Sensing Group Behavior

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Sensing Recap (So Far)

- Publication Recipe #1: *The "Surrogate Sensing" Recipe*
  - *Step 1:* Find/motivate an interesting new application (monitoring some aspect of a person's activities or context)
  - *Step 2:* Show that it is hard to measure/detect it using current "traditional" approaches
  - *Step 3:* Collect a new combination of "surrogate" measurements of the activity or context using readily available sensors (typically those sensors are not intended to measure this type of activity or context – hence "surrogate")
  - *Step 4:* Evaluate the quality/speed/accuracy of identifying the desired activity or context using those measurements
  - *Step 5:* Identify challenges, if any (e.g., resource demands, latency, environmental diversity, need for unsupervised learning, etc.) and show how to overcome them

GruMon
The Problem Statement

- "*Step 1:* Find/motivate an interesting new application (monitoring some aspect of a person's activities or context)"
  - What human activity/context monitoring challenge is the subject of this paper?
  - How is it motivated?

GruMon
Why is the Problem Difficult?

- "*Step 2:* Show that it is hard to measure or detect it using current traditional approaches"
  - Why is hard to detect groups?
  - What are "traditional approaches"?

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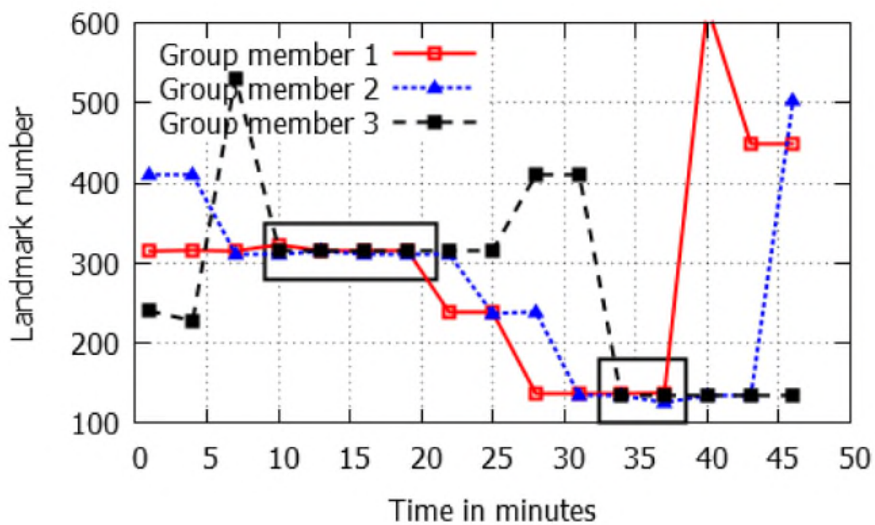
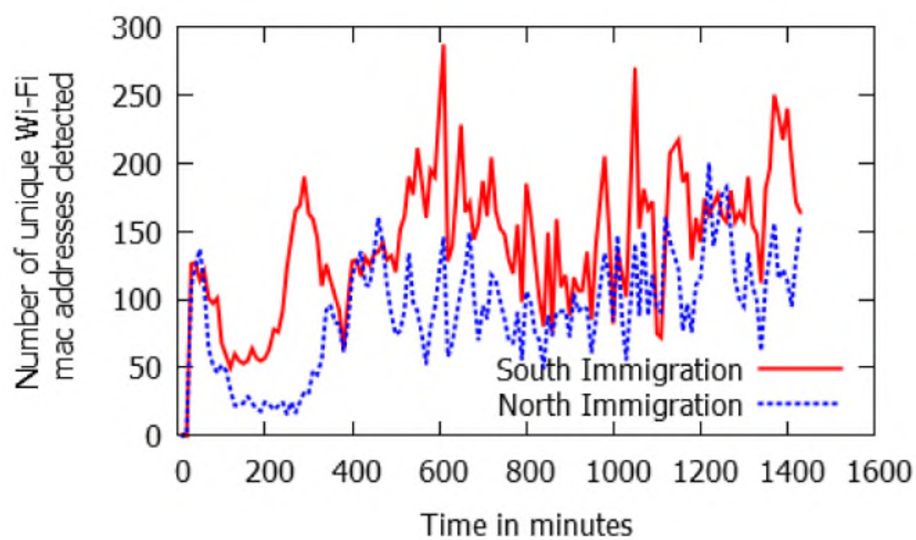


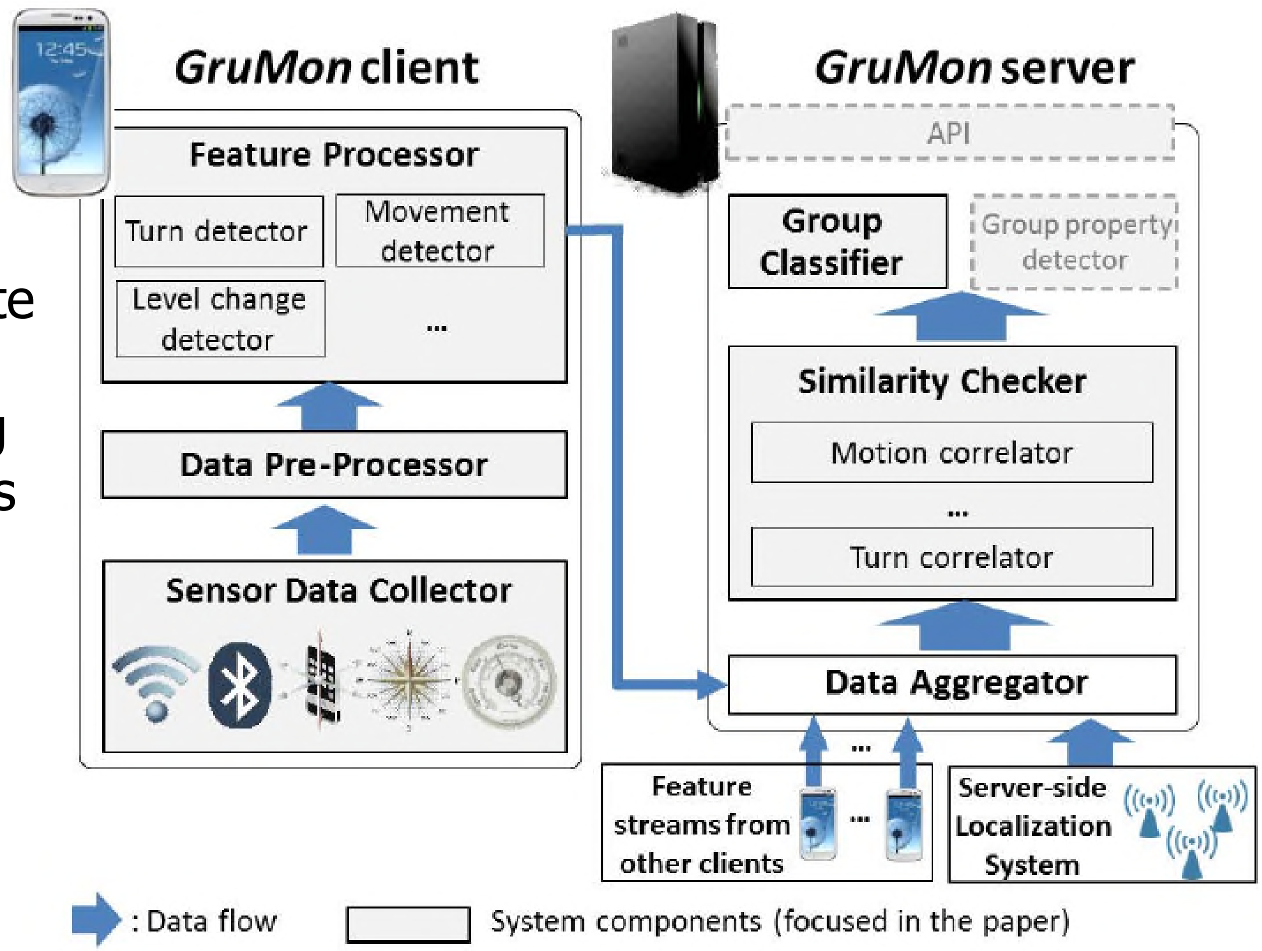


What’s wrong with

- Spatio-temporal clustering?
- Bluetooth-based group detection?
- Acoustic group detection?
- Social network based group detection?

