Sensor and Actuator Networks and the Internet of Things

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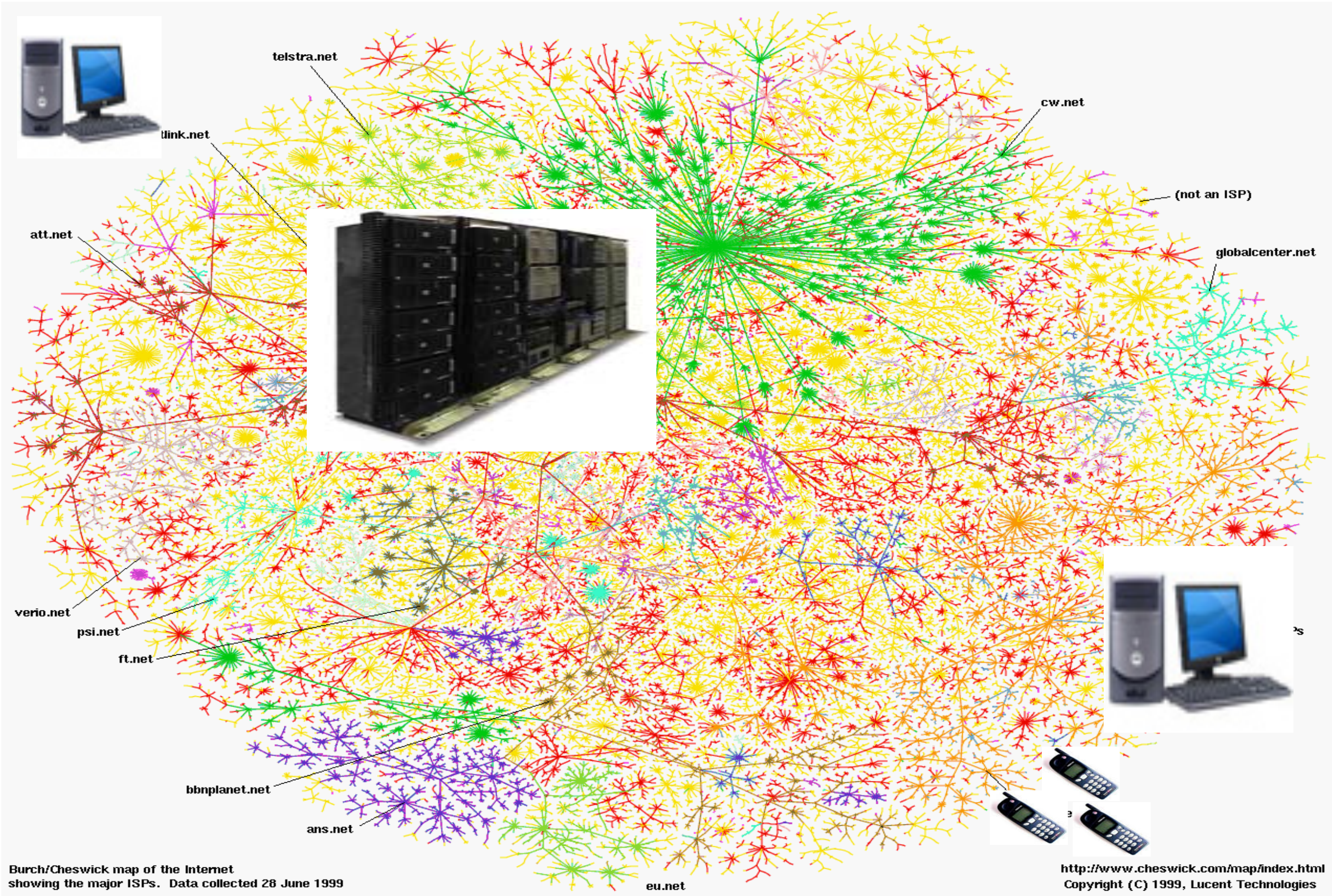
Overview

