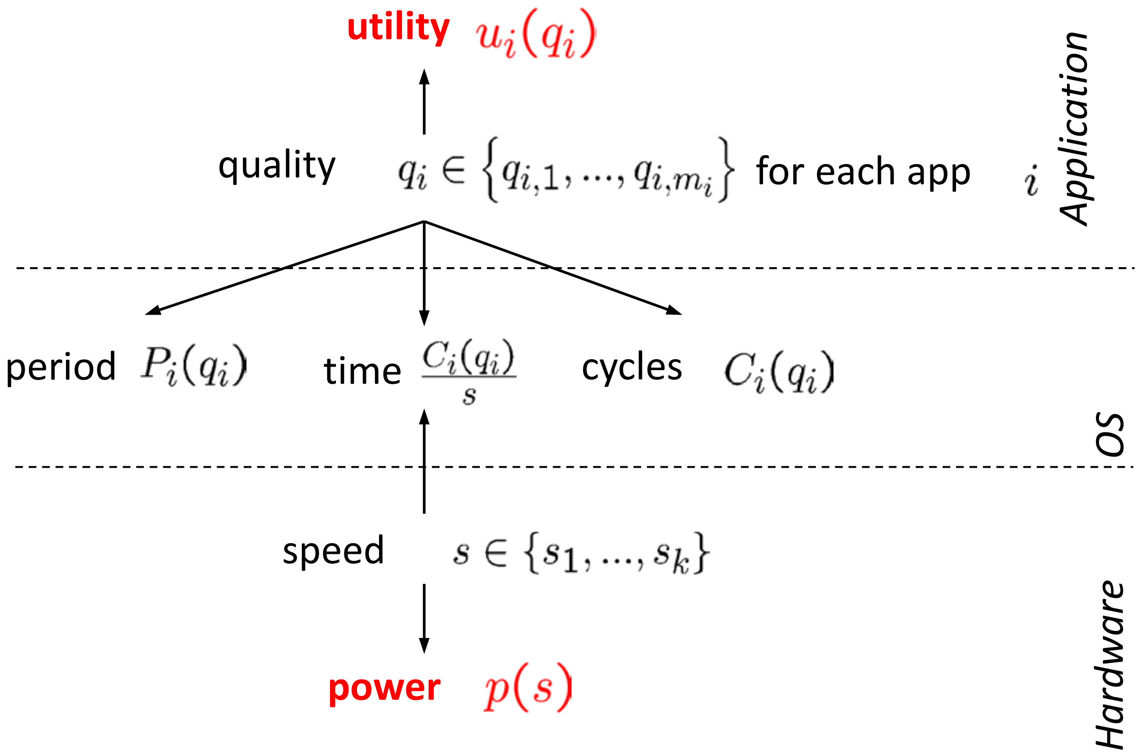


Content Production

Wanghong Yuan, Klara Nahrstedt, Srita Adve, Robin Kravets, Doug Jones, *“GRACE: A Cross-Layer Adaptation Framework for Mobile Multimedia Devices”*, **IEEE Trans. on Mobile Computing**, Volume 5, Issue 7, July 2006

GRACE-OS Architecture





Wanghong Yuan, Klara Nahrstedt, *"Energy-Efficient CPU Scheduling for Multimedia Applications"*, **ACM Trans. on Computer Systems**, Vol. 24, No. 3, Aug. 2006

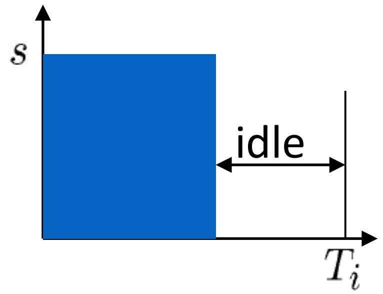
Energy-Aware Scheduling and Internal Adaptation

