# MobiCamp:

## a Campus-wide Testbed for Studying Mobile Physical Activities

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# Mobile Physical Activities

How many years have you spent on campus?

What activities do you perform on campus?

How to gain knowledge about campus life?

## Internet Access

How is the campus WLAN experience?

When, where and why performance goes bad?

How to improve and optimize the experience?

## Mobility & Social Interaction

How residents interact with different buildings?

Where do people go to spend time?

Whom do they stay with?

## Education

Do students attend classes?

How students distract during lecture?

Can we predict academic performance?

# MobiCamp Testbed @Tsinghua

Tsinghua campus covers an area of **~4.4km2** on which **~45,000** students and **~12,000** faculty and staff members are studying, working & living.

### Campus WLAN

~**2,700**+ APs (until Jan 2016) in **114**+ buildings
~**20,000** connected devices at peak
~**95,000** mobile phones

### Mobile Apps

TUNet & Tsinghua Now
installed on >**8,600** Android & >**6,500** iOS devices
~**2,300** opt-in volunteers contributes data

### Combination!

MobiCamp uses the *combination* of
enterprise WLAN data and mobile App user data
both *at a large scale*.

# Data Collection 01

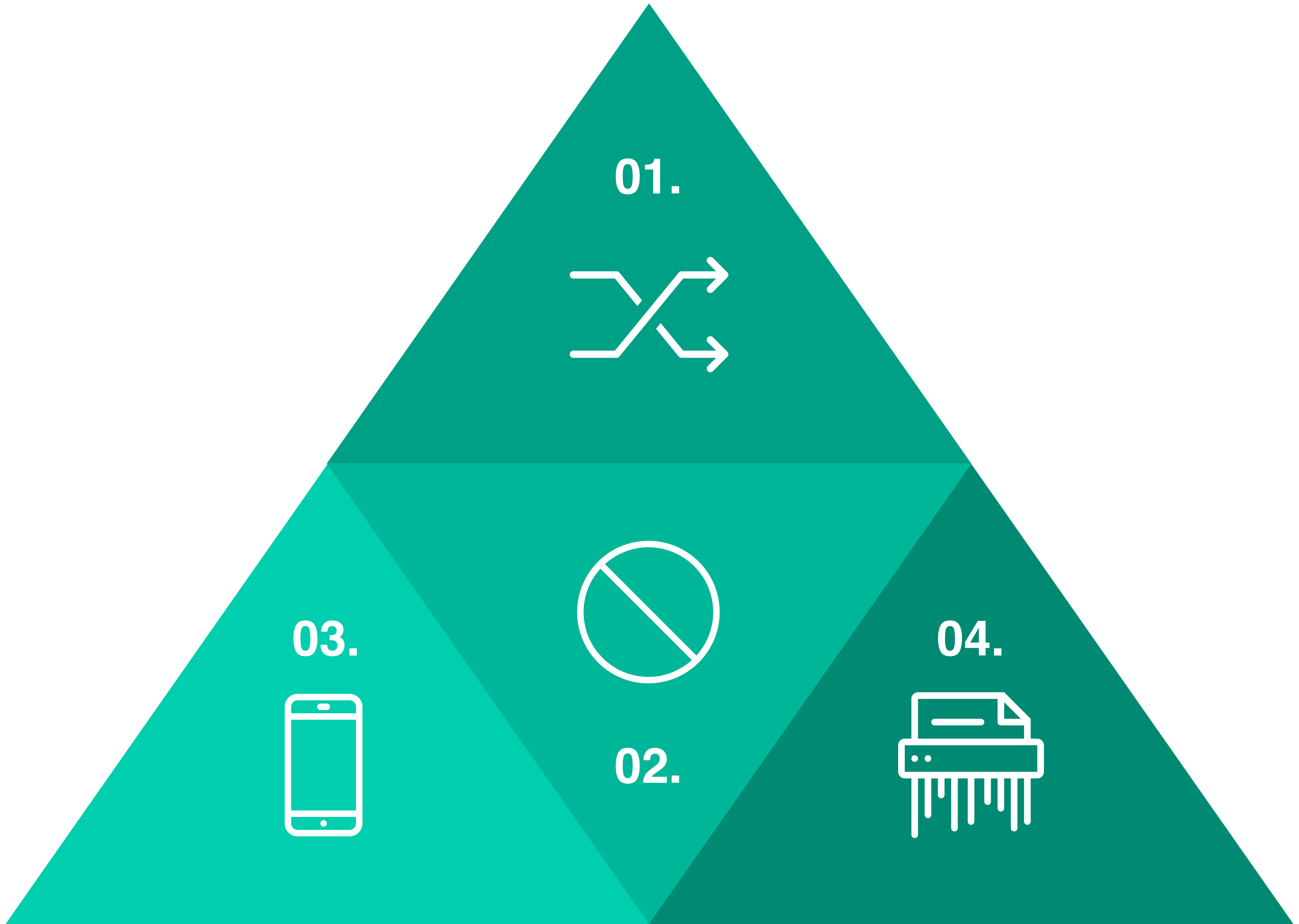
# Campus WLAN


- 2,700+ APs in 114 buildings (even more!)
- ~95,000 mobile phones
- **SNMP** traps and polls:
  - Association events
  - Packet RSSI (connected, rogue, probe)
  - Radio environment measurements
  - AP settings and attributes
- Mobility Detection
- Network Performance