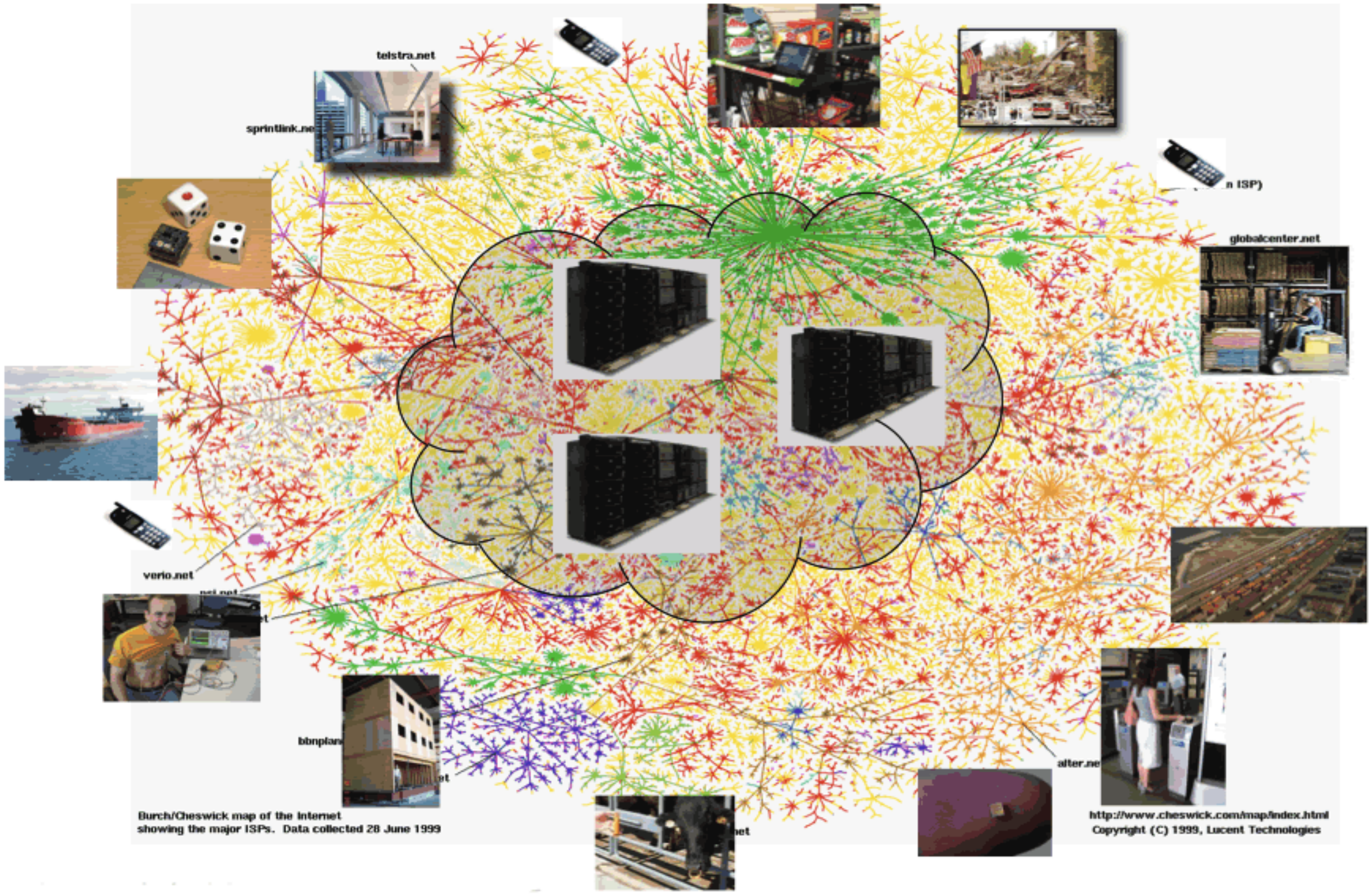
- WSANs and the Future Internet
- Smart Dust and the first generation of WSANs
- Shift to next generation WSANs and the IoT
- The Internet of People
- Analytics for IoT WSAN systems
- Capturing and employing collective behaviours

The Internet today



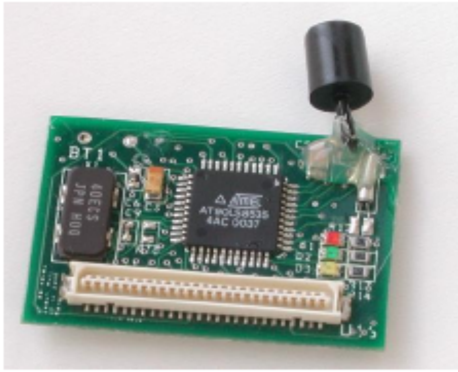
londonknowledgelab

The Internet of Things



Device evolution

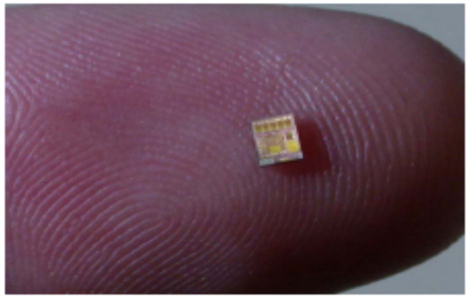
WeC (1999)



René (2000)

DOT (2001)

MICA (2002)



Speck (2003)

Problems and evolution

- Smart Dust faces significant problems
  - Energy harvesting
  - Maintenance
  - Programmability at the system level
- Mobility seen as significant for robustness/performance
- Popularity and proliferation of mobile networks
  - 400M sensors in mobile phones in 2014
- Shift of emphasis to smart-phone centric networks
  - e.g. sensor clouds around smart-phone core
- Shift of focus on data and human dynamics

The Internet of People

Business Week
March 2009

Core ingredients

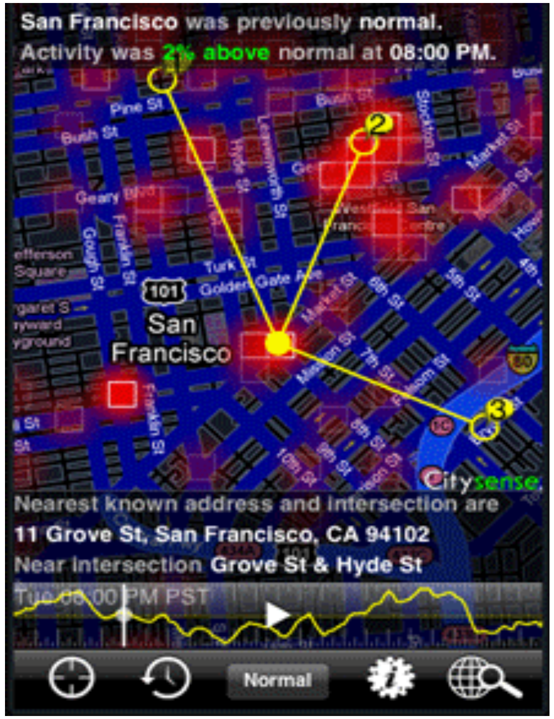
- Humans carry sensors and actuators on personal devices
- These devices interact with embedded systems such as building networks, Smart Dust, Personal Area Networks and RFID
- The IoT captures and processes the data
- Maintain, infer, characterize and provide intelligence