GruMon
The Solution

- "*Step 3:* Collect a new combination of surrogate measurements of the activity or context using readily available sensors (typically those sensors are not intended to measure this type of activity or context – hence "surrogate")



GruMon
The Solution

- "*Step 3:* Collect a new combination of surrogate measurements of the activity or context using readily available sensors (typically those sensors are not intended to measure this type of activity or context – hence "surrogate")
  - Step [1]: Each GruMon client detects diverse microactivity and location features using phone-embedded sensors. The features calculated on the clients are sent to Gru-
  - Mon server.
  - Step [2]: The server first computes similarities between each pair of GruMon clients, using cross-correlation of the time-series of the computed features.
  - Step [3]: The server then passes the pairwise similarities through a supervised binary SVM classifier, which classifies each pairwise edge as positive or group edge vs. negative or non-group edge, based on a pre-trained classification model.
  - Step [4]: Finally, the server runs a clustering algorithm on the positive edges returned by the binary classifier, to output sets of individual clients as groups.

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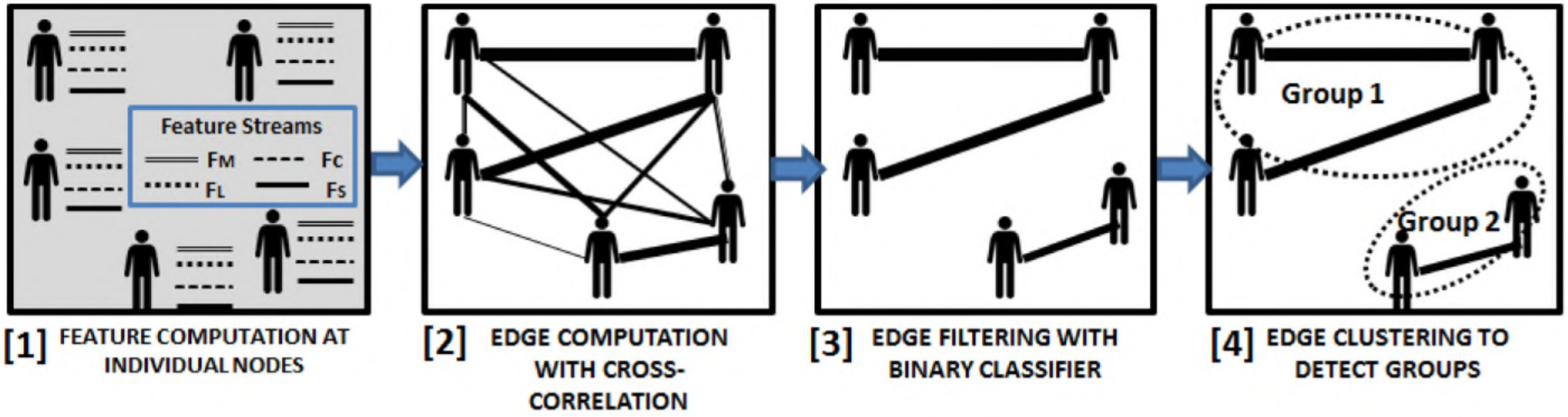
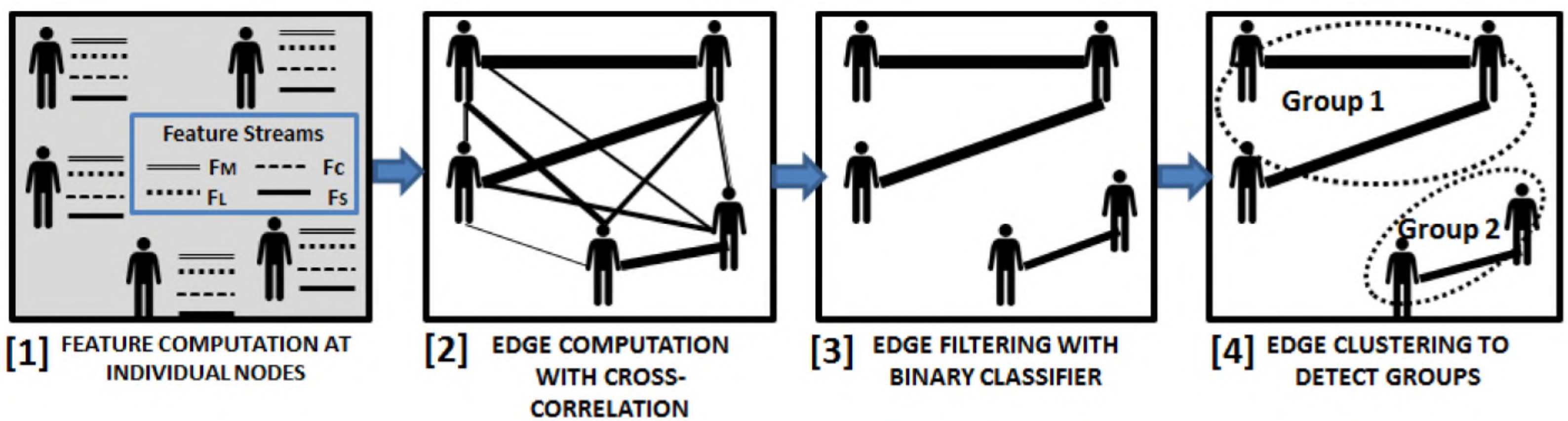


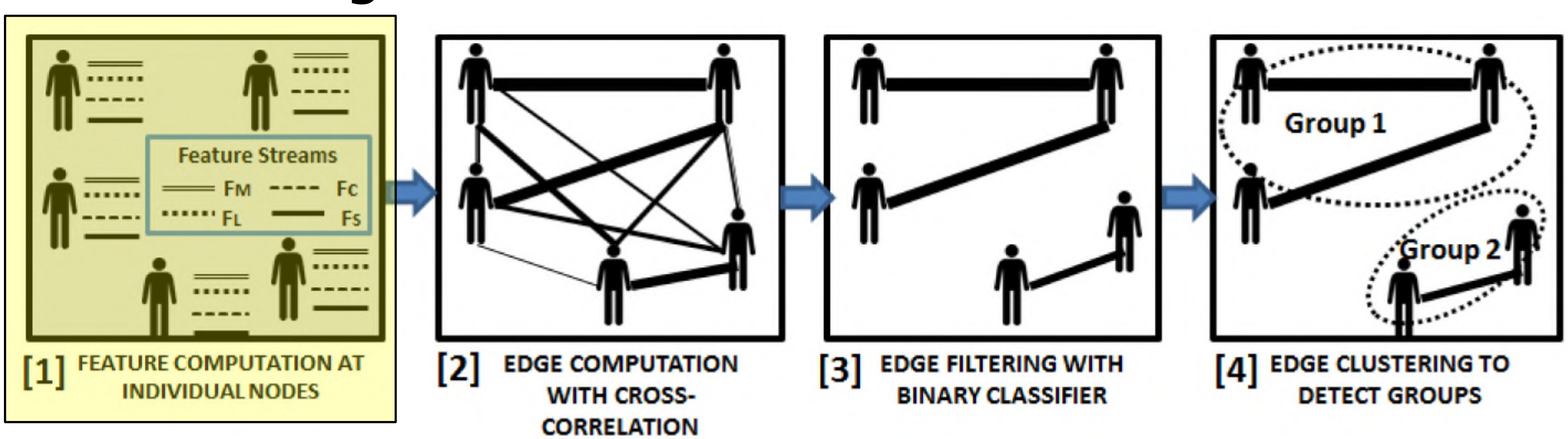
GruMon
Features – The Secret "Sauce"

- Location Features
- Motion Features
- Turn Features
- Level-change Features



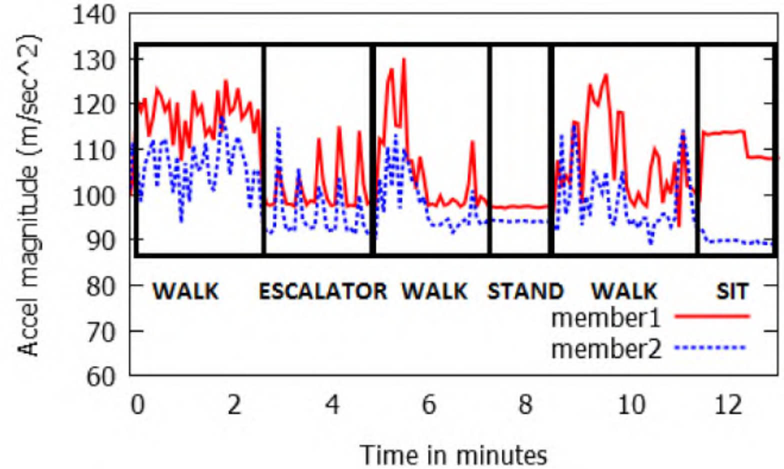
GruMon
Features – The Secret "Sauce"