# Mobile Apps

- TUNet & Tsinghua Now (~20%)
- ~2,300 opt-in volunteers
- **Mobile** data: [http://lab.mu](http://lab.mu)
  - WiFi environment: scan results, SSID…
  - Sensors: pedometer, SCREEN ON/OFF
  - User attributes
  - Education data
- Evaluation of mobility detection
- Actions when stay with others
- Classroom education measurements

# Combine Data




## 01. MAC Address Spoofing

Randomized MAC addresses!

Especially new iOS devices probe requests.

## 02. MAC Address Access Blocking

Both Android and iOS are blocking direct access to MAC.

We build an API for querying by connected AP and IP in SNMP.

## 03. Device *v.s.* User Identity

Not one-to-one relation!

We assign each MAC to its most frequent account.

## 04. Device Classification

Visitors / Stationary / Phones / Laptops

Based on device mobility.

01 Data Collection

# Mobility Detection 02

03 Applications

# Mobility from WLAN Data

Simple

Cost-effective

Labelling-free

Room-level

## Mobility Definition

**Stay interval** (start time, end time) &

**Appeared location** (RSSI fingerprint)

## Step 1: Sliding Window

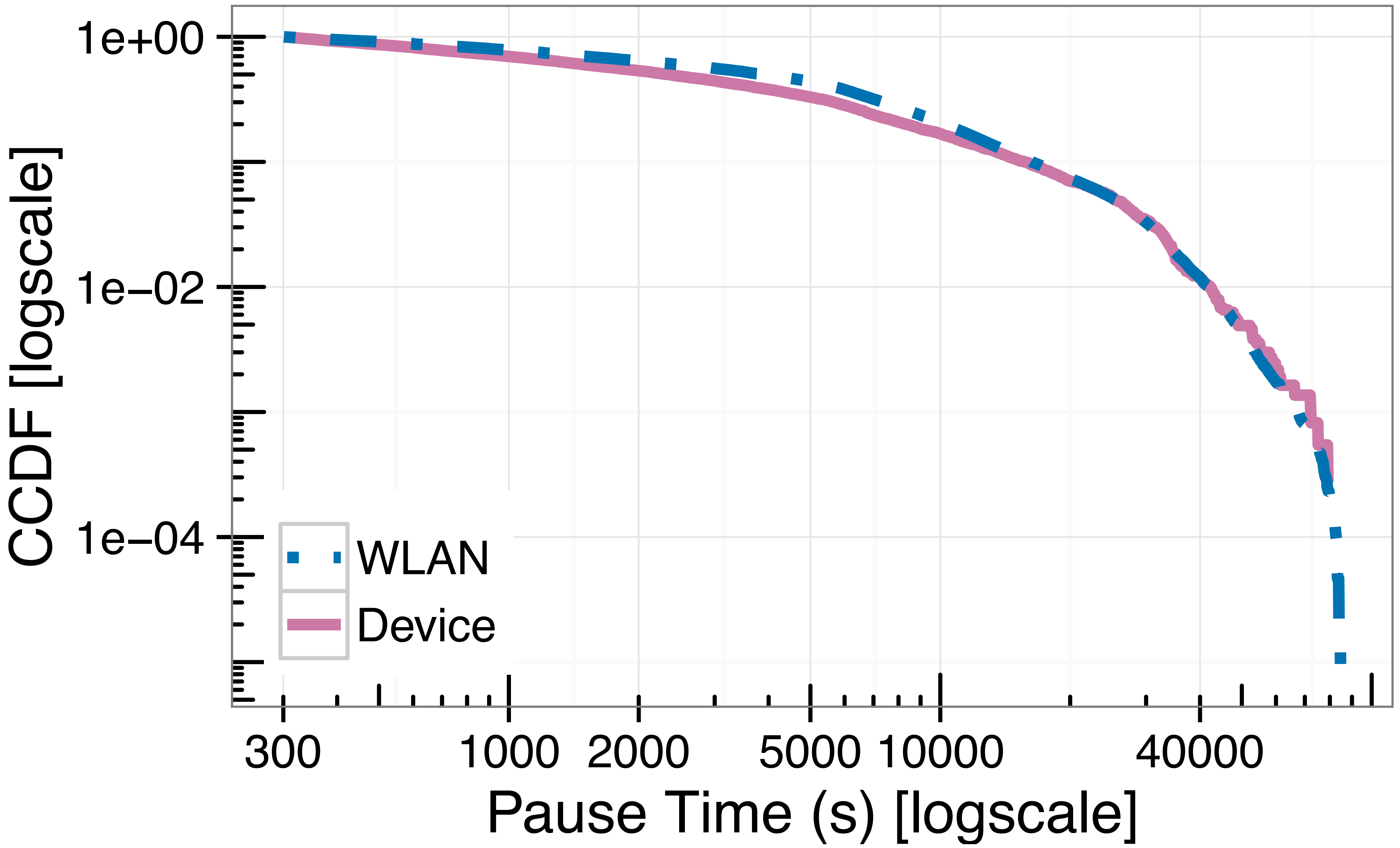
- Association & RSSI records -> Fingerprint Snapshots.
- Continuously kick out deprecated records and records of “far-away” APs.