New problems emerge

- IoT sensor network systems generate automatically massive data sets
- How to tell what is important and what is not
- How to find significant information
- One solution we currently investigate in our group
  - To combining behaviours, preferences, or ideas of a group of people to create novel insights
  - aka collective intelligence

Significant locations

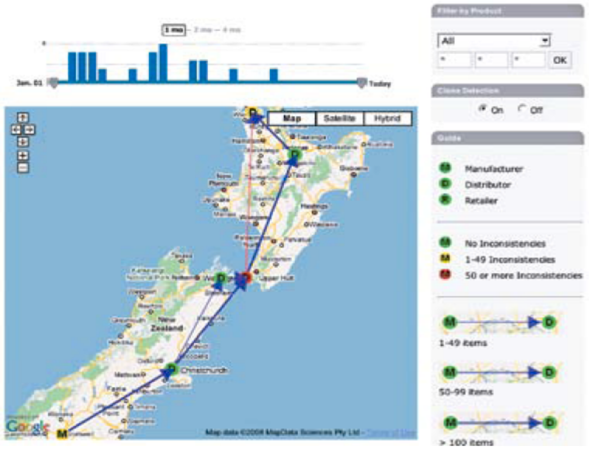
- Identify significant places
- Use mobile phone location records
- Identify hot-spots of activity
- Time specific
- Commercially available through Sense Networks
- Track real-world consumer behaviour



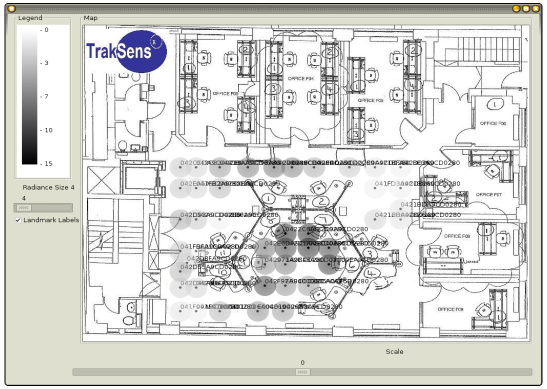
sensenetworks.com

RFID Analytics

- RFID-tagged products and locations
- Scan traffic at specific chock points
- Analyse traffic and identify hot-spots or problem areas
- Visual tools
- Different spatial resolution



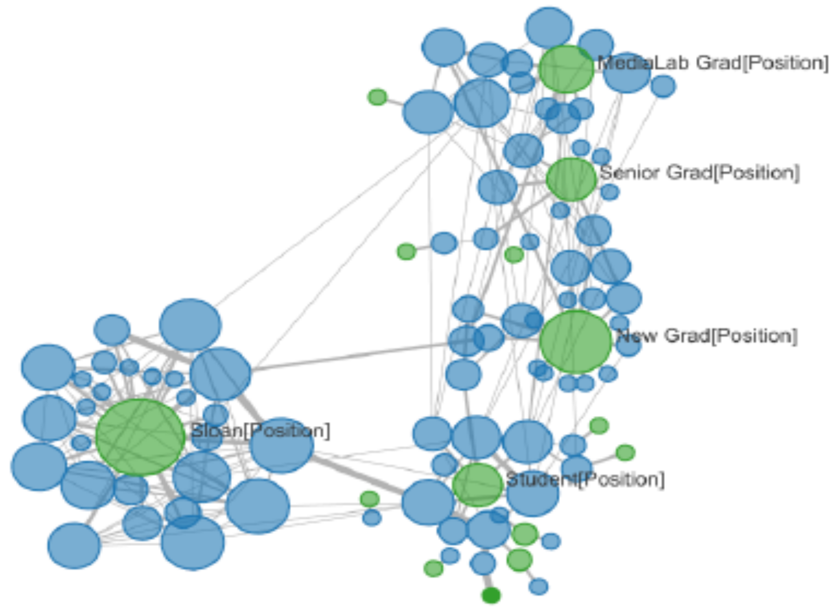
Illic *et al*, Auto-ID Lab Zurich



TrakSens

Social networks

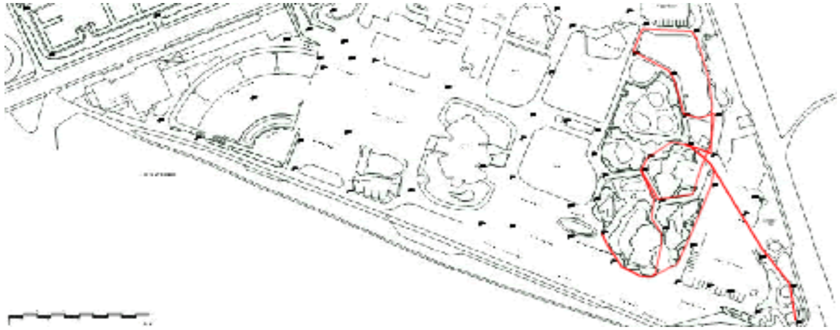
- Observe social networks in the real world
- Tag and rank location of individual
- Identify meetings through collocation or device-to-device interaction
- Create social network graph
- Conduct analysis
- Reality mining data set



