RAIS

Real-time Analytics for Internet of Sports

Marie Curie European Training Network

DATA ANALYSIS AND VISUALIZATION – EXTRASENSORY DATASET

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Introduction

- Human Activity Recognition (HAR): Recognize the activity being performed by an individual at a given moment [1]

- Human Context Recognition (HCR): Recognize the context (environment, location, interaction) that the activity is being performed [2]

- The combination of the two is important for a better understanding of the human activities

- Wide variety of applications related to personal assistance and recommendations

Overview of Extrasensory Dataset, Vaizman et al. (2017) [3]

- Link: **http://extrasensory.ucsd.edu/**
- **Participants:** 60
- **Devices:** smartphones and smartwatches
- **Sensors:** accelerometer, gyroscope, magnetometer, watch accelerometer, location, audio, etc.
- **Labels:** Physical Activities (e.g., walking, running), Daily Activities (e.g., sleeping , Locations (e.g., school, work, home)
- **Data Volume:** 300.000+ minutes
- **Advantages**
  - Collected in real-world settings when participants were busy with their daily routines
  - It provides a more realistic picture of a person’s life as compared to a scripted lab data collection which constrains users to a few basic activities.
  - Complex activities (e.g., washing dishes, drinking alcohol, sitting in a bus, watching tv and eating)

Data Collection Approach

- Data was collected using the ExtraSensory smartphone app (ExtraSensory App).

- The app automatically collects sensor measurements in a 20-second "recording session“ every minute
- The labels were reported in different ways:
  - Active reporting
  - Notification
  - Label Selection
  - History view

Real-life conditions

- Everyday devices
- Unconstraint device placement
- Intimate environment
- Natural behavioral content