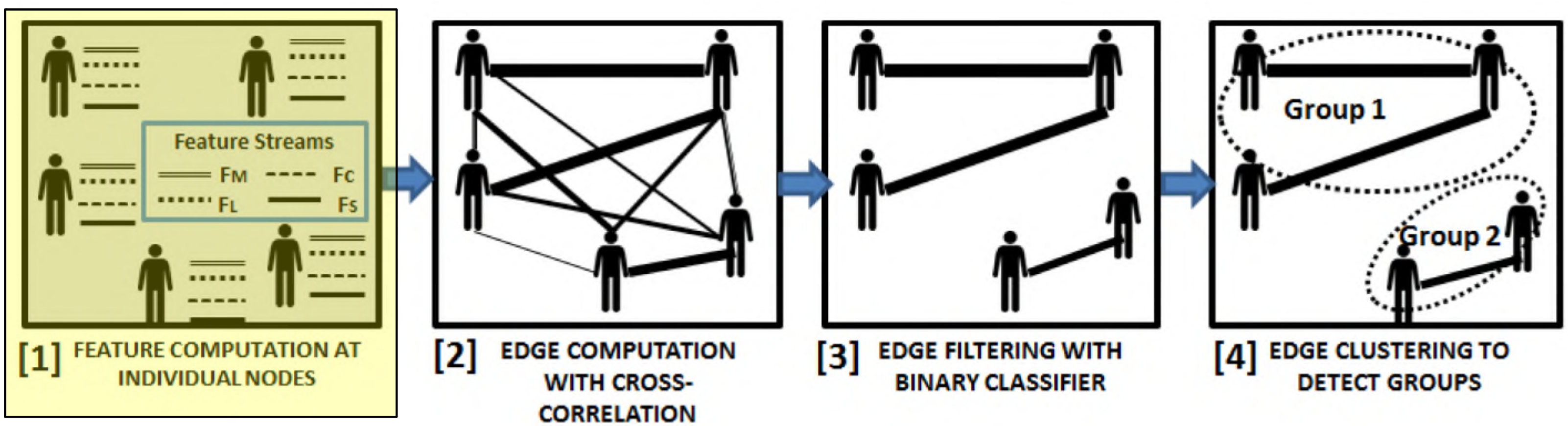
- Location Features: *Insight – Collocation may be coincidental; correlated transitions are a much better indicator of group behavior.*
- Motion Features
- Turn Features
- Level-change Features



GruMon
Features – The Secret "Sauce"

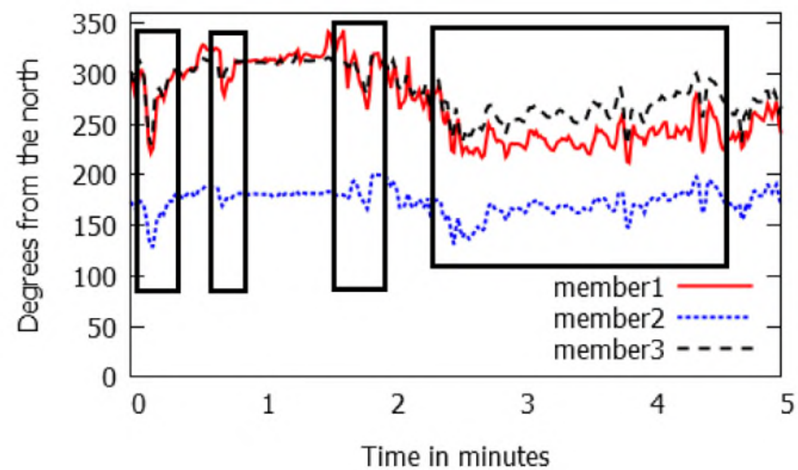
- Location Features
- Motion Features: *Exploit correlations in motion patterns*
- Turn Features
- Level-change Features

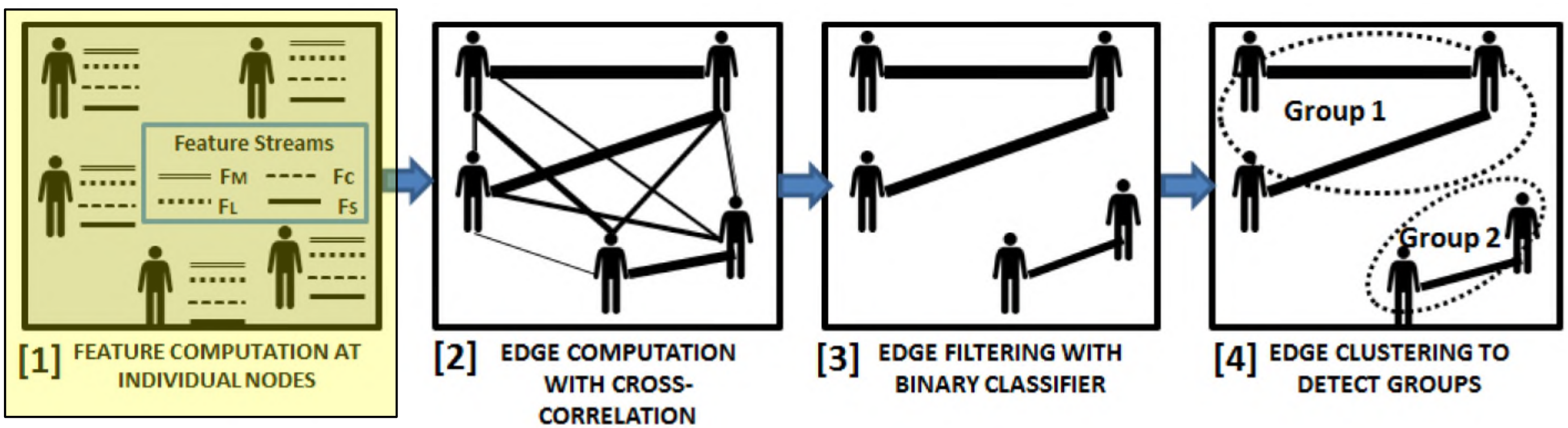




GruMon
Features – The Secret "Sauce"

- Location Features
- Motion Features
- Turn Features: *Detect correlated **change** in angle, while **walking only***
- Level-change Features