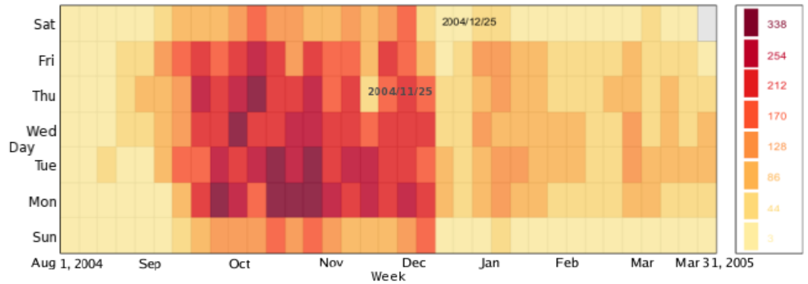
Shen *et al*, UC Davies

Patterns of behaviour

- Identify typical behaviours
- Possibly context and task specific
- Applications in navigational assistance, personalisation, recommendations
- Best-trails i.e. most popular pathways followed
  - GPS data from London Zoo
- Daily activity patterns
  - Reality Mining data



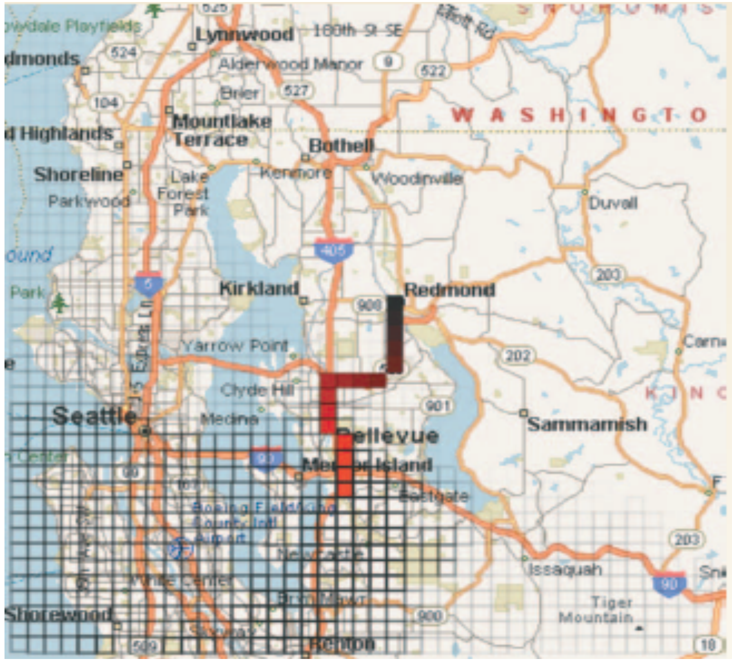
Experience Recorder



Shen *et al*, UC Davies

Prediction

- Predict driver destination
- Use dense grid to identify locations
- Metric representations of space extremely costly
- Machine learning to identify common behaviours
- Used for navigational assistance

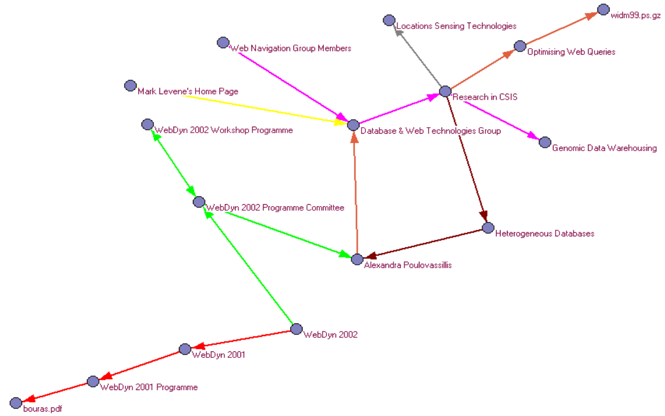


Krumm *et al*
Microsoft Research

Navigational assistance

- Find best route between two places
- Use data from an expert data set
- Taxi drivers are considered experts in this task
- Navigate like a cabbie
- Similarities of geographic navigation and web navigation

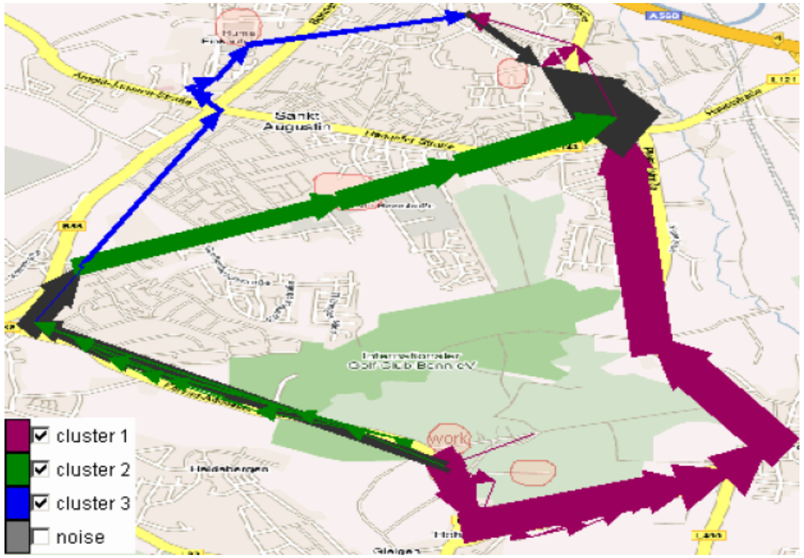
Ziebart *et al*, CMU



Navigationzone.net

Summarization

- Reduce a complex data set to typical behaviours
- GSM tracks over metropolitan area
- Cluster typical behaviours in profiles
- Use road graph to identify sequences
- Topological descriptions of space are more efficient



Adrienko *et al*
Fraunhofer IAIS

Our group's point-of-view

- Spatiality/physicality sets most constraints, thus the starting point
- Reality is a semantic-spatiotemporal environment
  - pervasive computing technology to capture user behavior
  - identify significant landmarks and pathways
  - trail-based processing
- Core ingredients
  - trails
  - metrics of significance
  - suffix-tree based algorithms