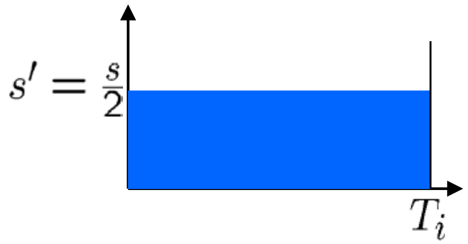
- Enforce decisions on quality and energy
- Budget-based earliest deadline first
  - Each app has a soft deadline
  - Each app has a cycle budget
    - Recharged to $C_i(q_i)$ at a new period
    - Decreased by # of cycles the app uses
  - Run app w/ earliest deadline and +budget at the coordinated speed

Idea: slow down frame execution

- BUT within time budget $T_i = \frac{C_i}{s}$

If know actual cycle demand C' for a frame **then** execute it at speed $s' = \frac{C'}{T_i}$





$$p(s) \times \frac{T_i}{2} = \frac{s^3 T_i}{2}$$

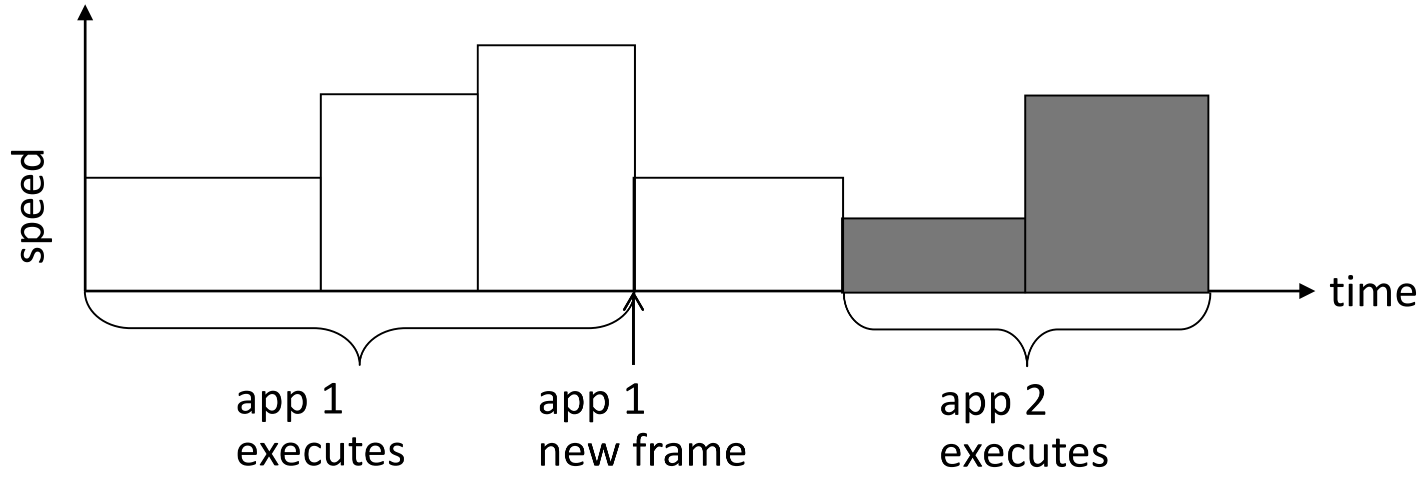
$$p(\tfrac{s}{2}) \times T_i = \frac{s^3 T_i}{8}$$

