Using Wi-Fi Mobility Classification on a Mobile Phone for Energy Efficient Activity Tracking

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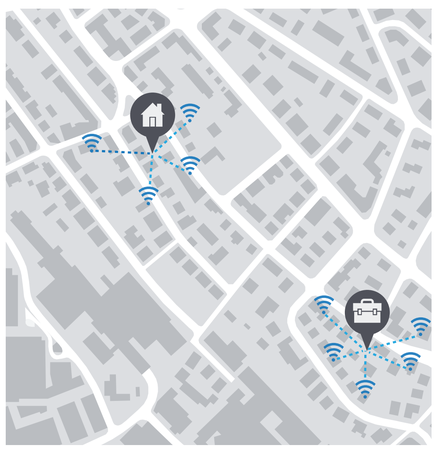
Motivation and Goals

- Prevent using energy consuming sensors for location tracking when user is stationary
- Provide solution usable across wide range of devices
- Maximize precision of stationary state classification

Classification Methods

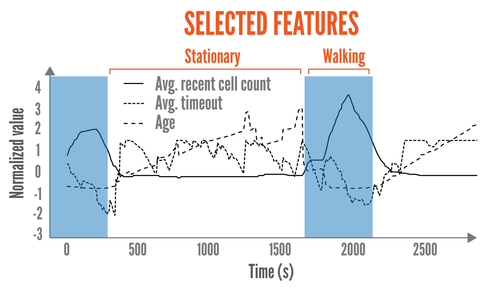


Place-based

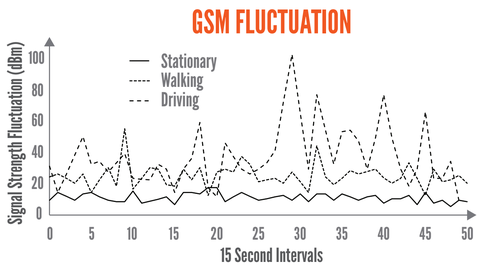
Long-term
Learning database of known Places for a specific user

Short-term
Places are stored in-memory
Fast learning rate

Context-based
Comparison of current set of connected APs with last stable one



Feature-based
Various features of current and recent APs such as age, timeout or number of connected APs



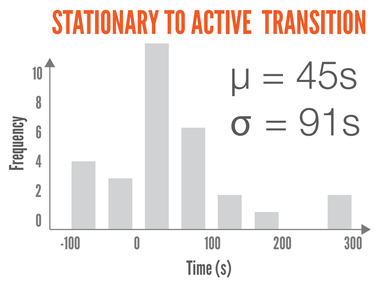
Fluctuation
Calculating difference of APs signal levels between consecutive scan reading

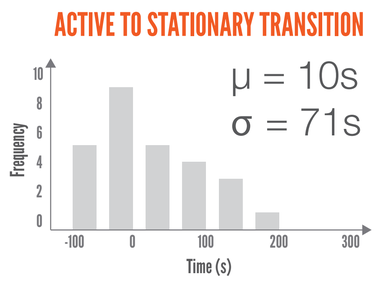
Evaluation

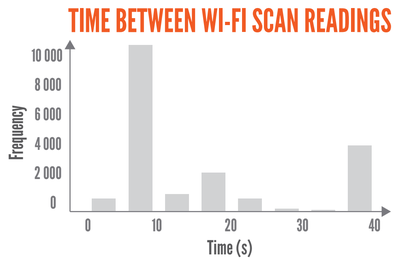
Dataset
How big?

7	users	112	reports
8	devices	8 000	Wi-Fi APs
3	months	18 000	Wi-Fi scans
		126	hours

Transition Time
How responsive?

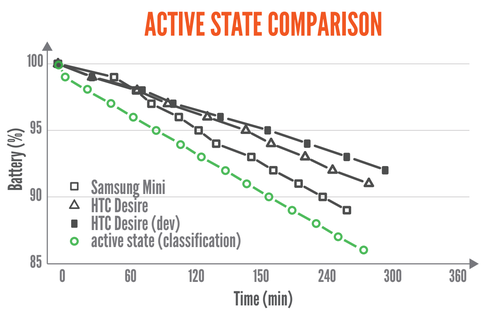


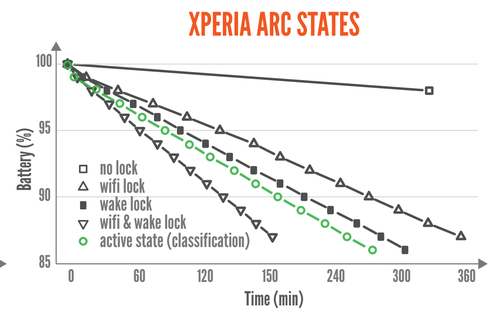




8s - 60%
16s - 11%
40s - 27%

Battery Consumption
How efficient?





Results
How precise?

	Ground Truth				
	Stationary	Walking	Driving	Precision	Recall
Stationary	93.39%	26.48%	15.66%	91.8%	97.3%
Active	2.59%	66.91%	73.22%	91.0%	75.9%
Unknown	4.02%	6.61%	11.12%	-	-
#	13136	2094	2050		

Mobility Classification Process

Data collection
Innitiate Wi-Fi scan and read results
Empty scan confirmation

Preprocessing
Data abstraction
Cell, c_i = (ID, RSSI)
Current Cells, $C^n = \{c_1^n, c_2^n, ..., c_x^n\}$
Recent Cell,
$r_i = (c_i, age, timeout, \mu_{RSSI}, \sigma_{RSSI})$
Recent Cells, $R^n = \{r_1^n, r_2^n, ..., r_x^n\}$

Classification
One or more classification methods $m_1, m_2, ..., m_n$ with assigned weights $w_1, w_2, ..., w_n$

Evaluation
Final mobility state computation
Calculate next data collection time