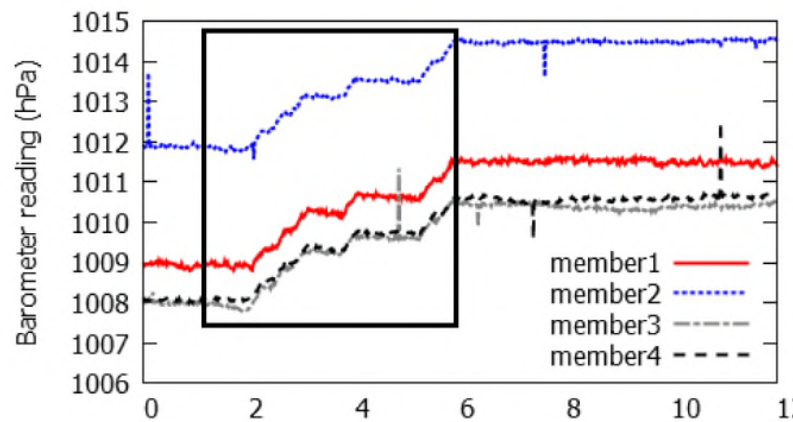


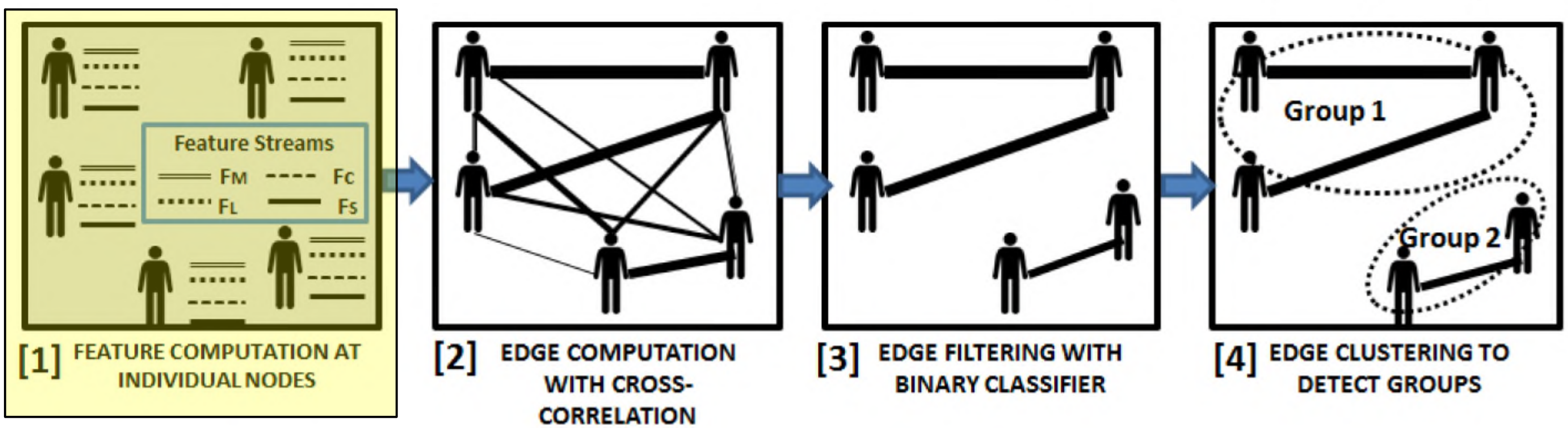


GruMon

Features – The Secret "Sauce"

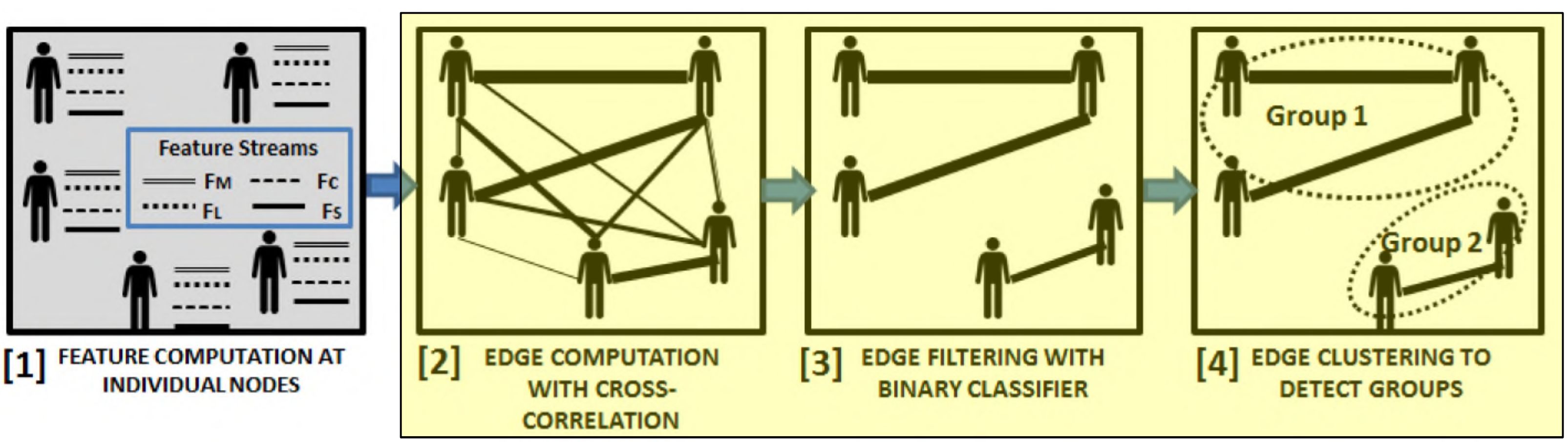
- Location Features
- Motion Features
- Turn Features
- Level-change Features:
  Detect correlated changes in barometer reading





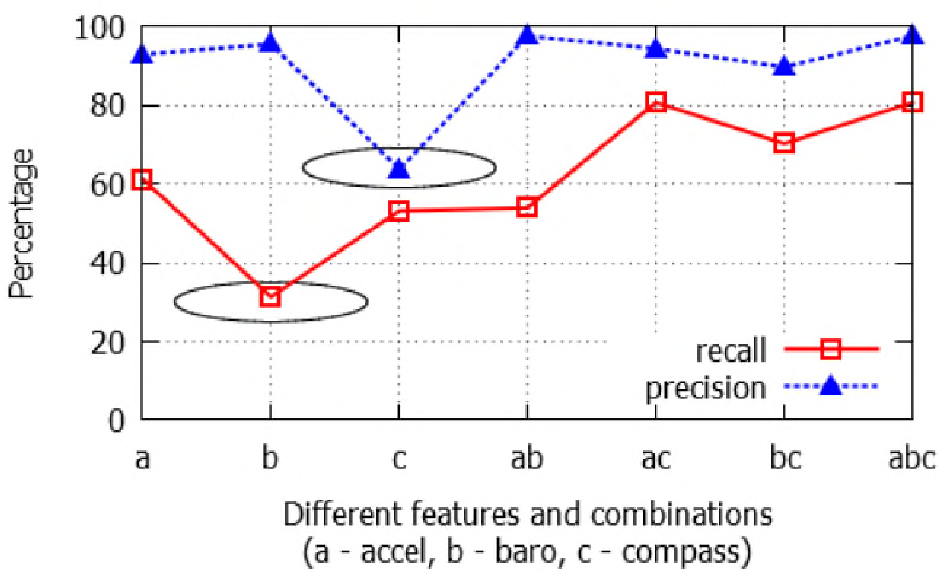
GruMon
The Rest of the Algorithm

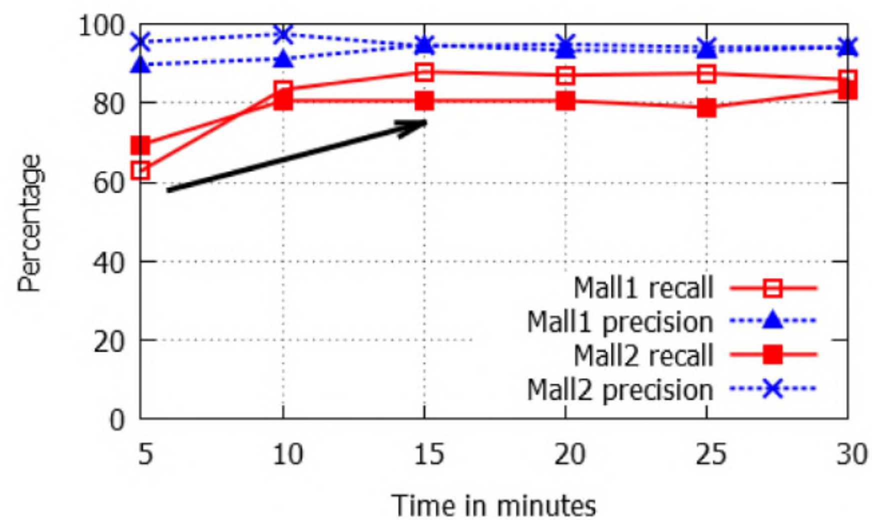
- Features converted into binary time-series
  - Different features weighted differently
- Correlations are computed between time-series and classified into two types: positive and negative
- Clusters of positively correlated nodes are computed



Evaluation

- "*Step 4:* Evaluate the quality/speed/accuracy of identifying the desired activity or context using those measurements"





QueueVadis
The Problem Statement

- "*Step 1:* Find/motivate an interesting new application (monitoring some aspect of a person's activities or context)"
  - What human activity/context monitoring challenge is the subject of this paper?
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QueueVadis
Why is the Problem Difficult?