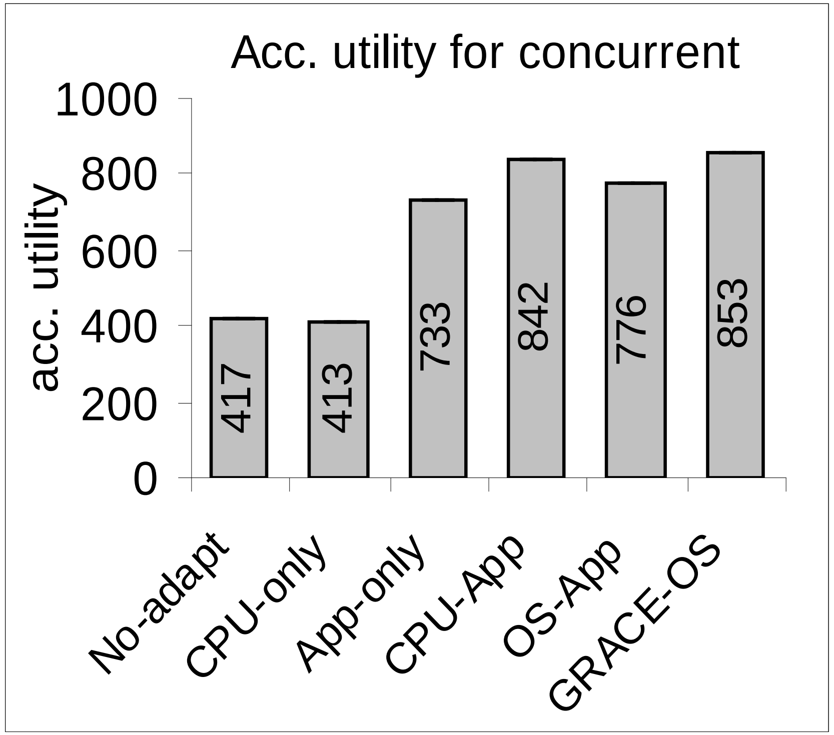
Speed Schedule

- Speed schedule for each application
  - A list of switching points (*c, s*)
  - Speed changes to *s* when cycle usage is *c*

    (0, 100MHz), (10^6, 200MHz), ($2x10^6$, 400MHz)