## Step 2: Merge Snapshots

Successive “similar” snapshots are merged into large one.

AP
Closeness
Scans from Common Devices
CDF
AP closeness
whole campus
6Jiao
ZJ17
0
0.2
0.4
0.6
0.8
1
0.0001
0.001
0.01
0.1
1

# Evaluations




Mobility derived from WLAN data.

✓v.s. from mobile device data.

✓v.s. manual logs.

01 Data Collection
02 Mobility Detection

# MobiCamp Applications 03

# Applications

### Physical Activities

★Activities among Heterogeneous Buildings

★Distractions during Co-location

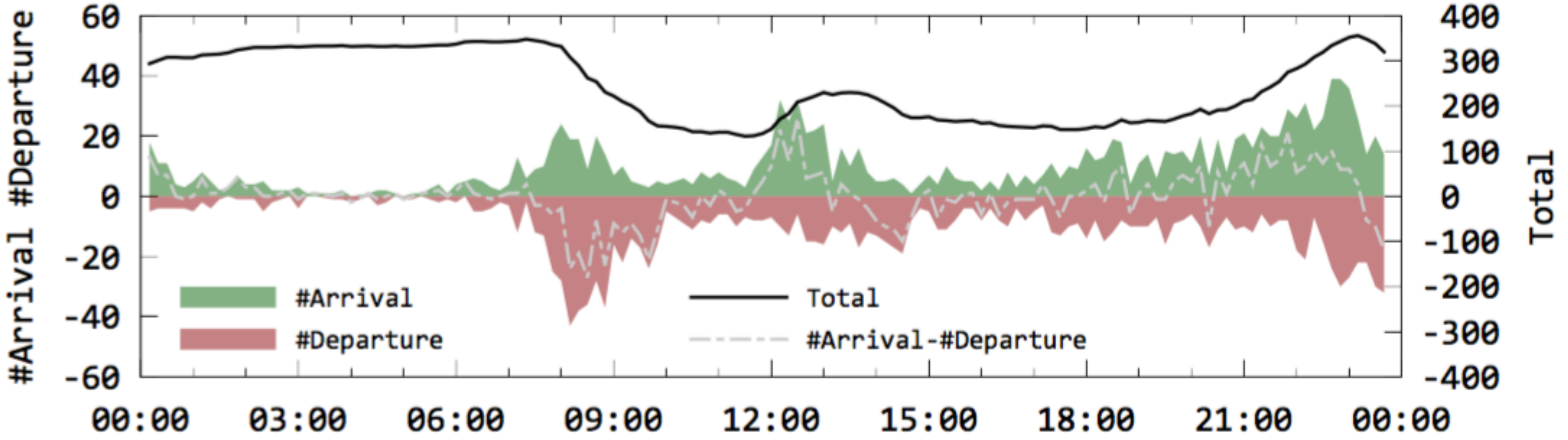
### Network Performance

★Characterizing and Improving WiFi Latency
in Large-scale Operational Networks

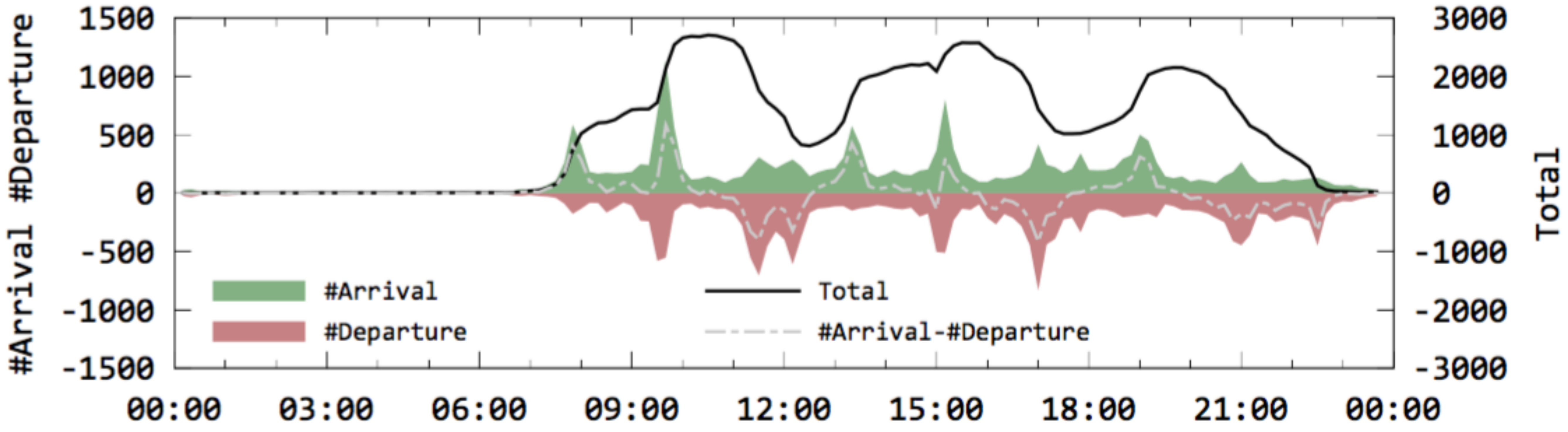
### Education

★Classroom Education Measurements via
Large-scale WiFi Networks