A landmark is

- A location
  - A scanning station
  - A popular place
  - A nodal point according to Space Syntax
- A person
  - A mobile phone-carrying individual
  - A mote-tagged conference attendee
- A (physical or data) object
  - A URI
  - An RFID-tagged artefact

Identifying landmarks

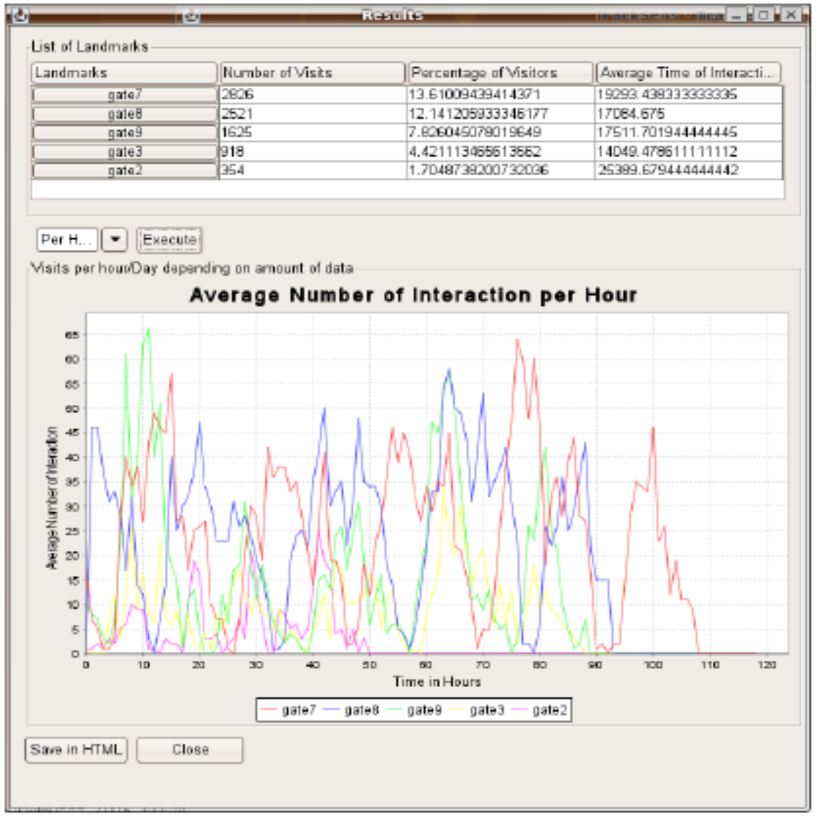
- *A-priori*
  - Defined by system-specific characteristics
  - Bluetooth, WLAN, GSM etc access point
  - RFID, mote or other tag
  - Construction of space graph e.g. Space Syntax
- *A-posteriori*
  - Identify significance through use
  - e.g. Minimum Volume Embedding Algorithm

Experiments on 3 main data sets

- Dartmouth University
  - campus-wide wifi network
- Reality Mining
  - User movement over a mobile phone network
- Cityware
  - Bluetooth scanning at Bath

Dataset	Interactions	Users	Landmarks
Dartmouth	1,782,931	4,745	623
Reality Mining	2,536,034	89	32,628

Landmark analytics



- Statistics per landmark
  - Total number of visits
  - Visit frequency
  - Average and total dwell time
  - Per hour, per day, per week etc