Change speed within a frame

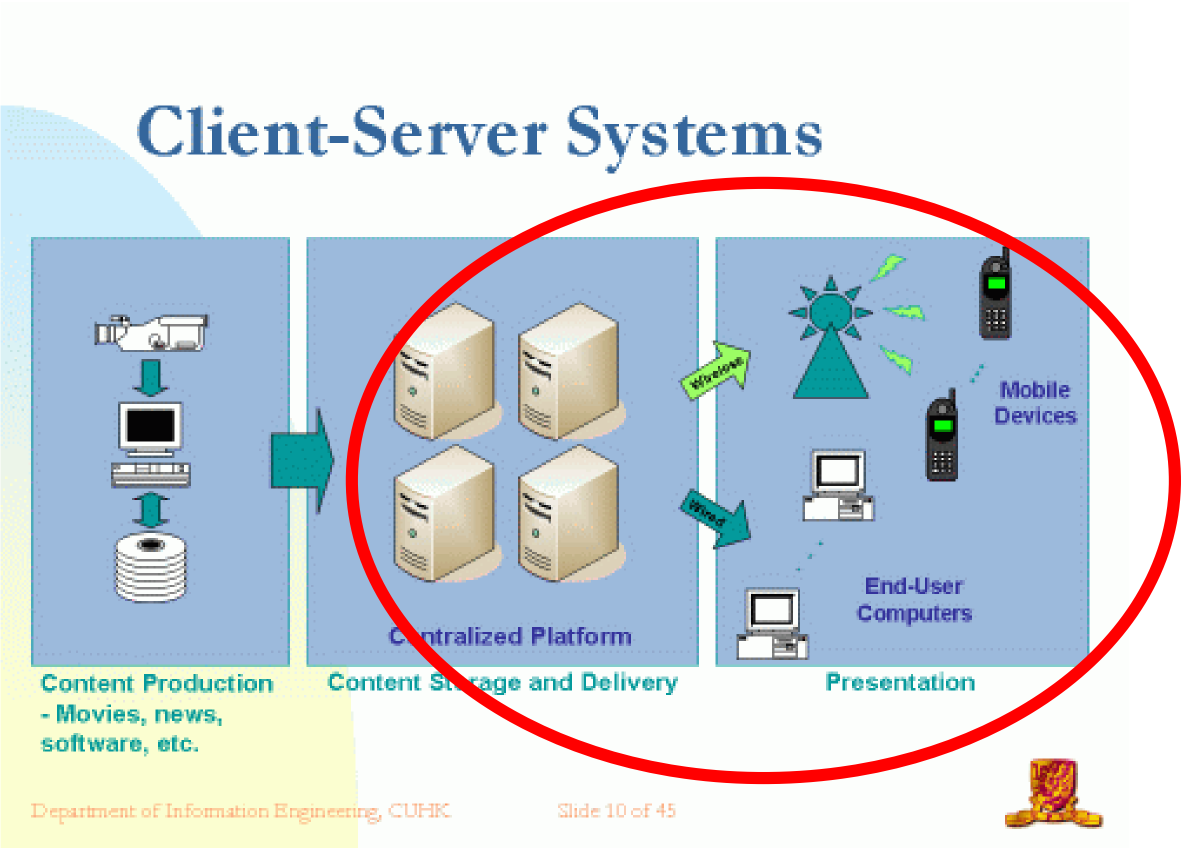




H.263 encoding

Content Playback

- Different Streaming Techniques
  - Bitrate streaming, bitrate throttling, on-off, dynamic adaptive streaming over HTTP (DASH), fast caching
- Different Upload Techniques
  - Usage of progressive download
  - Download-and-play
  - Local playback strategies
- Different Wireless Technologies
  - 3G and LTE



Content Playback

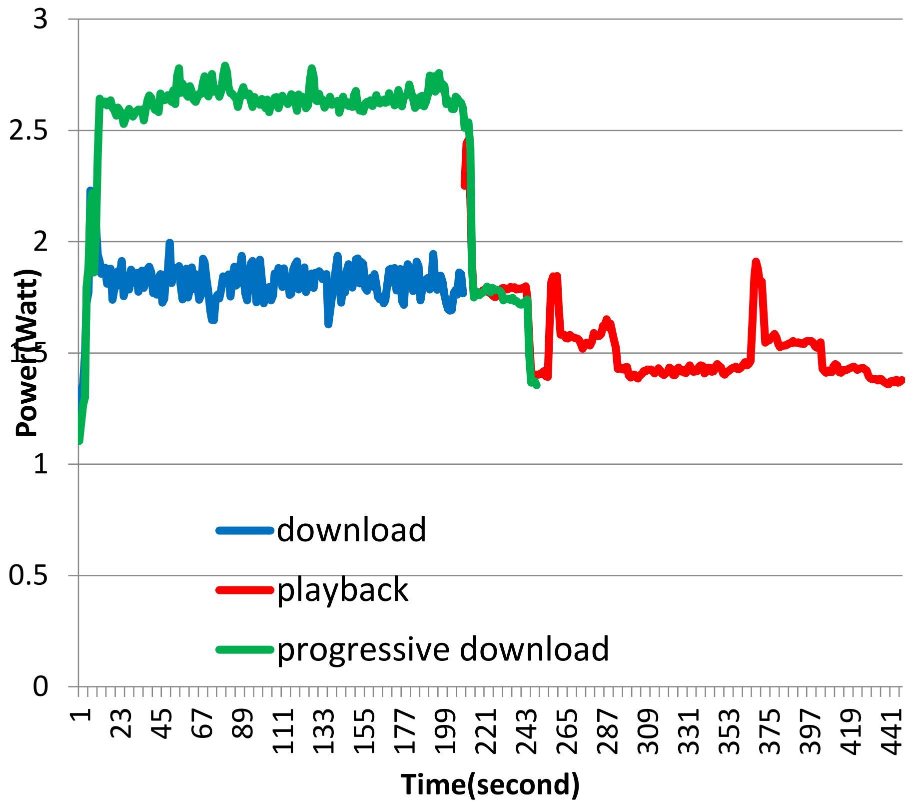
Content Playback: Concerned Techniques

- Progressive download
  - HTTP/TCP
  - No resource reservation
  - Media server pushes data to the clients as fast as possible
  - Client starts playback once enough data has been downloaded