# Activities among Heterogeneous Buildings

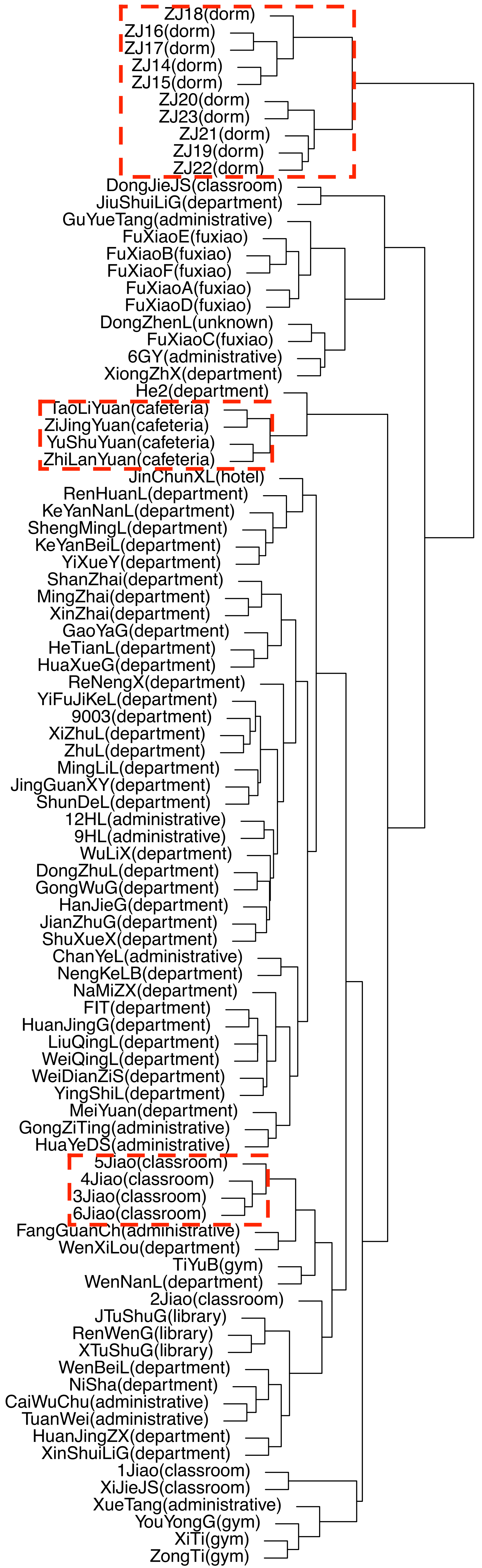



(a) dorm apartment ZJ17

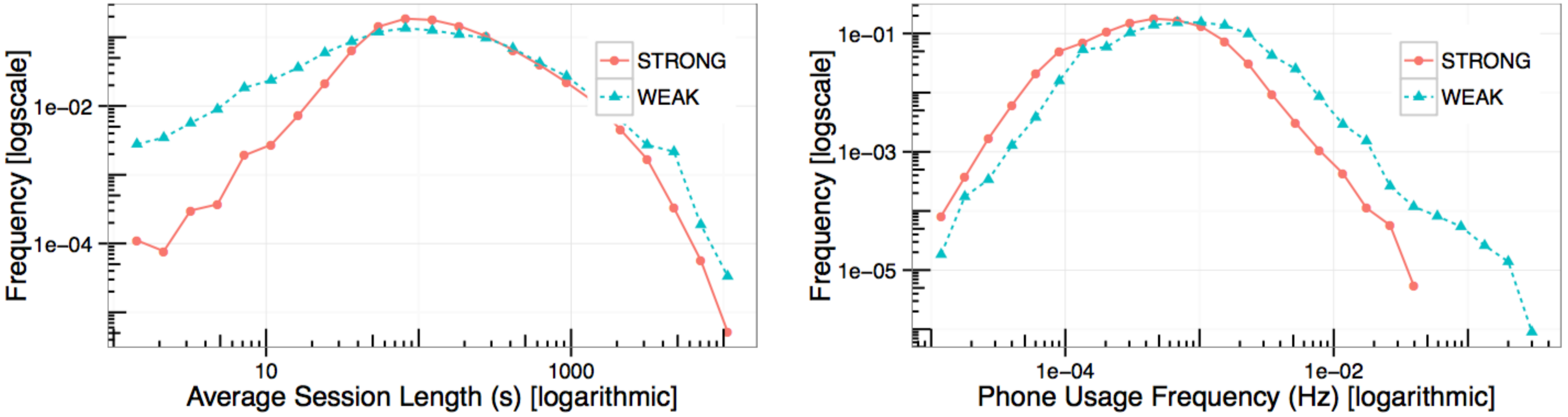



(b) classroom building 6Jiao

**Figure 4: Flows in different buildings.**



# Distractions during Co-location

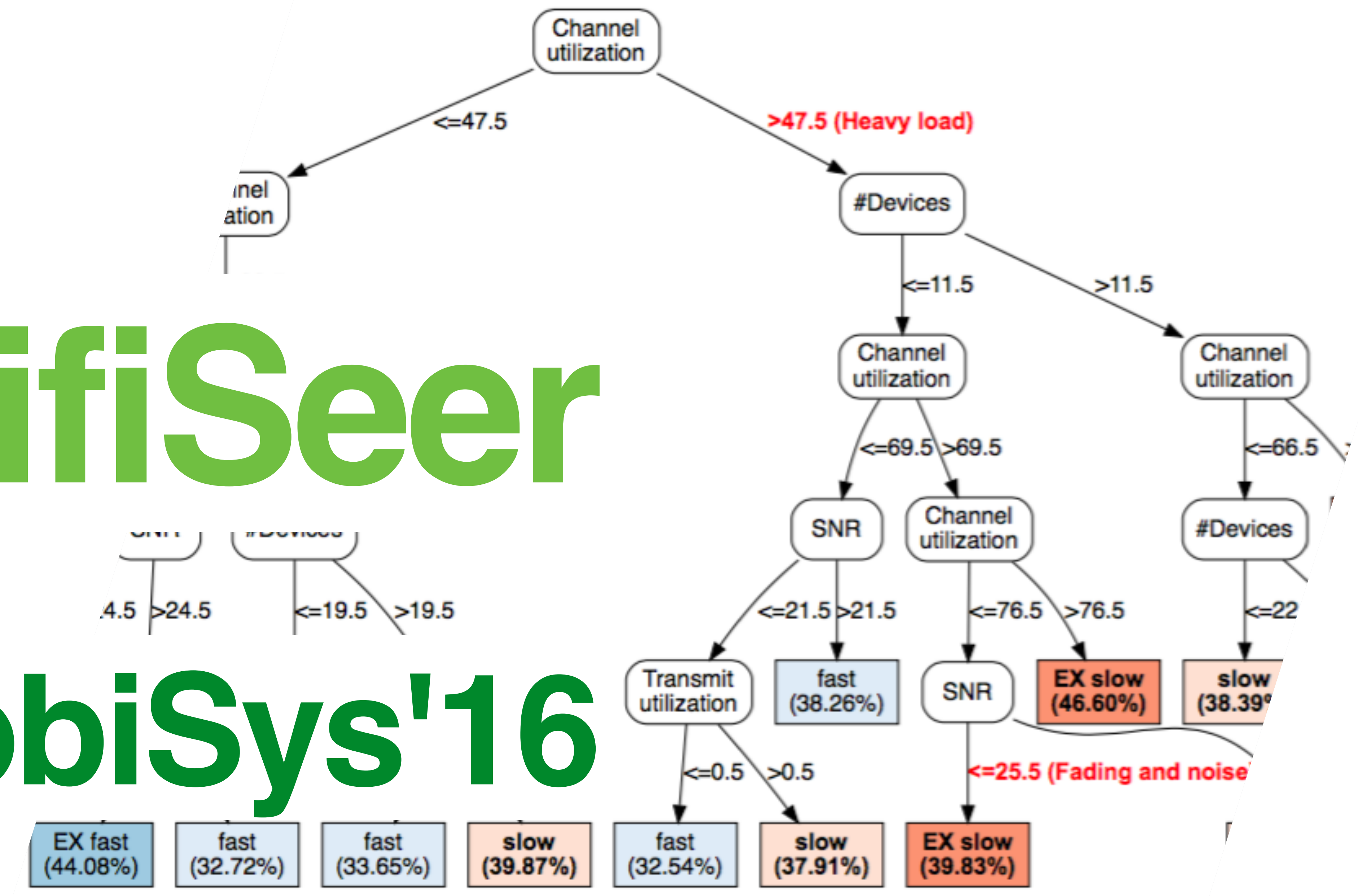



(a) Length of All Sessions (b) Frequency of Short Sessions

- People tend to use phone burstly under weak social ties.