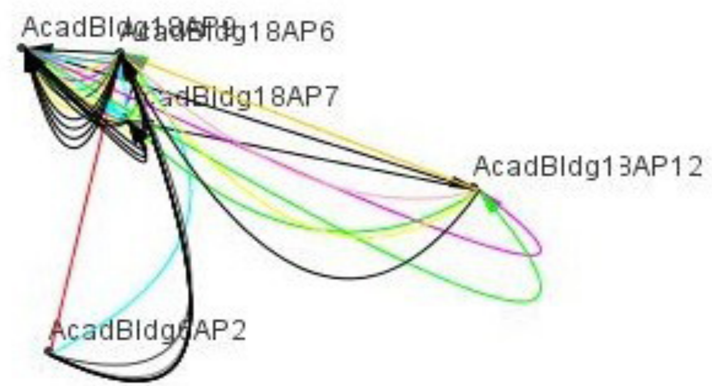
Trail analytics

Best trails using different metrics

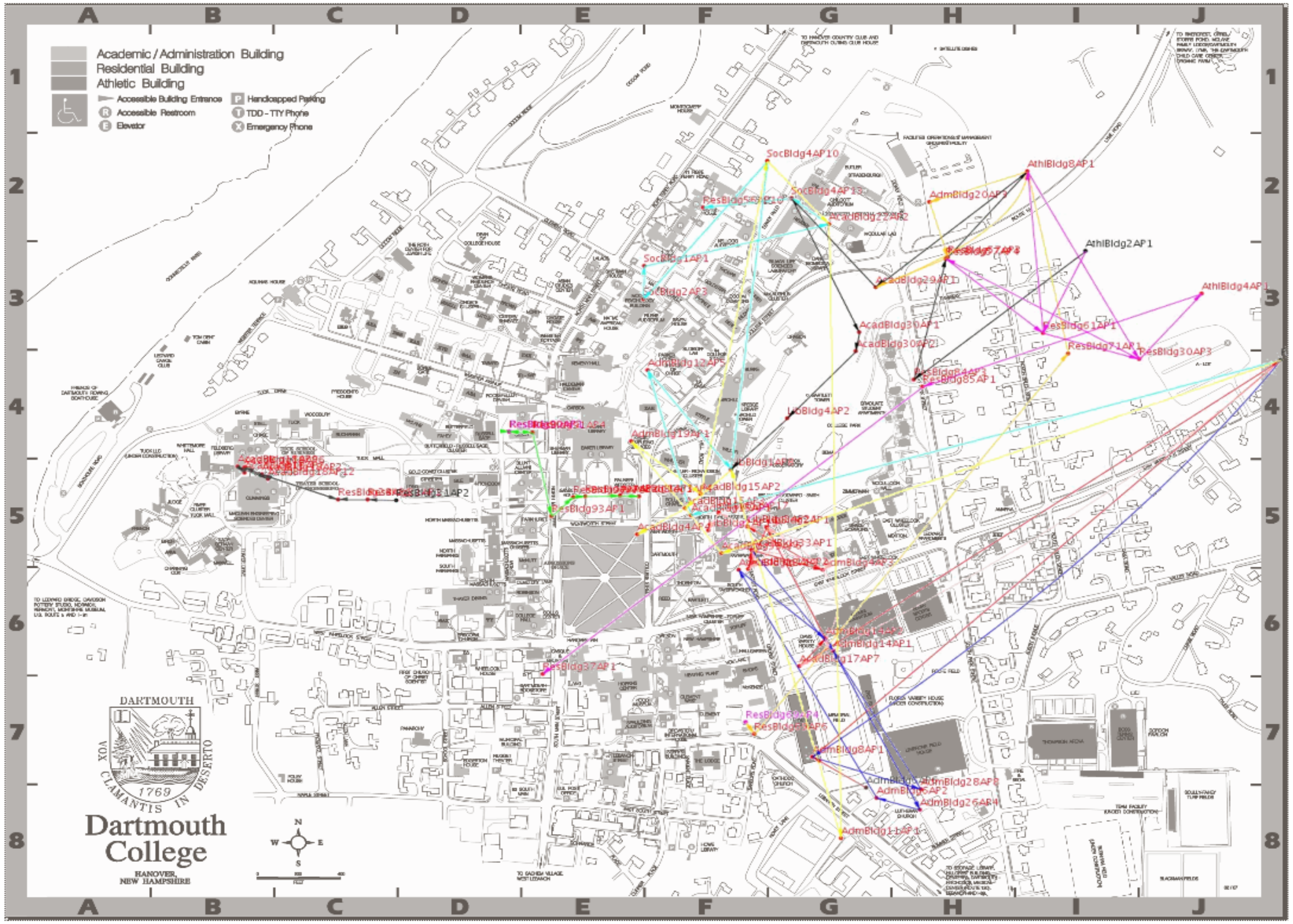
- frequency, time, orientation, hybrid

and constraints

- start and end at specific landmark
- passes through specific landmark
- minimum, maximum, exact trail length
- time of day, week, month etc
- nodes tagged with specific meta-data
- user-specific



Examples (1/4)



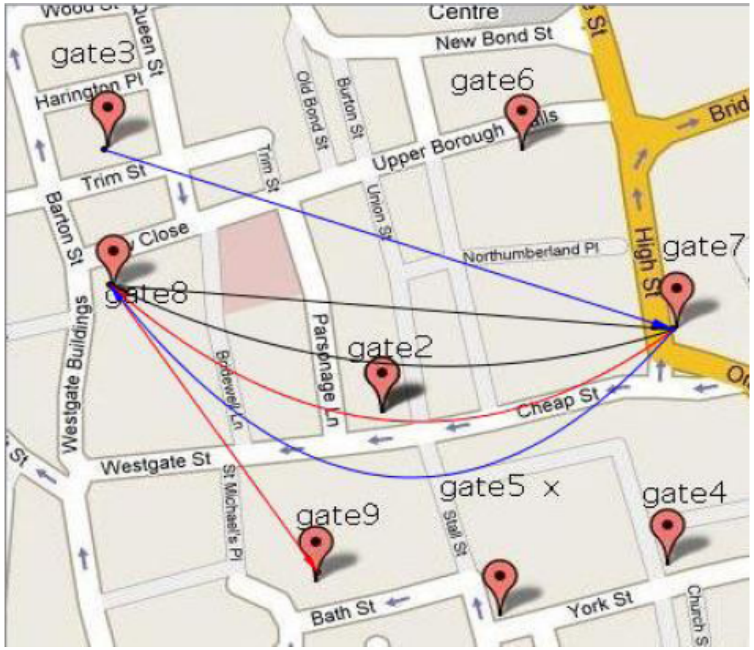
Top-10 trails by frequency

Dartmouth data set

Wi-Fi associations

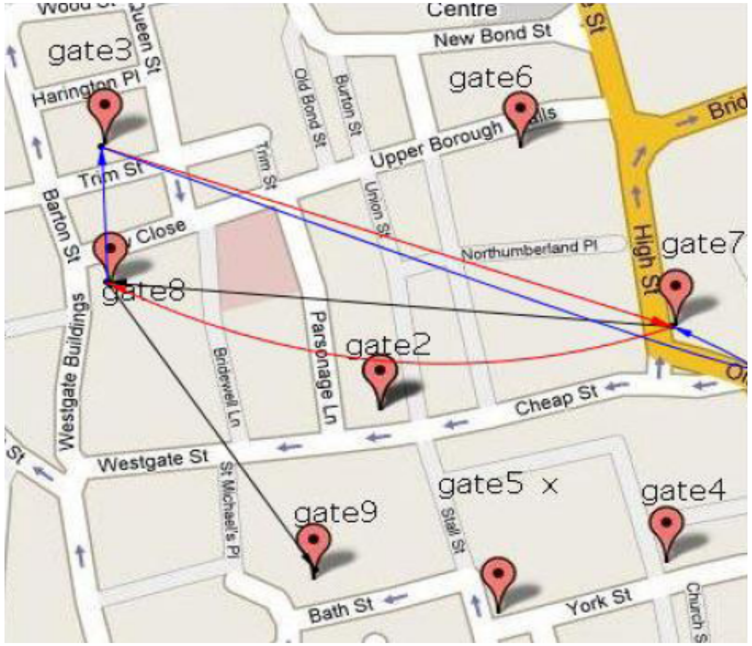
3-year period

Examples (2/4)