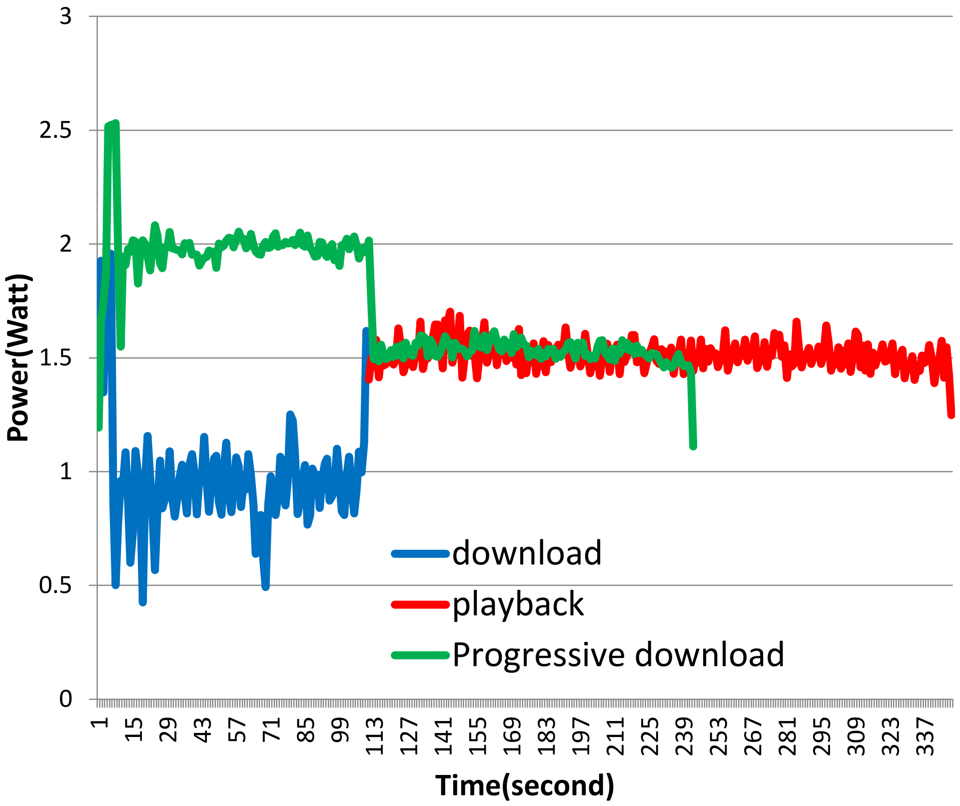
- Research Problem:
  - What are the factors that influence energy consumption?
- Download Technology
  - Progressive download vs. Traditional TCP download-and-play
- Network Access Technology
  - WCDMA (3G) vs. WLAN 802.11g
- Mobile Device
  - Nokia N95

Source: Y. Xiao et al, “Energy Consumption of Mobile YouTube: Quantitative Measurement and Analysis”, 2008