# WifiSeer

## MobiSys'16

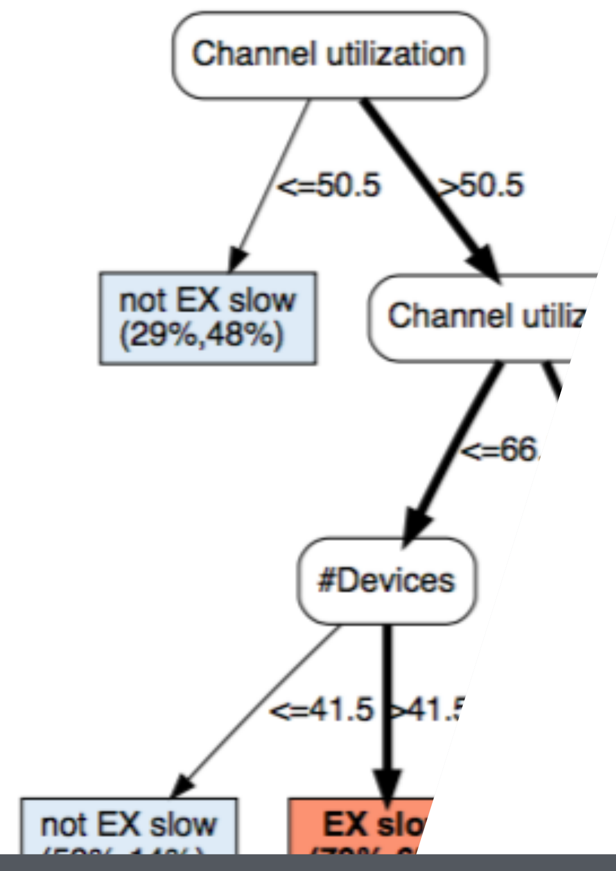



ɫeling the effects of radio factors on WiFi latency. The percent of the major class in

ɔlem time and places of 6Jiao.

| Time | %[EX slow] | %Data |
|---|---|---|
| Morning | 36% | 0.80% |
| Afternoon | 35% | 0.82% |
| -Evening in Fig. 11) | 51% | 0.28% |
| nd-Morning | 33% | 0.13% |

centage of EX slow) is significantly high [EX slow] [41]). The global %[EX slow] U-WLAN (Fig. 4). In this way, we found 92 places out of 1368 on Tsinghua campus. For shows the problem time and places regarding a g named 6Jiao (the sixth classroom building, also Tsinghua).
h problem time and place, we build a decision cision trees in total) based on factors that oper take action on to affect latencies. The specific of the decision trees is shown in the third column of erall, the median precision and recall of those decision 59 and 0.64, respectively.
ion tree identifies a *high WiFi latency condition* as the ion of the factors and their values on the path from the EX slow node. For example, Fig. 11 shows the decision