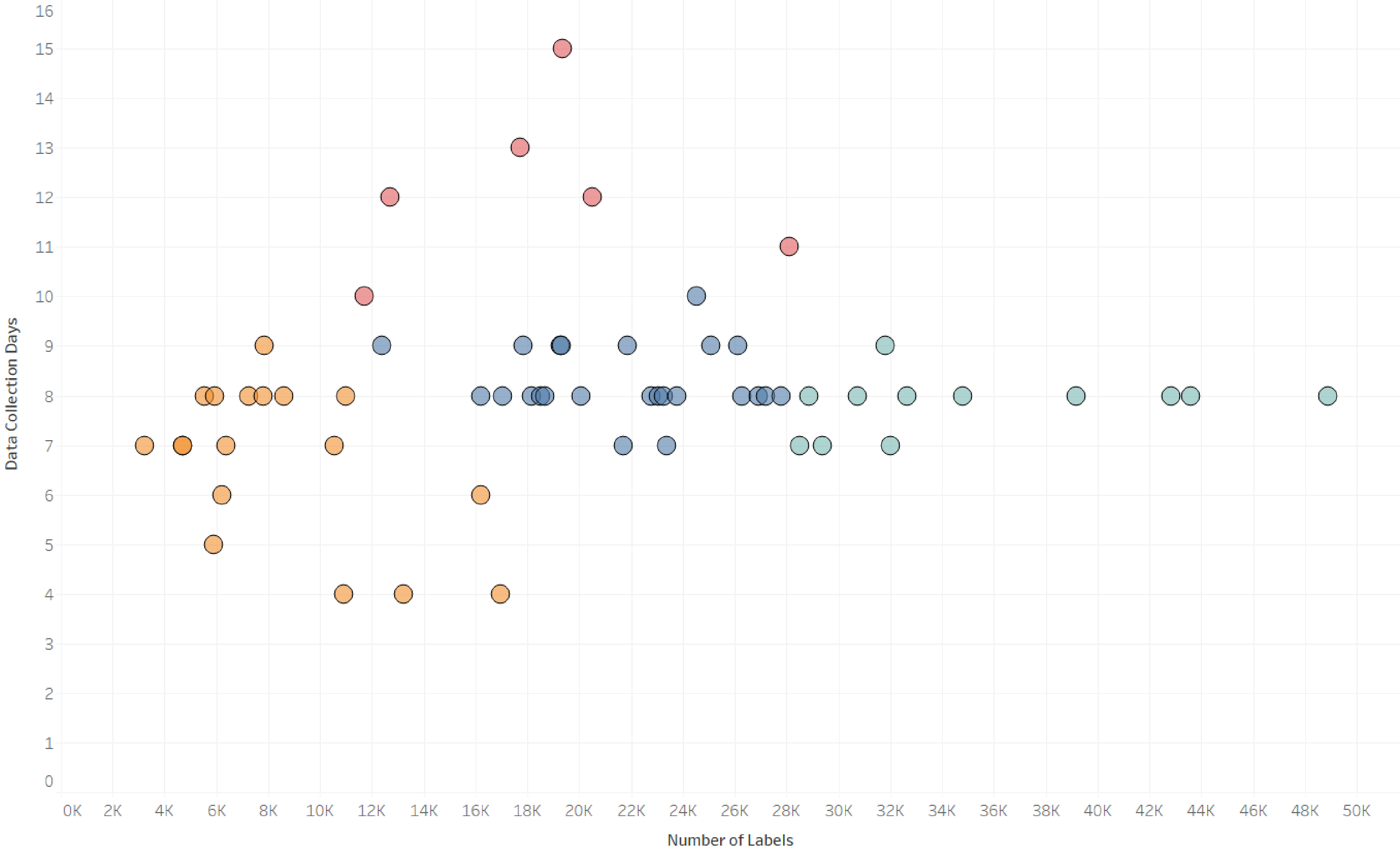
Missing and Unbalanced Data

- User experiments conducted in real-world settings face some problems that is hard to overcome during data collection:
  - Participants turn off sensors to avoid battery drain or for private reasons
  - Participants tend to forget, get bored or unable to report labels
  - Participants do not carry their smartphone or wear the smartwatch continuously
  - Sensor malfunction or other technical or connectivity issues have been reported

Result: Unbalanced labels and missing sensor data

The Extrasensory dataset, highlights the inevitable problem of **missing**, **unlabeled** and **unbalanced** data (days, users, sensors, labels)