Progressive download vs. Traditional TCP download –and-play

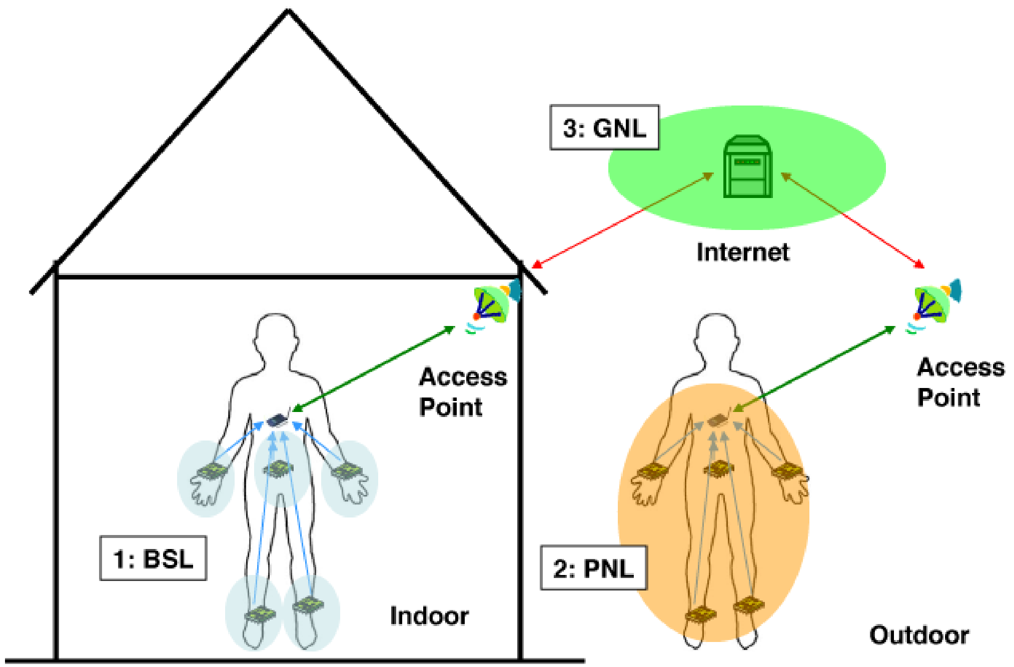


WCDMA



WLAN

Source: Y. Xiao et al, "Energy Consumption of