Top-3 trails by time

Exact length 3

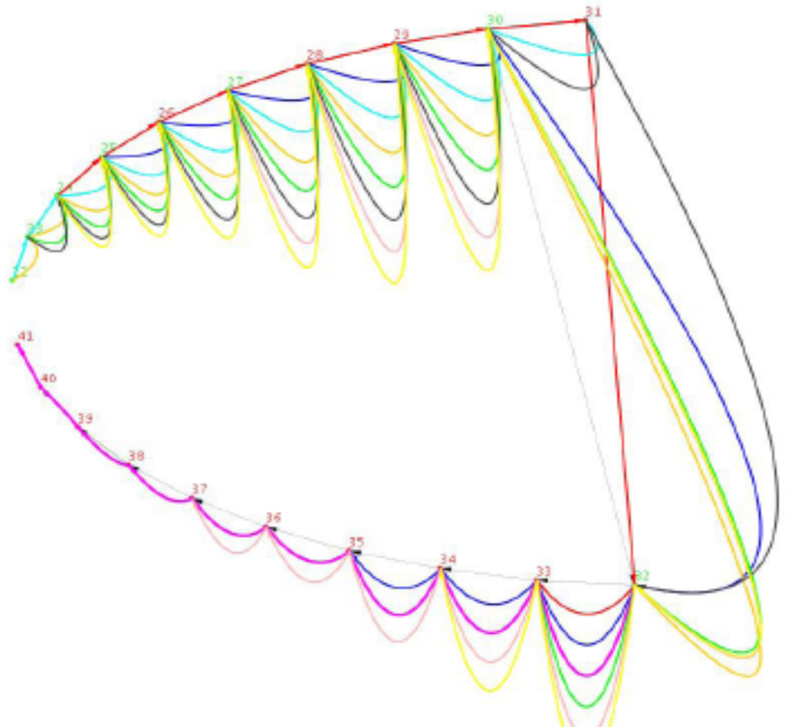


Top-3 trails weighted

Exact length 3

Cityware data set, 3-month period

Examples (3/4)



Hard to interpret visually

Nodes are individuals

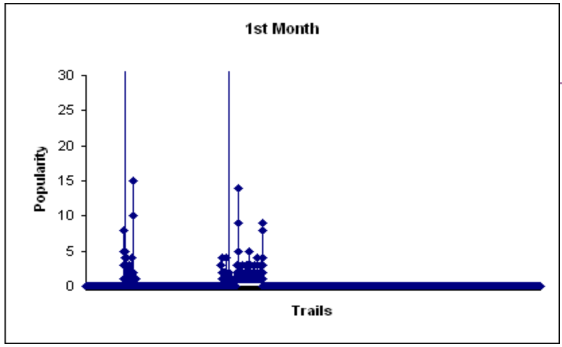
Trails show patterns of contact

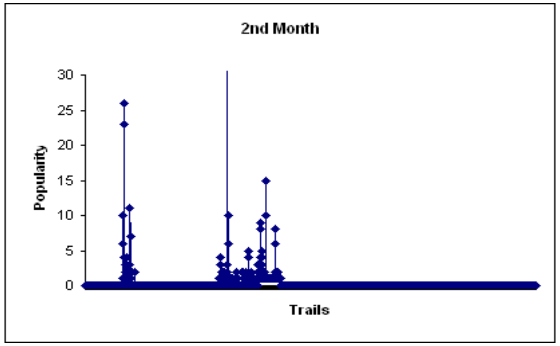
Top-10 trails by frequency

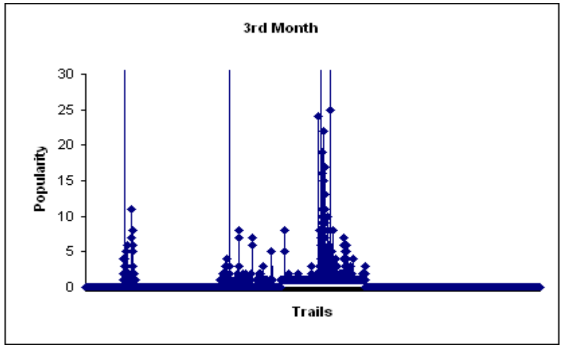
At least 7 different landmarks

Intel imote data set

Examples (4/4)







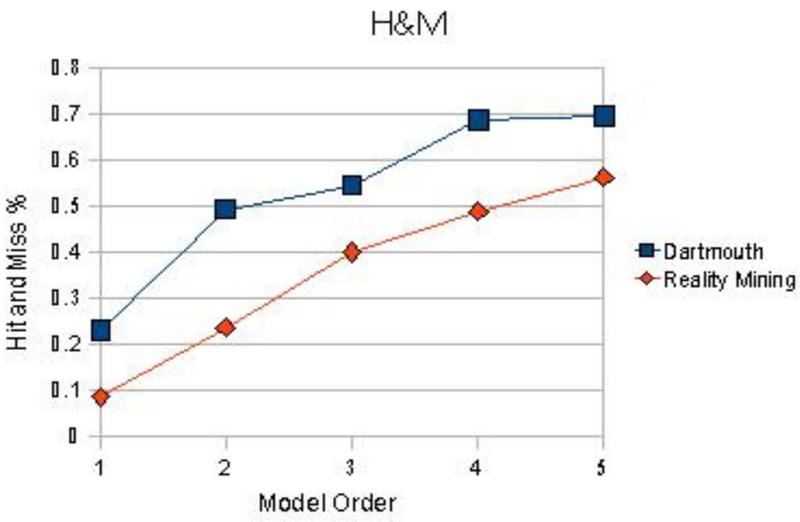
Concept drift: best-trail evolution over time