Participants: Days and Labels

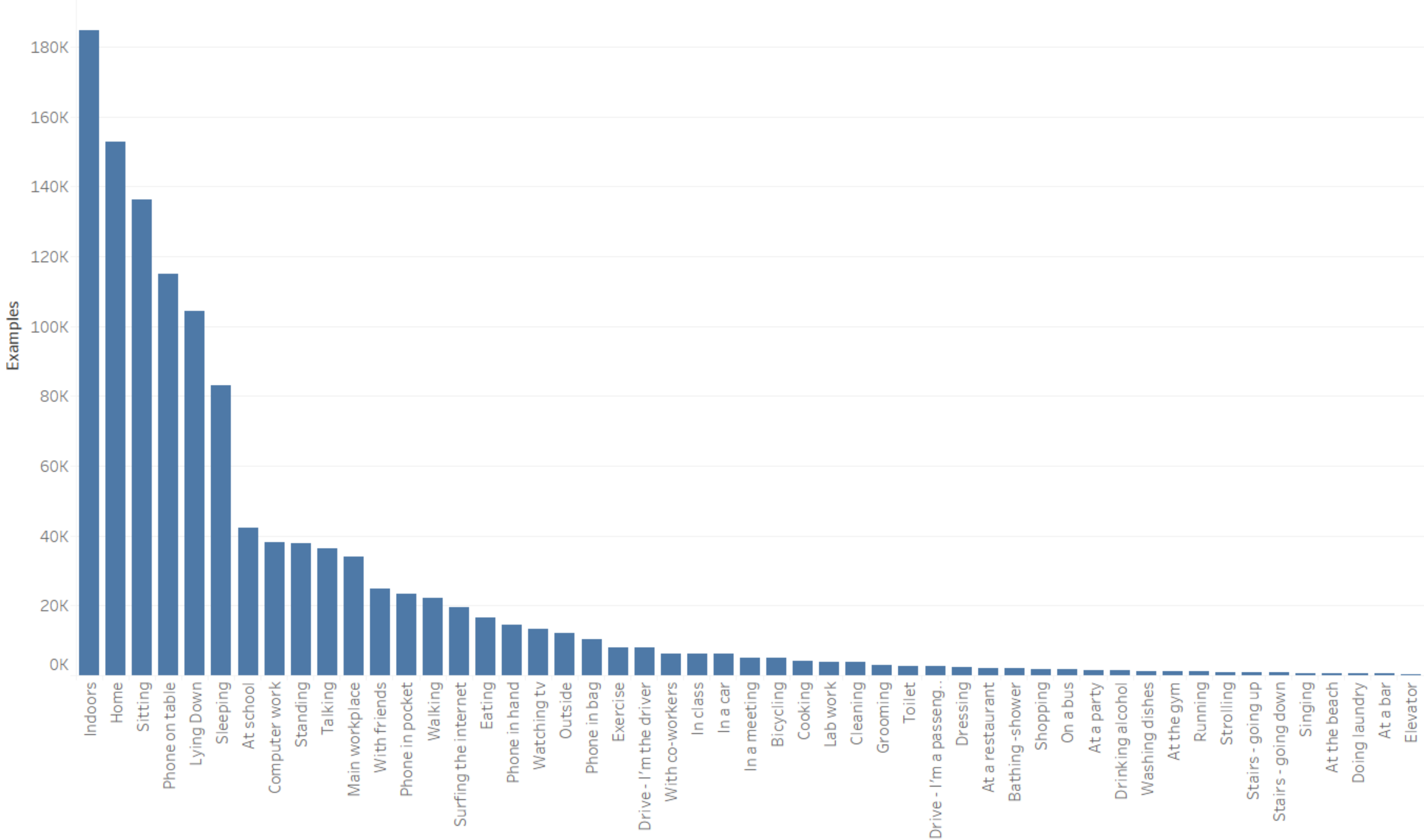


Types of Labels

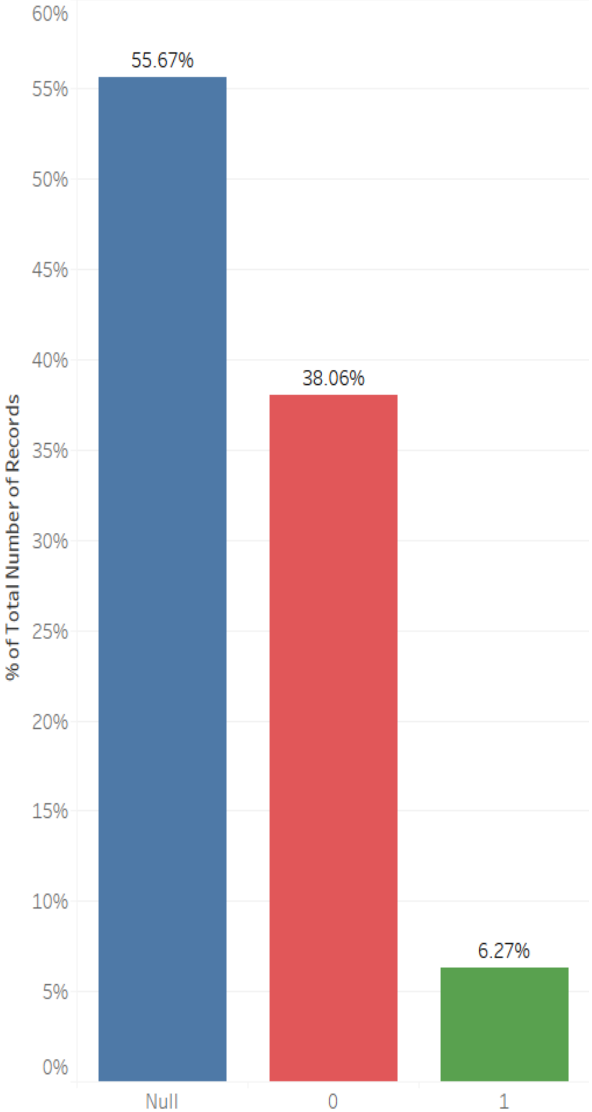
51 different labels:

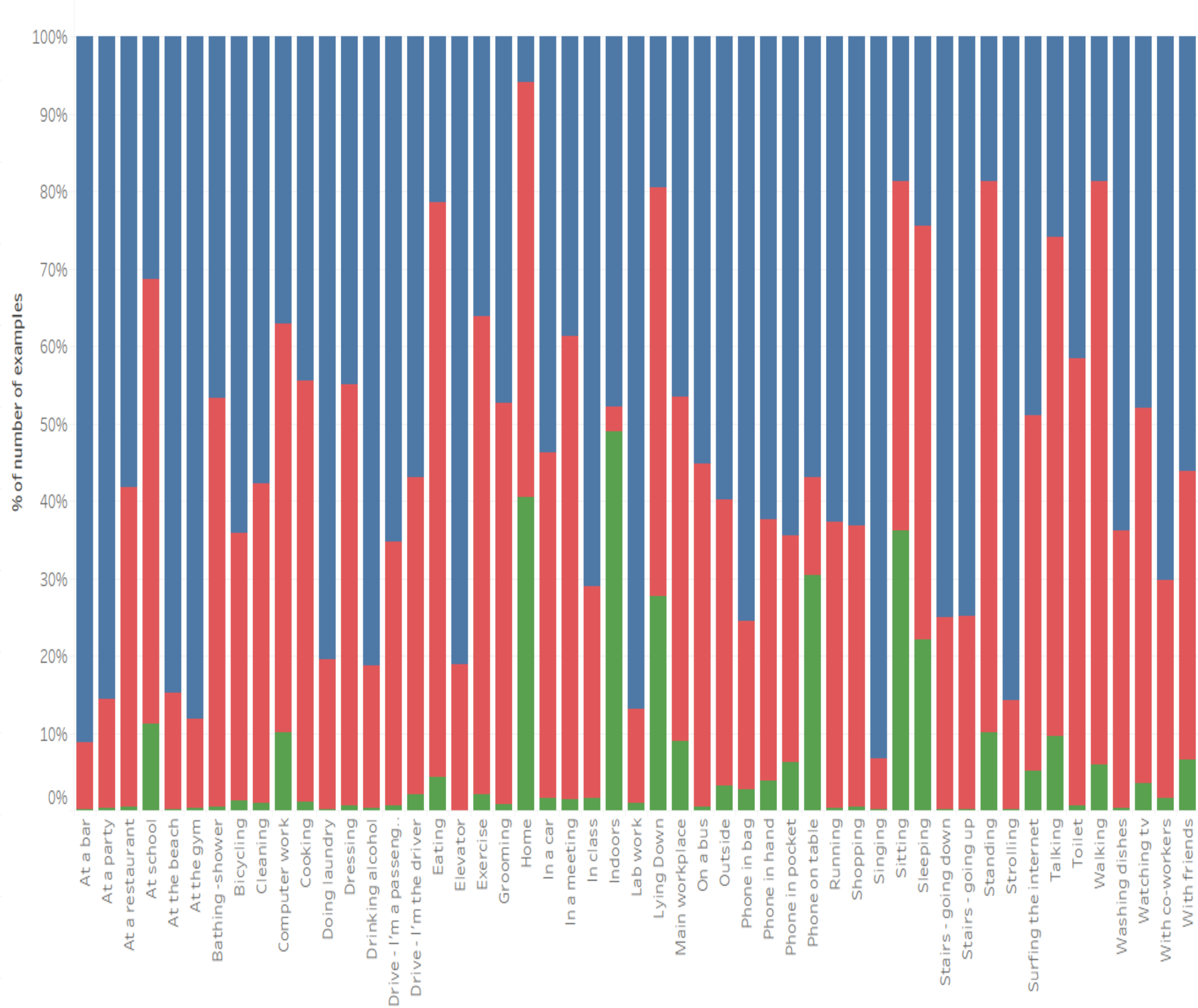
- **Physical and Daily Living and Other Activities:** walking, running, standing, sitting, lying down, sleeping stairs up&down, cooking, bathing, toilet, cleaning, grooming, computer work, eating, dressing, talking, driving, surfing the internet, watching tv, doing laundry, drinking alcohol, singing, shopping, bicycling
- **Social interactions:** with friends, with co-workers
- **Locations and environments:** indoors, outside, home, school, bar, restaurant, workplace, gym, beach, class, party, car, meeting, bus, elevator
- **Phone positions:** hand, bag, table, pocket