Mobile YouTube: Quantitative Measurement and Analysis", 2008



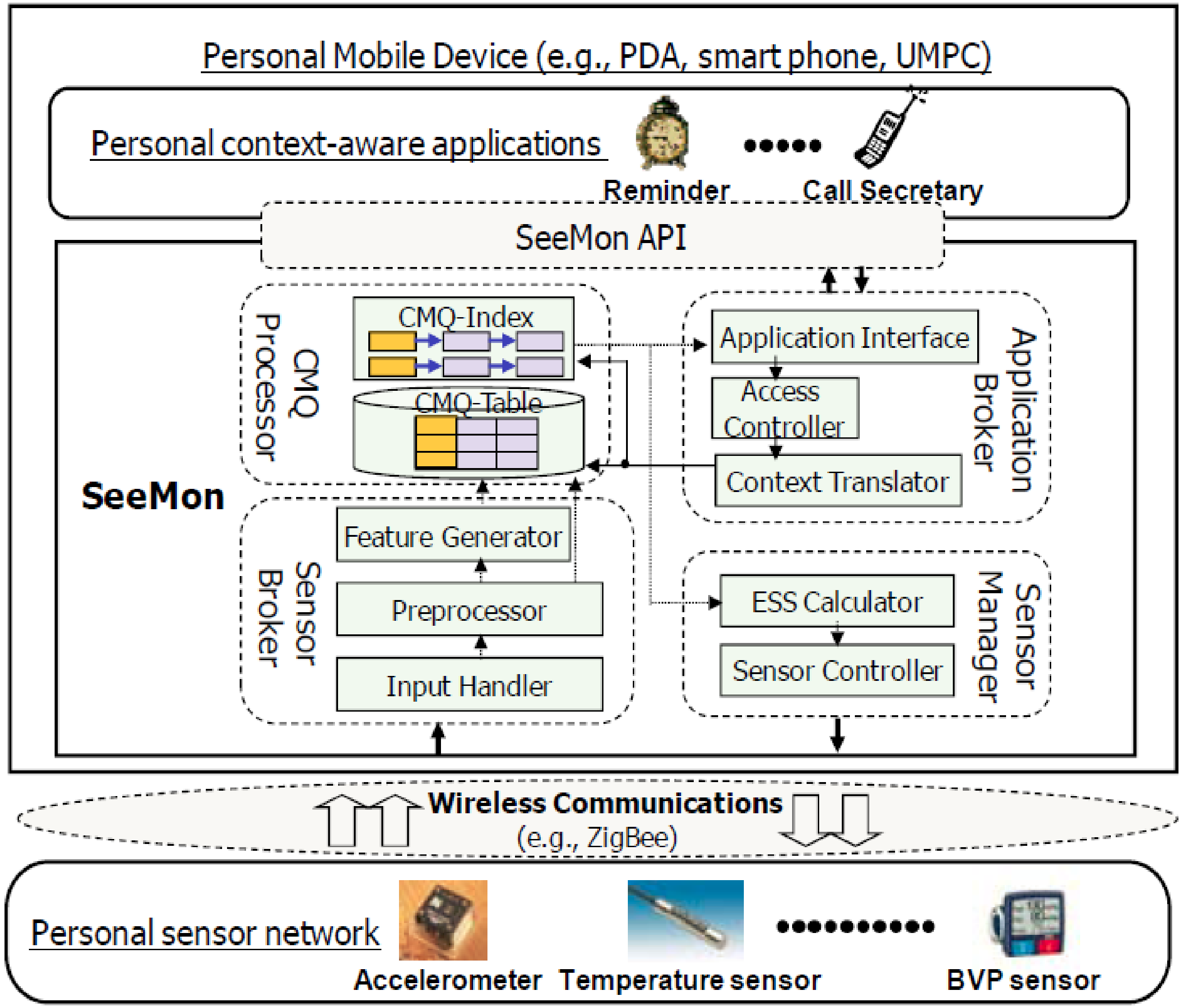
Source: http://www.eecs.berkeley.edu/~yang/software/WAR/