Classroom-Weekday-E
high WiFi latency cor

Table 9: Prevalent
appear in more th

MODEL RADIO FACTOR EFFECTS | DIAGNOSE HIGH WIFI LATENCY | SELECT A LOW LATENCY AP

## Characterizing and Improving WiFi Latency in Large-scale Operational Networks

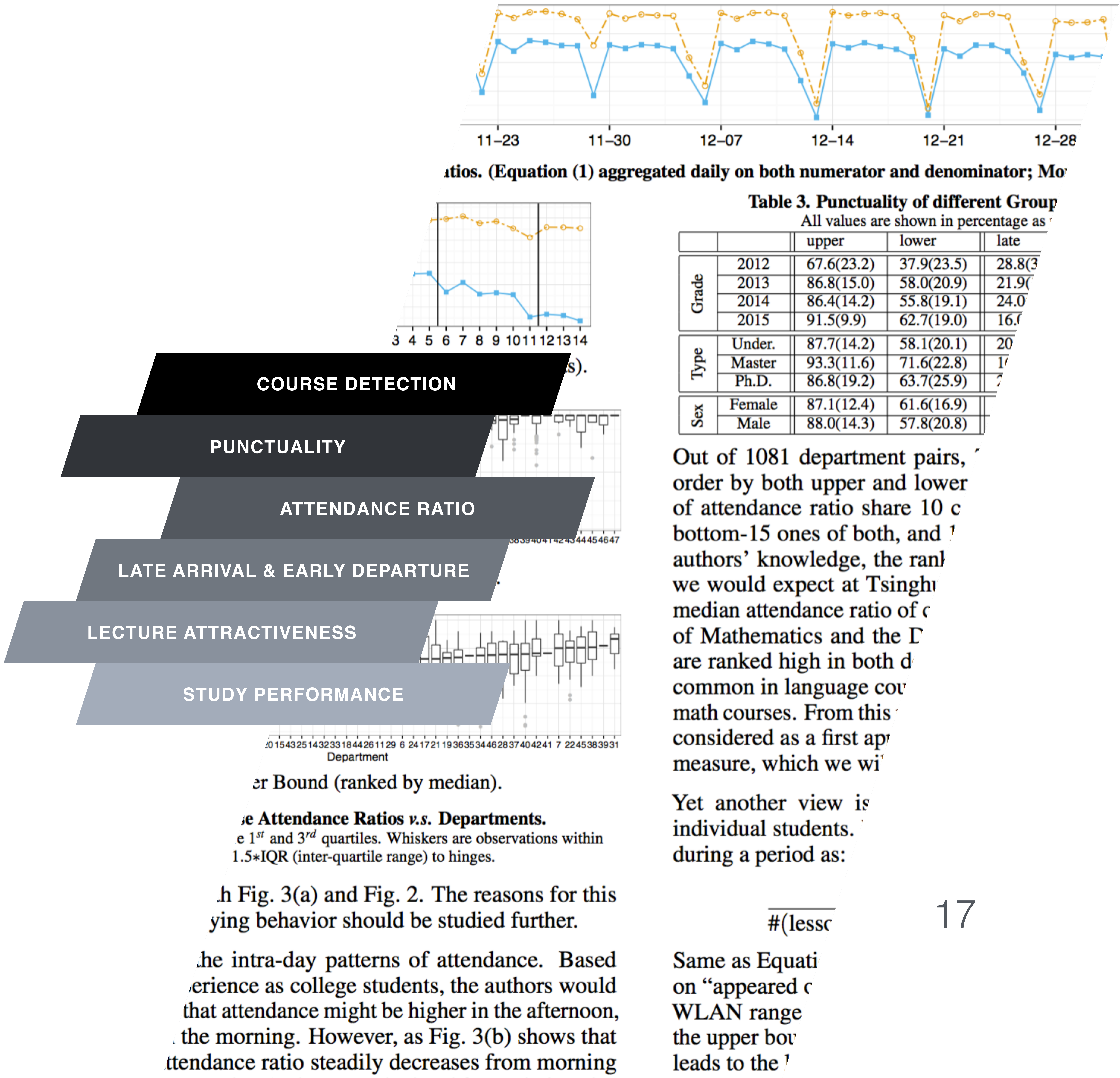
- ✤ WLAN data
- ✤ Measure WiFi latency
- ✤ Machine learning models
- ✤ AP selection by mobile Apps