Number of Examples per Label



Labels: Relevant (1) – Not Relevant (0)

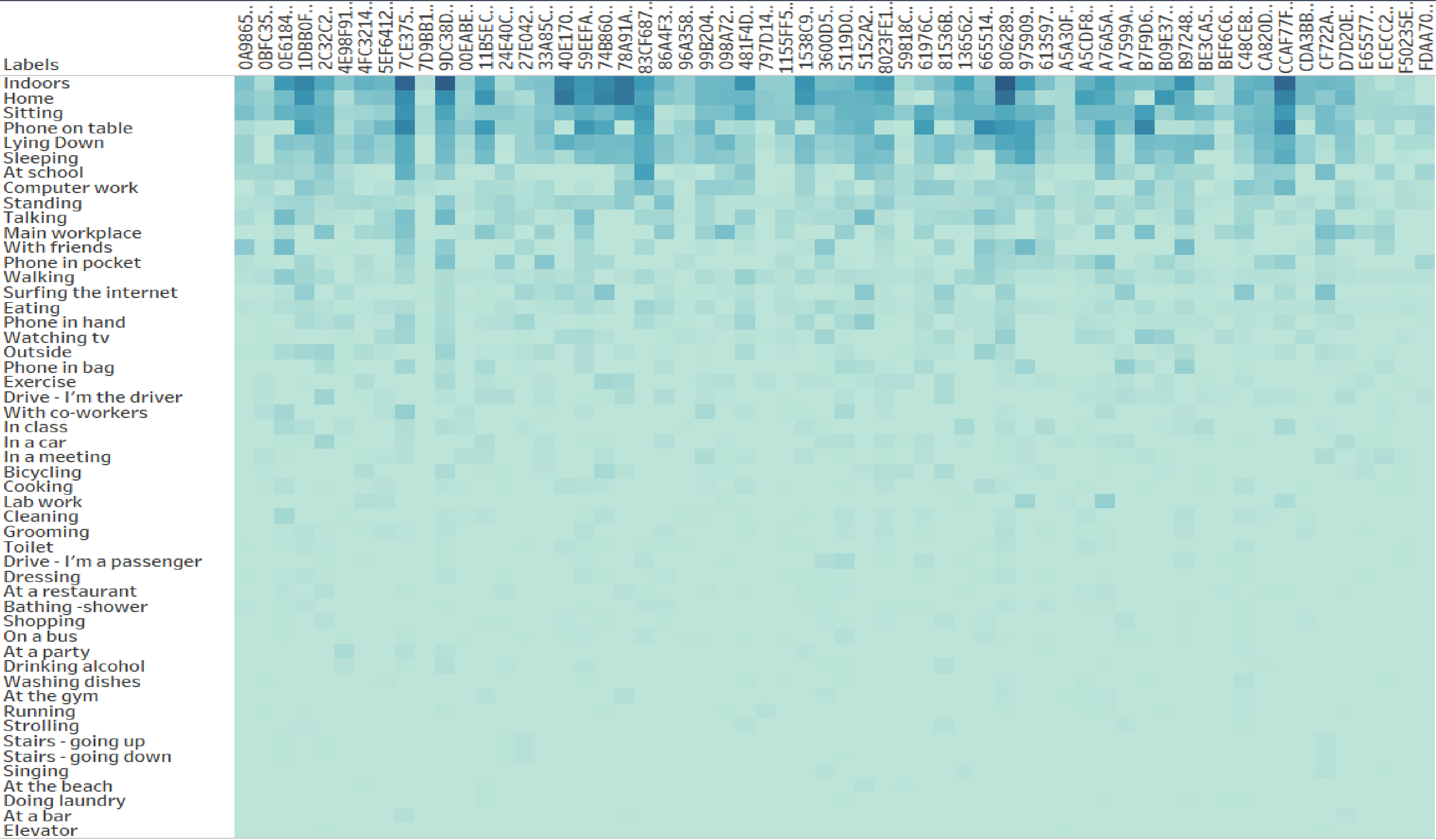




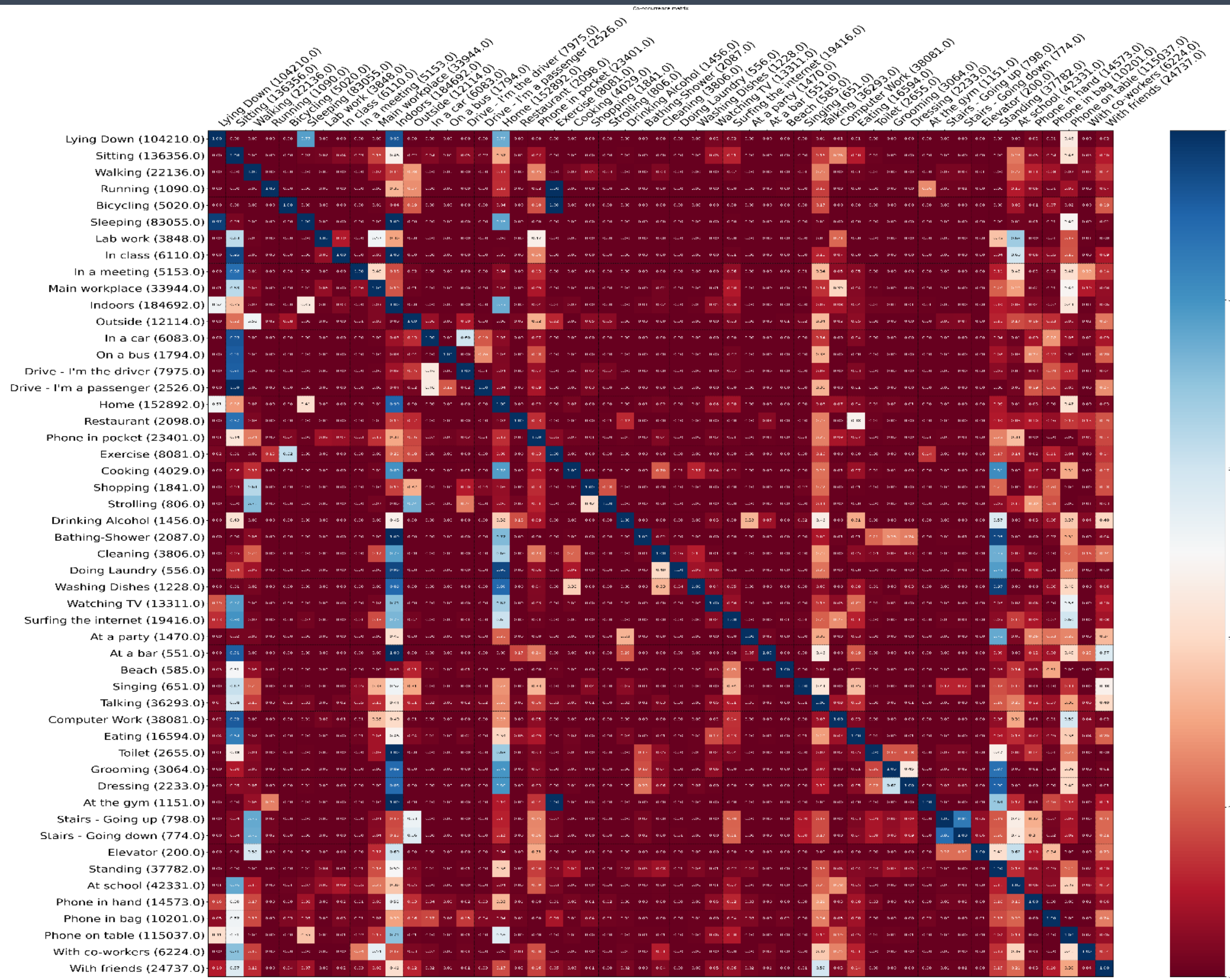
Labels Collected per day

	2015							2016	
	June	July	August	September	October	November	December	May	June
1			917	9,995	6,782	4,774	10,655		11,806
2			902	9,576	8,120	5,572	12,988		6,494
3			1,547	7,789	6,456	6,755	12,655		
4			1,522	9,022	4,734	6,611	17,046		
5	931		5,507	7,227	8,301	4,992	15,420		
6	1,925		4,651	5,895	5,108	15,735	17,207		
7	1,467		2,090	6,342	2,214	12,555	14,117		
8	2,051			8,348	7,861	6,358	15,314		
9	2,551			14,405	14,378	9,487	17,548		
10	984			14,519	7,860	7,885	18,513		
11			594	9,521	8,068	6,705	7,112		
12			4,478	4,426	8,506	5,252	6,700		
13			2,730	3,446	14,211	2,240	6,276		
14			4,933	4,683	15,866	2,003	3,260		