http://www.eecs.berkeley.edu/~yang/software/WAR/

Impact on Software Architectures

SeeMon

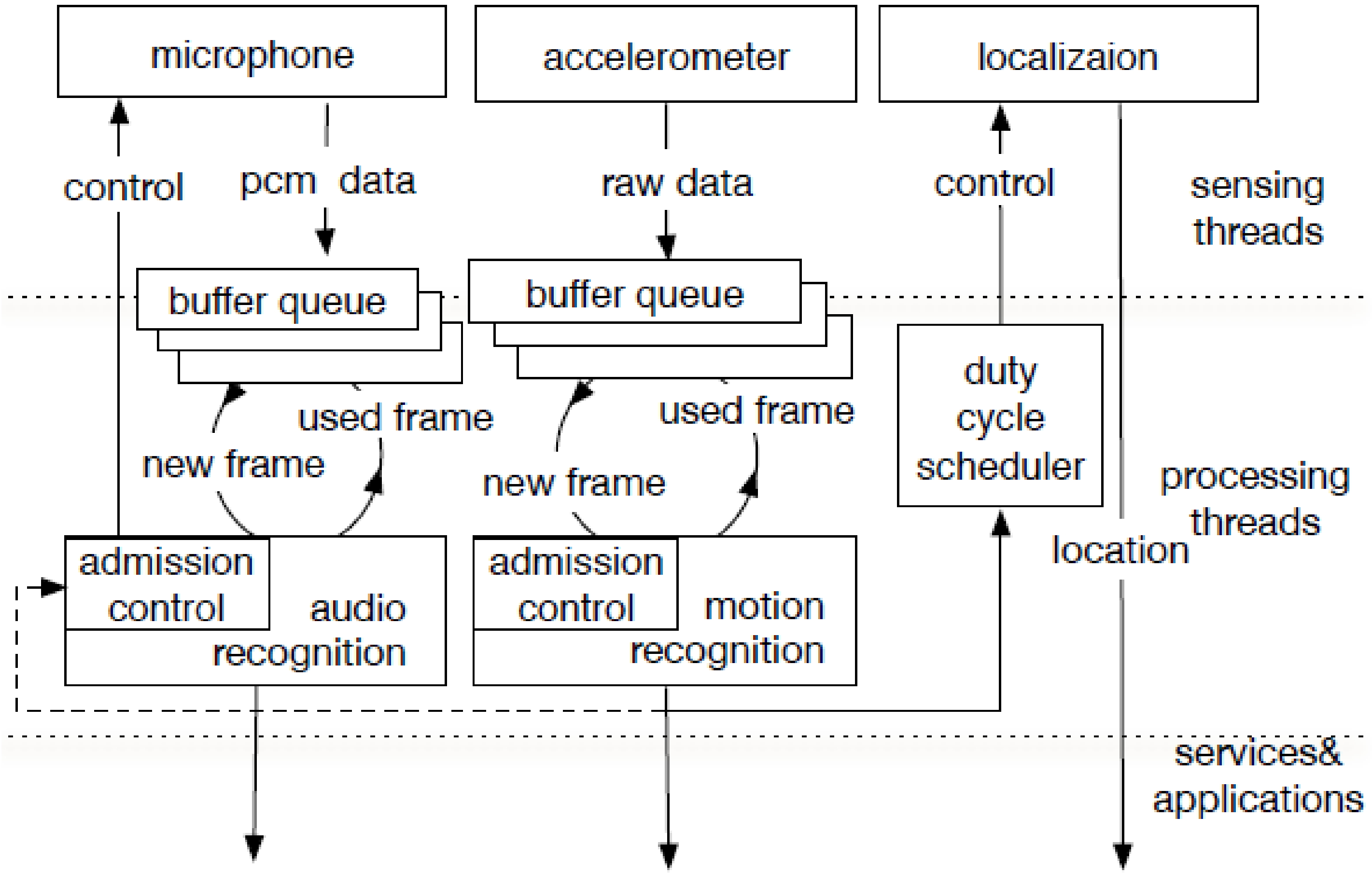
- Architecture:
  - External body sensors connected to mobile phone
    - Accelerometer, temperature, …
  - Sensor Processing for feature / context extraction
    - Sensor Broker, Context Monitoring Query Processor (CMQ)
    - Context (location, activity) Detection
  - Efficient Sensor Set (ESS)
    - Essential sensor set is event-driven duty cycle
- Energy Efficiency:
  - Two-tiered:
    1. Wireless body sensor network is independent from phone (offload of energy and minimization of wireless comm)
    2. Feature-level context evaluation reduces computational load



Source: S. Kang et al, "Seemon: Scalable and energy-efficient context monitoring framework for sensor-rich mobile environments", MobiSys 2008

Jigsaw

- Architecture
  - Sensors in phone
    - Accelerometer, microphone, GPS
  - Sensor Processing
    - Each sensor is adjusted for its best fitting duty
    - Accelerometer acts as primary sensor
    - GPS (localization) only enabled when needed
- Energy Efficiency
  1. Major benefit is gained from sensor management
  2. GPS expensive on energy (0.44 on Nokia N95), hence using it only when needed saves energy
     - Current accelerometer (MMA8450Q) can be as low as 27 uA in power



Source: H. Lu, et al, “The jigsaw continuous sensing engine for mobile phone applications”, ACM SenSys 2010.

Conclusion

- Tremendous growth of Internet of Everything, especially Internet of Mobile Things

- Tremendous Challenges:
  - Resource Constrained Environments
    - Energy
    - Mobility
  - Scale of “things”
  - Diversity of “things”

- Tremendous Opportunities:
  - New Sensors,
  - New Applications,
  - Multi-core/GPU mobile devices,
  - New parallel systems and technologies,
  - New Optimized Programming Environments

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