- "*Step 2:* Show that it is hard to measure or detect it using current traditional approaches"
  - Why is hard to detect queues?
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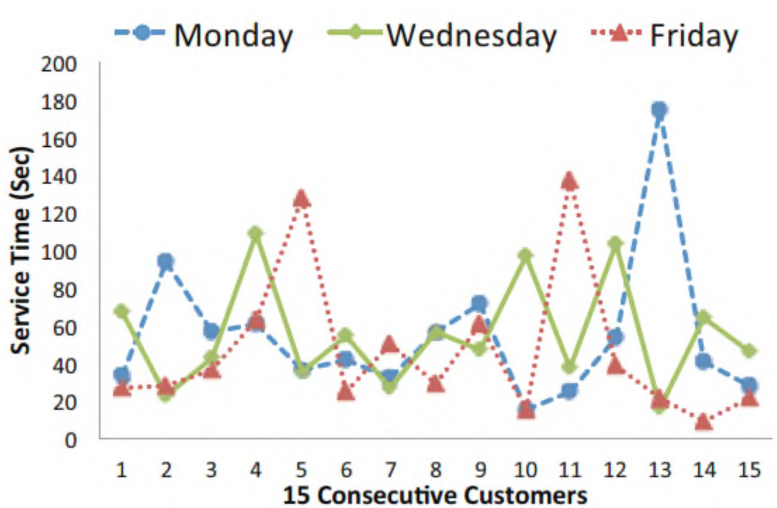
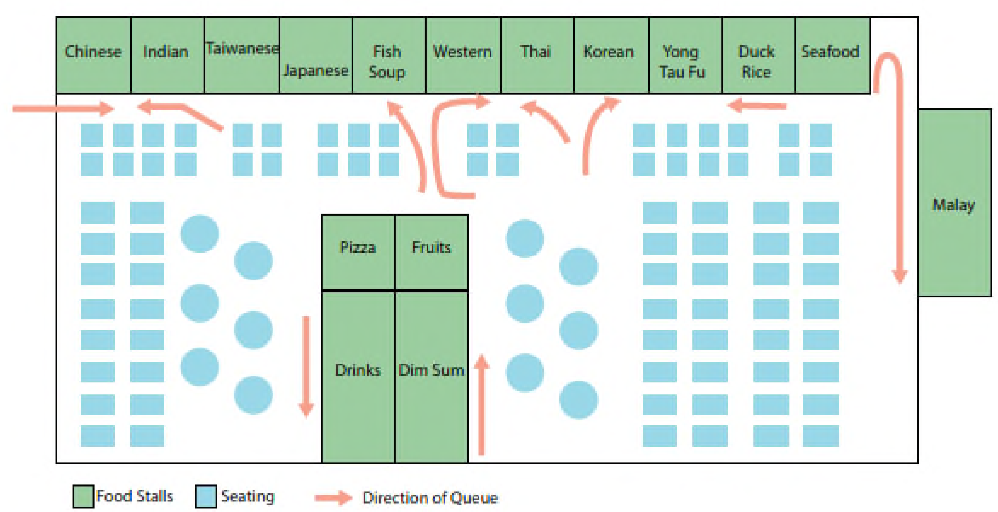


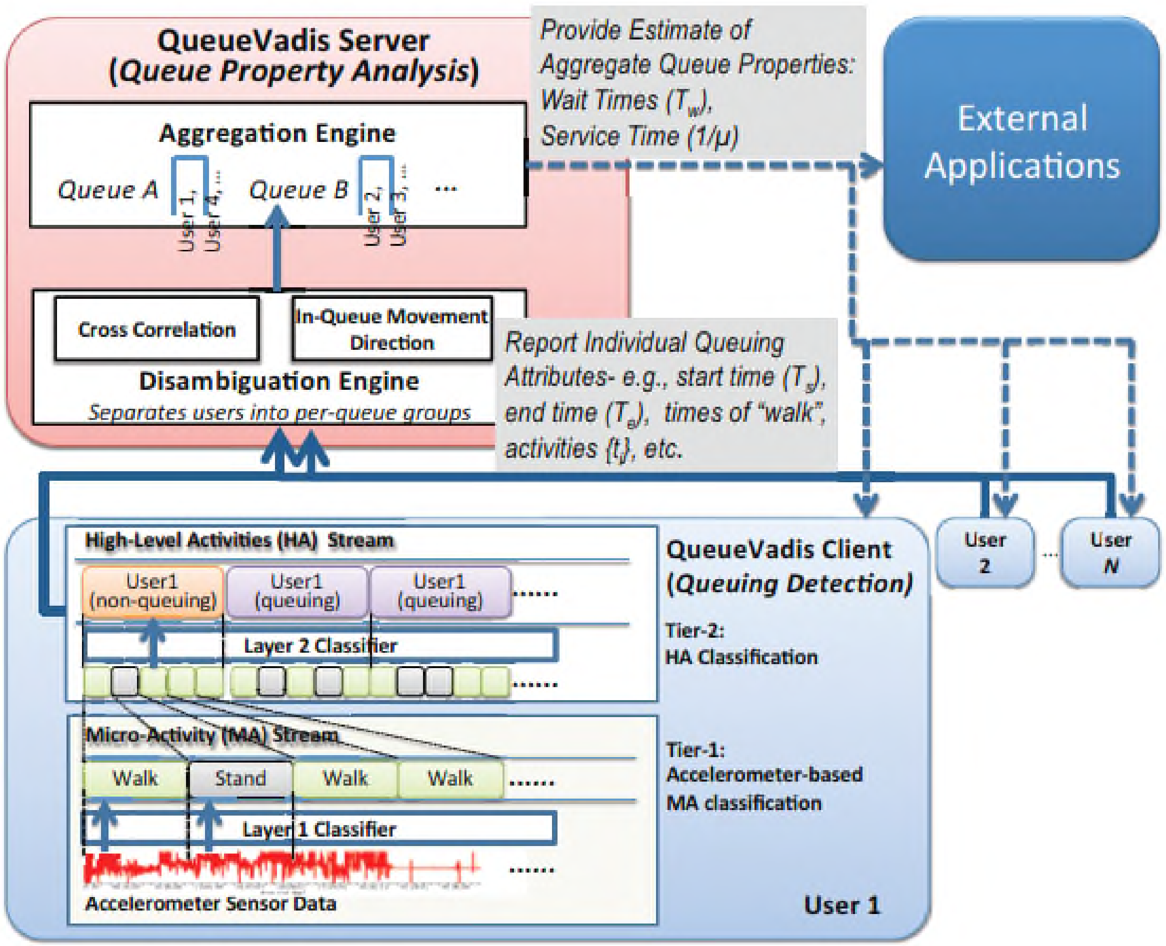


Goals

- Detect queues of arbitrary shapes
- Adapt to various service times
- Disambiguate multiple nearby queues
- Work at low participation rates
- Minimize detection latency
- Offer resource efficiency
- Use no additional infrastructure

QueueVadis
The Solution

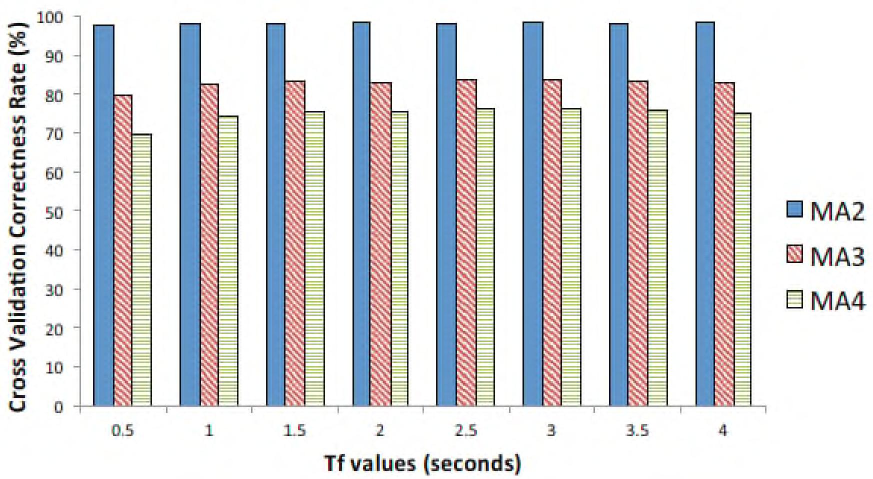
- "*Step 3:* Collect a new combination of surrogate measurements of the activity or context using readily available sensors (typically those sensors are not intended to measure this type of activity or context – hence "surrogate")