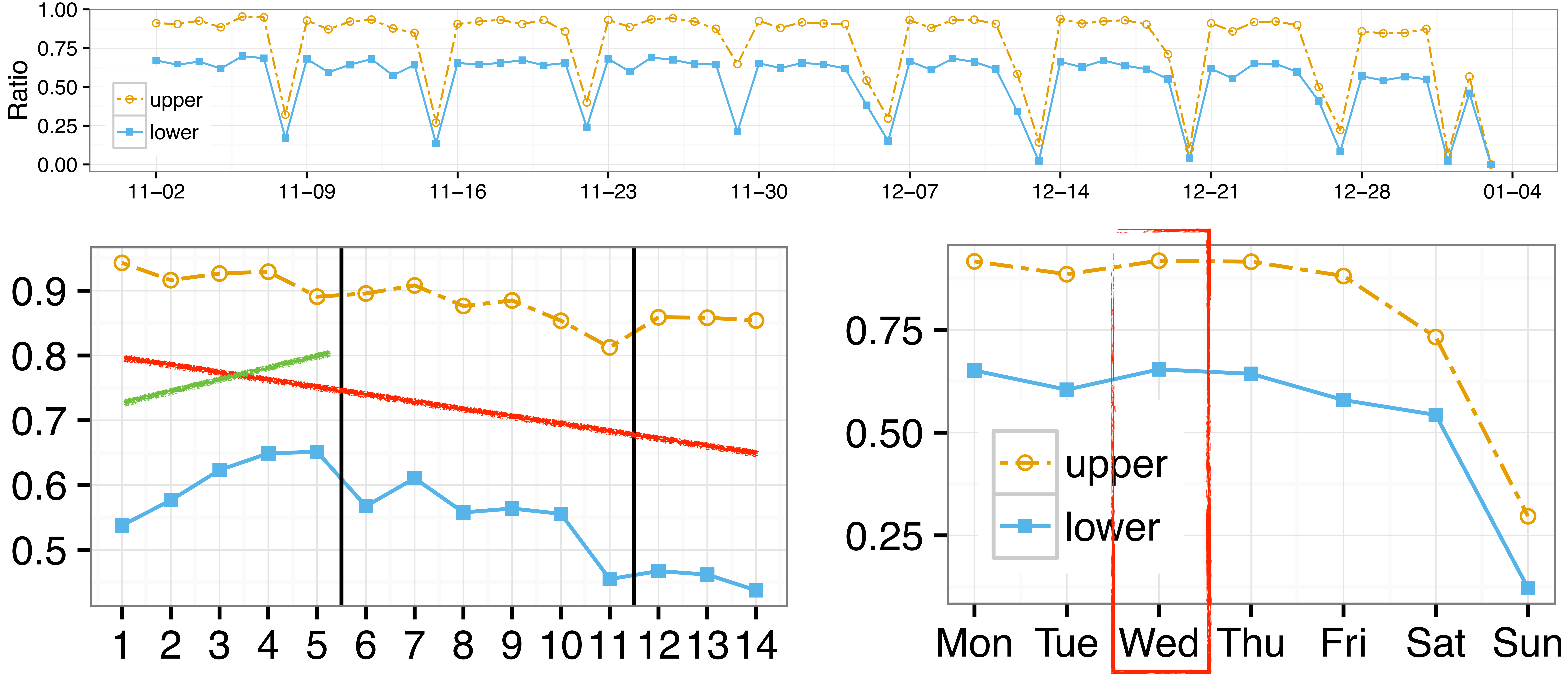
✤ Welcome to **Session VII** 😄

# EDUM

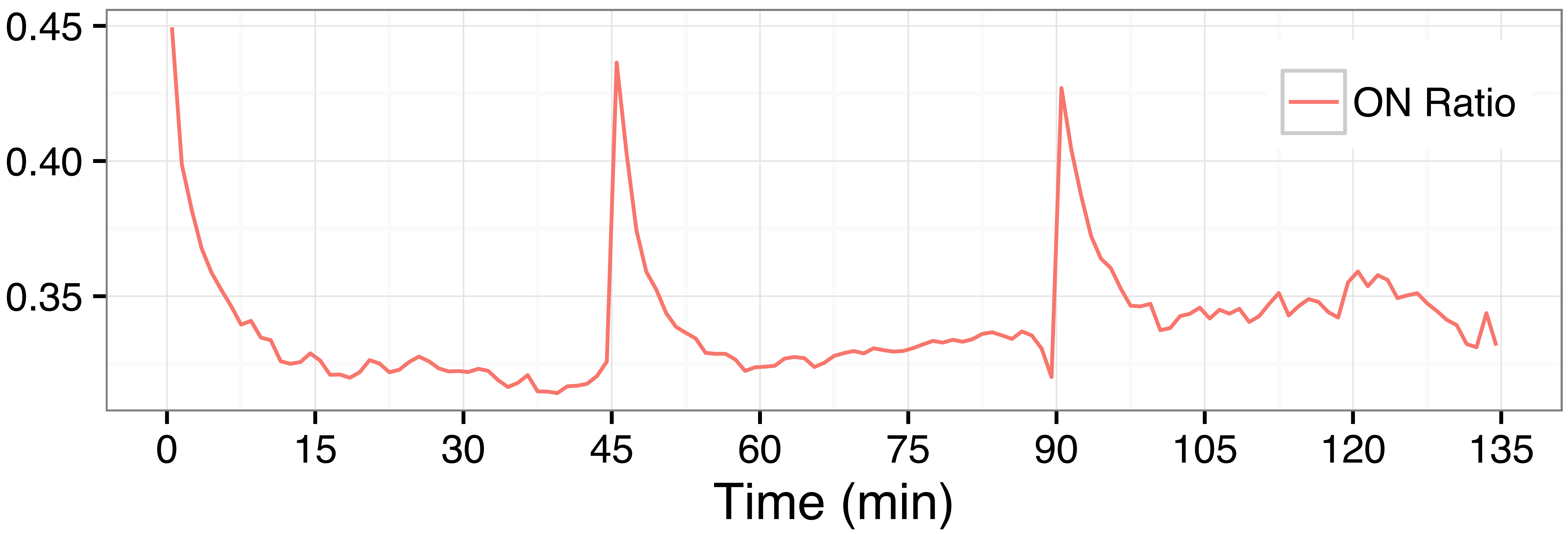
## UbiComp’16

**Classroom Education Measurements via Large-scale WiFi Networks**





Ratio
1.00
0.75
0.50
0.25
0.00
upper
lower
11–02
11–09
11–16
11–23
11–30
12–07
12–14
12–21
12–28
01–04
0.9
0.8
0.7
0.6
0.5
1 2 3 4 5 6 7 8 9 10 11 12 13 14
0.75
0.50
0.25
upper
lower
Mon Tue Wed Thu Fri Sat Sun


0.45
0.40
0.35
ON Ratio
0
15
30
45
60
75
90
105
120
135
Time (min)

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http://github.com/zmy

http://netman.cs.tsinghua.edu.cn

# ¡Gracias!