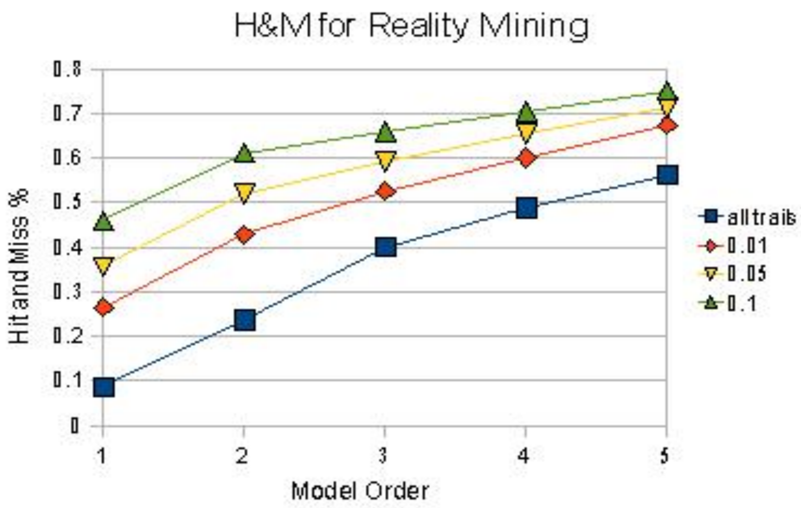
Reality-mining data set

Popular trails algorithm

Mobile phone (cellular and Bluetooth) over 9 months

Hit and Miss results

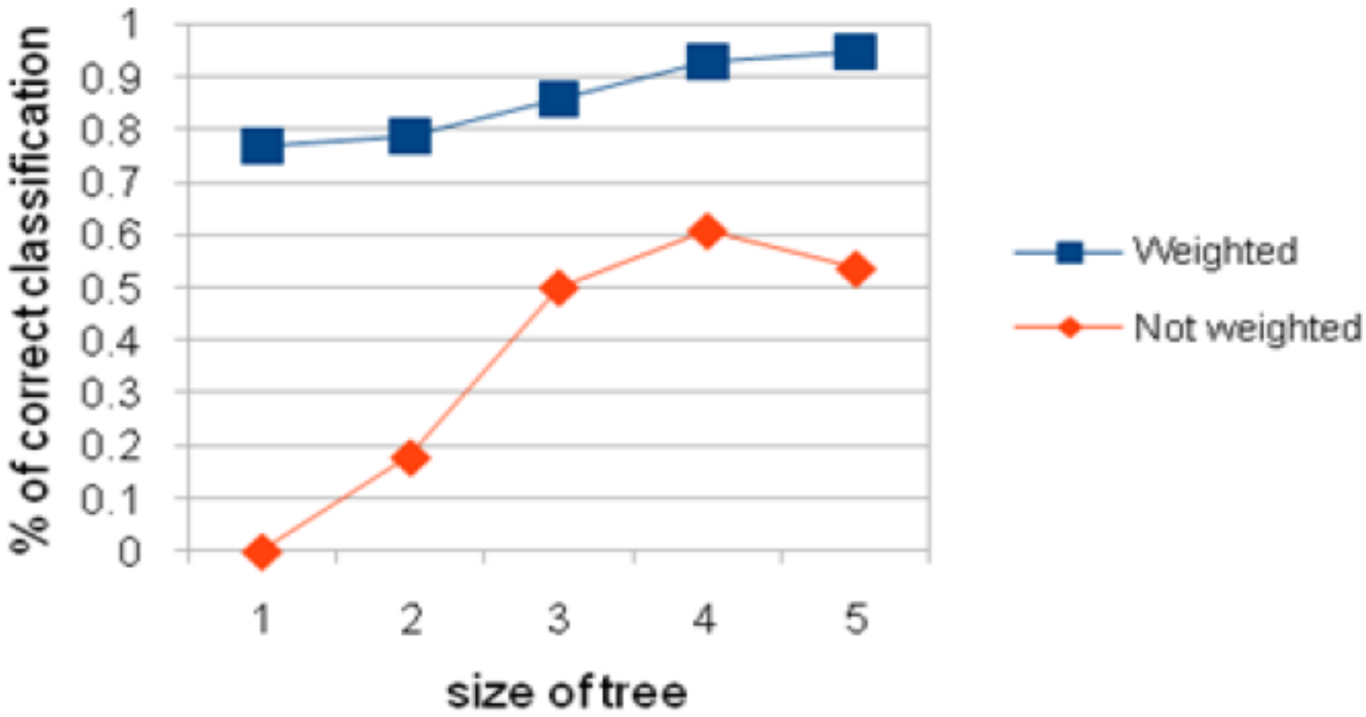




Using all trails in the data set.

Using best trails only.

Identify individual without ID



Reality-mining data set

Identify user 39 using 2 months for training and test on next month

Summary

- New model for WSANs
- Data capture and connectivity to the IoT
- Significant developments in recent years
- Analytics, prediction, classification