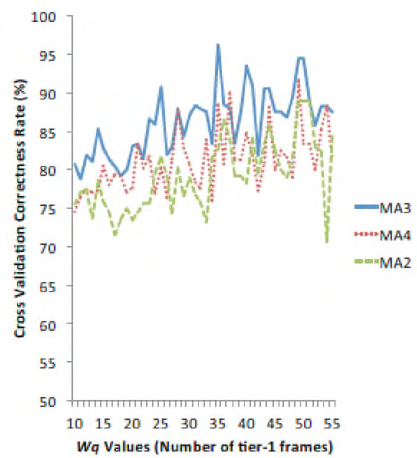


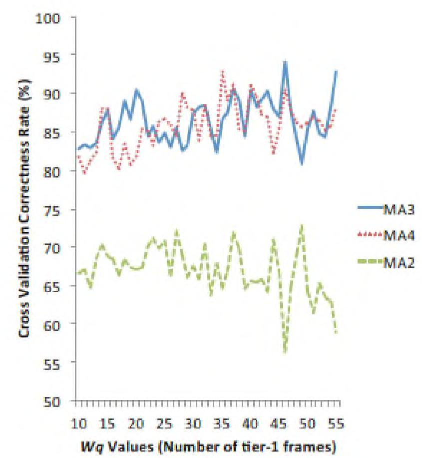
QueueVadis
The Solution

- "*Step 3:* Collect a new combination of surrogate measurements of the activity or context using readily available sensors (typically those sensors are not intended to measure this type of activity or context – hence surrogate)" + "*Step 4:* Evaluate…"
  - Use Accelerometers
  - Micro-activity detection: Accelerometer features → activity label

    (MA2: static/motion; MA3: Static/Walk/Other; MA4: Static/Stepping/Walking/Other)
  - High-level activity detection: Sequence of labels → queuing episodes

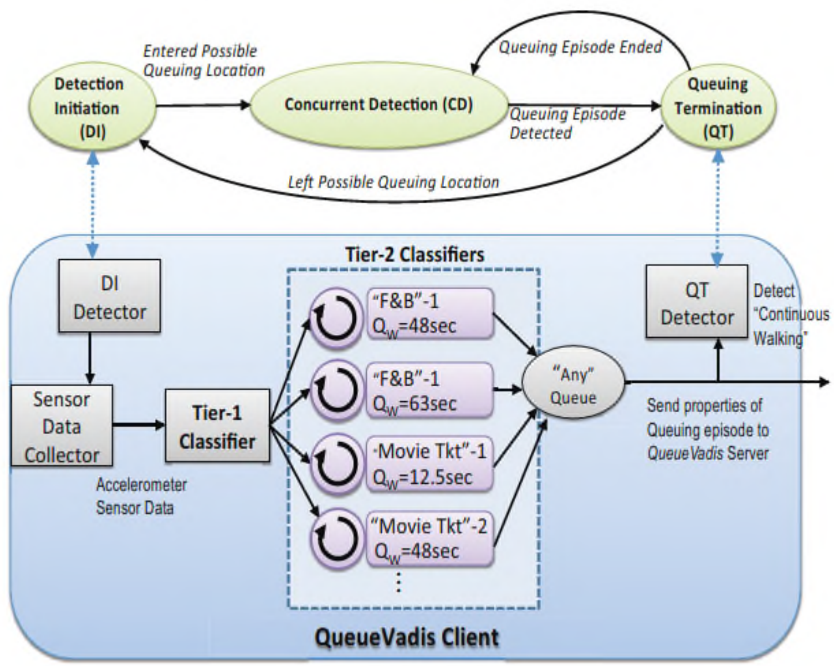






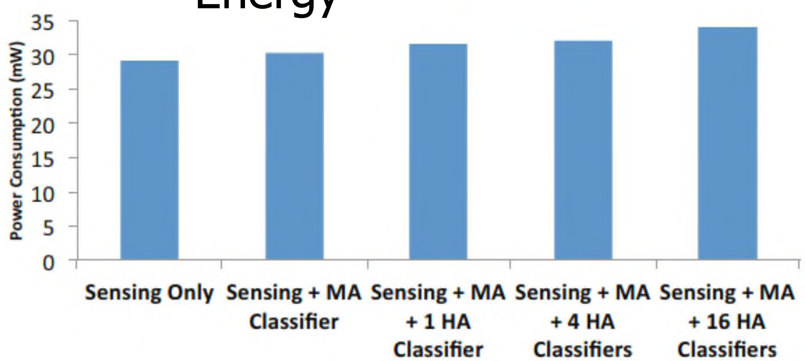
QueueVadis
Challenges

- *Step 5:* Identify challenges, if any (e.g., resource demands, latency, environmental diversity, need for unsupervised learning, etc.) and show how to overcome them
  - No Optimal frame length
  - Termination detection
  - Early departure



QueueVadis
Evaluation

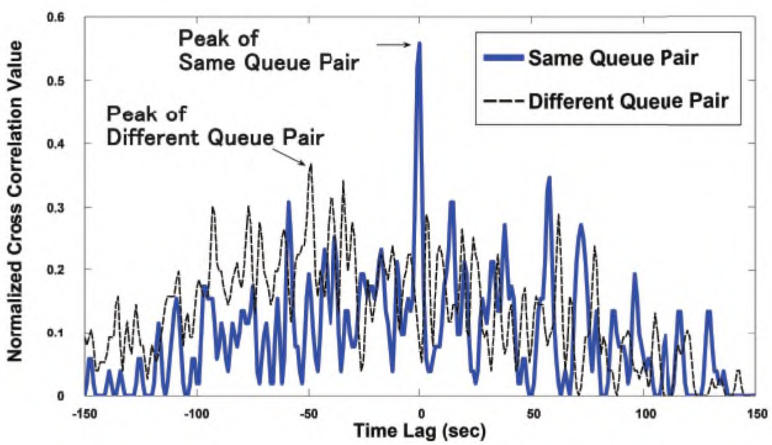
Energy



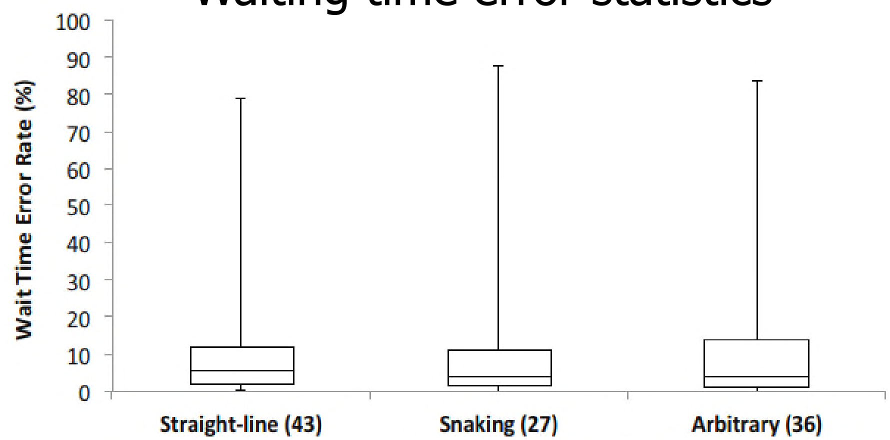
Waiting time

	Ground Truth	Fraction of the Individual with *QueueVadis* 100%	80%	60%	40%	20%	10%
Mean (sec)	25.01	21.81	21.54	22.02	22.17	21.24	22.70
Mean Stdev.	N/A	11.53	11.21	11.32	11.29	10.34	12.99

Same queue detection (MA time-series correlation)



Waiting time error statistics



Each bar represents 0th, 25th, 50th, 75th, and 100th percentiles in the distribution from the bottom to the top.

QueueVadis
Evaluation: Queue Disambiguation

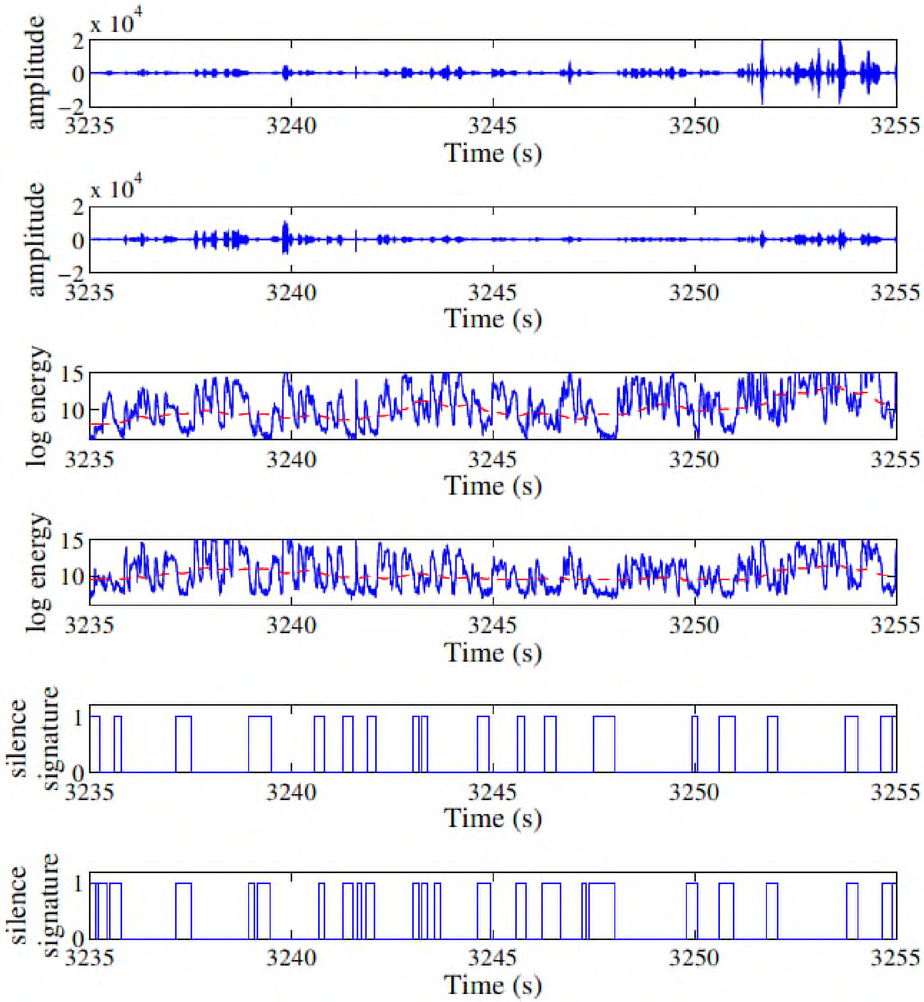
		Predicted Class		Accuracy
		Same Queue	Diff. Queue	(%)
Class	Same Queue	47	14	77.04
	Diff. Queue	3	50	93.34

No. of Intermed. People (K)	0	1	2	3	4
Classification Accuracy	0.83	0.73	0.55	0.34	0.21

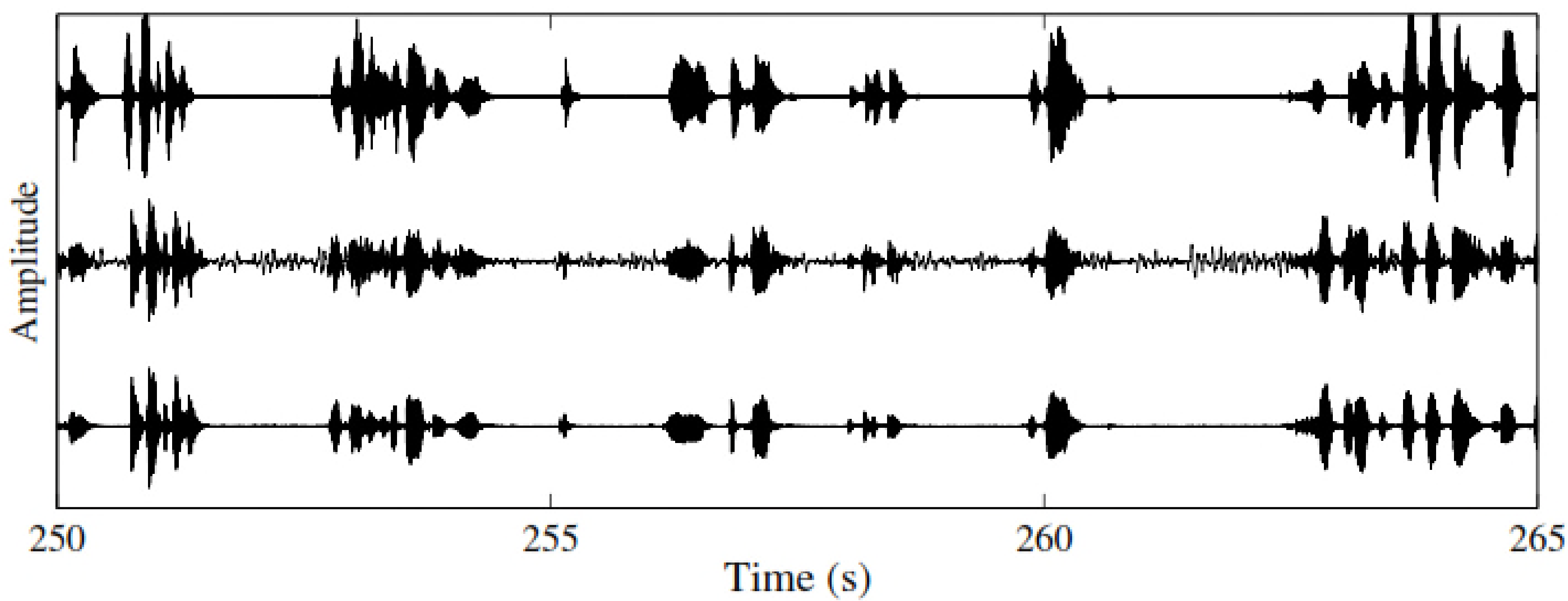
Frac. of People with *QueueVadis*	100%	80%	60%	40%	20%
Classification Accuracy	0.78	0.74	0.71	0.63	0.60

Detecting Colocation (Group Activity)

- Main Idea: Silence patterns are a good “feature” for detecting co-location.
- Cosine similarity between two time-series decides if they are collocated

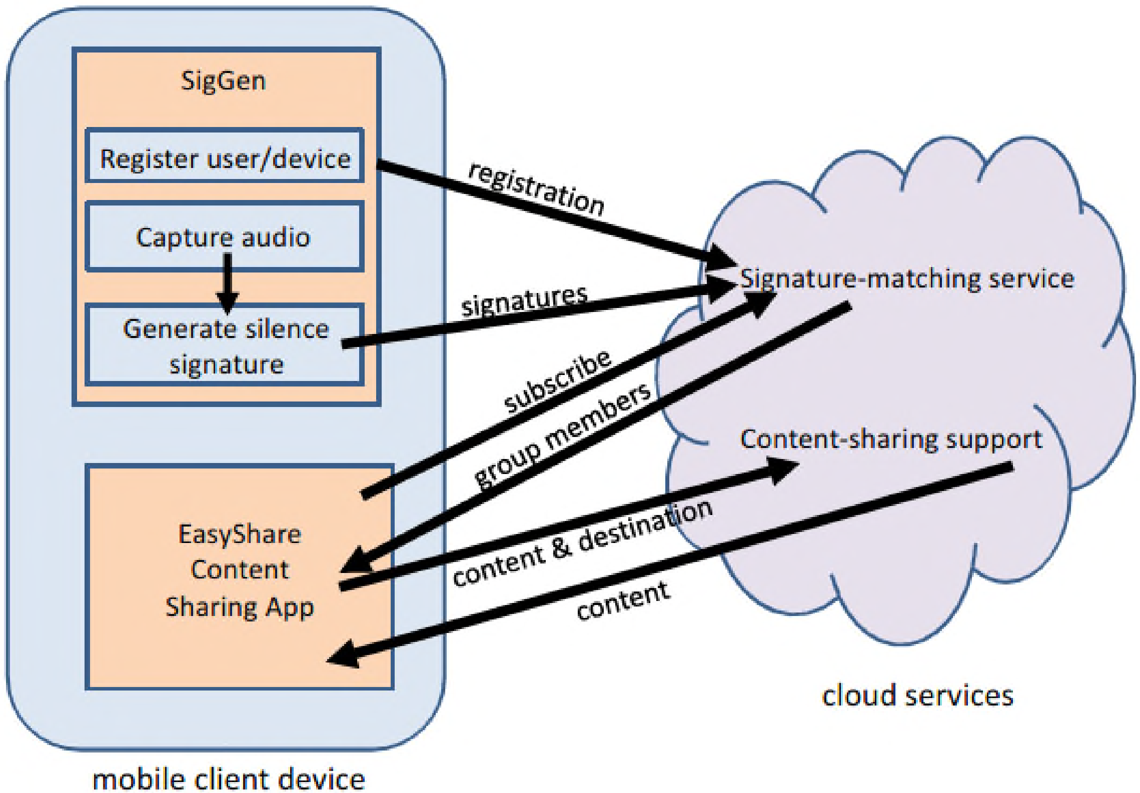


Detecting Colocation (Group Activity)



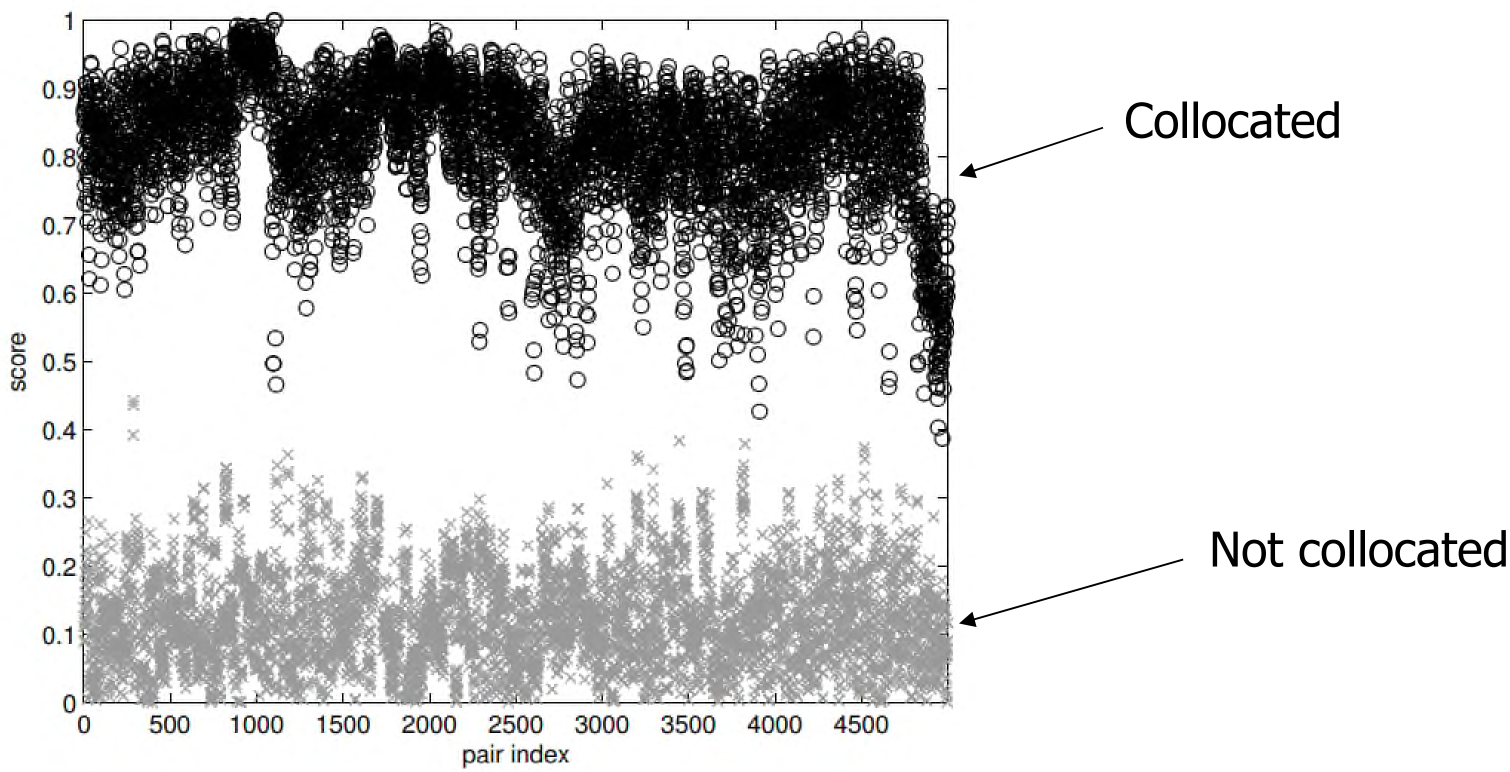
Implicit Group Creation Based on Matching Signatures

- Devices share their silence signature time-series.
- Central service matches the time-series to determine which devices are co-located
- Co-located devices form groups that can be used for content sharing



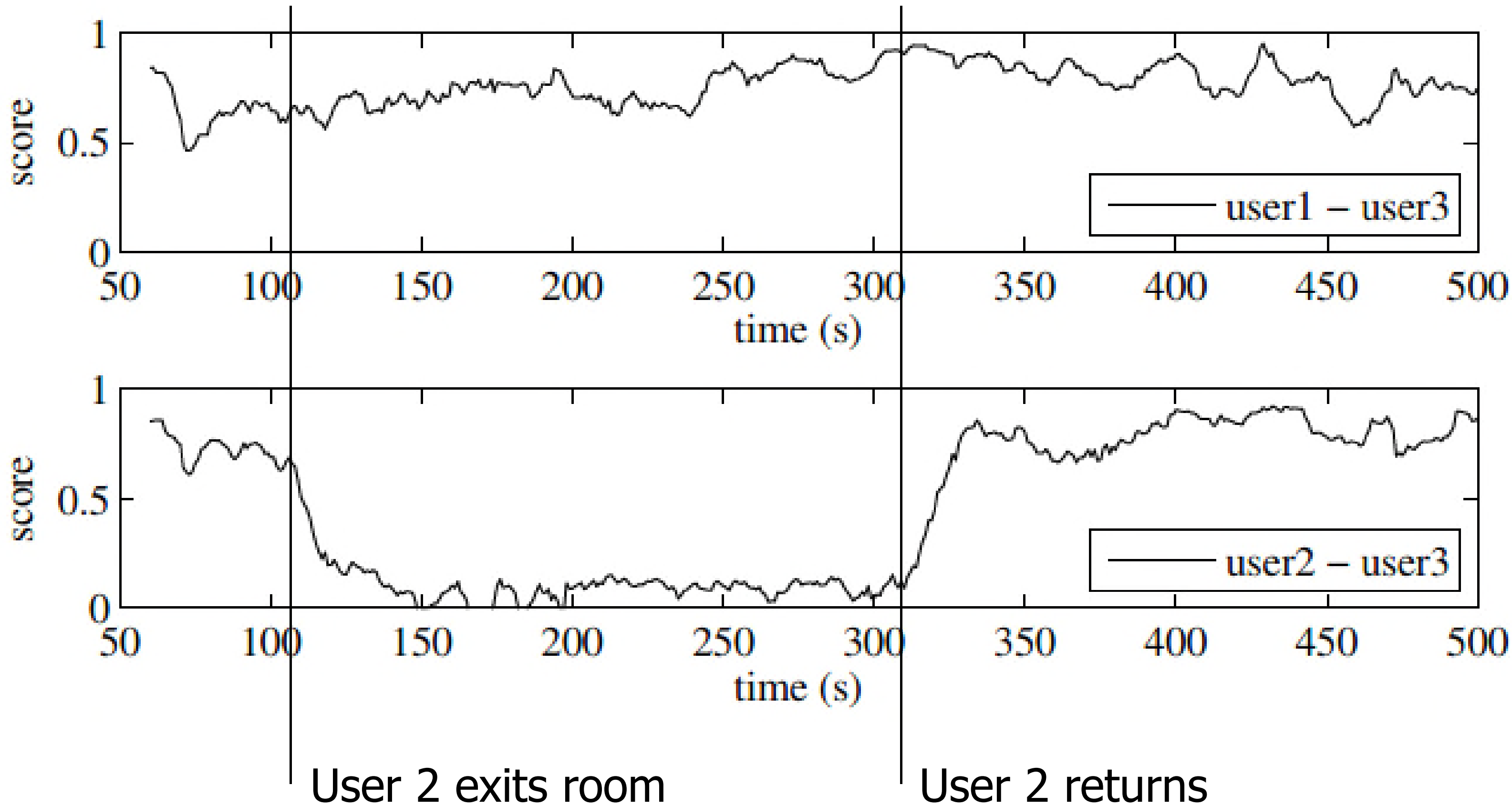
Evaluation

- The cosine similarity metric for collocated and non-collocated devices.



Evaluation

- Collocation detection latency



Challenges

- Participation via telecons
- Purses, pockets, and pants
- Network delay and jitter

Homework

Homework for 2/21 (in lieu of readings): The Ubicomp 2017 Exercise

- Pick a Ubicomp 2017 paper that is written according to the "Surrogate Sensing Recipe" (http://ubicomp.org/ubicomp2017/program/program.html)
- Prepare a 5-slide presentation (one presentation per group) with the following slides:
  - Slide 1: Describe the new application: What aspect of a person's activities or context is being monitored? How is this application motivated?
  - Slide 2: Why is it hard to measure/detect it using current "traditional" approaches?
  - Slide 3: What's the main idea? What new combination of surrogate measurements is used to monitor/detect the activity or context?
  - Slides 4-5: Identify challenges overcome in this paper, supported by evaluation results.
- Send me the title of the paper and slides by Tuesday night (PPT or PDF). Be prepared to present the paper in class on Wednesday.