15			5,174	3,920	14,041	243	4,591		
16			2,576	5,746	11,185	2,158	5,839		
17			4,355	8,084	8,851	10,749	5,487		
18			4,572	7,713	9,479	10,371	5,280		
19			14,603	2,168	7,146	9,290	3,136		
20			18,722		7,783	9,341	1,467		
21			16,466		6,178	4,789	1,033		
22			9,589	877	13,014	5,678			
23		267	9,883	8,187	4,288	6,725			
24		2,094	7,624	17,404	3,865	9,190		689	
25		1,231	12,305	15,457	5,395	9,680		4,319	
26		1,769	18,829	8,064	5,775	10,011		6,323	
27		595	16,454	9,475	6,362	9,129		9,673	
28		251	15,168	12,330	4,734	6,989		8,072	
29			12,543	11,483	4,979	10,407		5,737	
30			10,782	3,396	8,708	7,492		9,654	
31		367	12,402		3,350			12,025	

Number of Labels - Participants



Co-Occurrence Matrix



Where is the phone (co-occurrence)?

	Phone in bag	Phone in hand	Phone in pocket	Phone on table
Bicycling	25.47%	4.60%	63.74%	6.19%
Cleaning	0.00%	3.63%	50.31%	46.06%
Computer Work	2.07%	1.75%	8.12%	88.05%
Cooking	4.00%	14.68%	18.22%	63.11%
Doing Laundry	0.00%	20.52%	14.41%	65.07%
Dressing	0.72%	0.00%	7.87%	91.42%
Drinking Alcohol	11.88%	5.06%	15.68%	67.38%
Running	8.89%	33.33%	10.56%	47.22%
Watching TV	0.51%	8.87%	5.09%	85.54%
Washing Dishes	12.93%	0.00%	7.36%	79.71%
Toilet	1.57%	34.14%	7.22%	57.08%
Talking	10.54%	17.95%	24.70%	46.81%
Strolling	30.40%	50.10%	18.87%	0.63%
Standing	9.73%	12.86%	32.57%	44.84%
Stairs-Going Up	3.33%	46.77%	37.52%	12.38%
Stairs-Going Do..	2.58%	48.25%	36.83%	12.34%
Sleeping	1.29%	2.60%	0.24%	95.87%
Sitting	6.52%	8.95%	12.55%	71.98%
Singing	0.00%	2.83%	68.55%	28.62%
Shopping	51.52%	16.57%	31.91%	0.00%
Walking	16.60%	24.16%	53.98%	5.27%

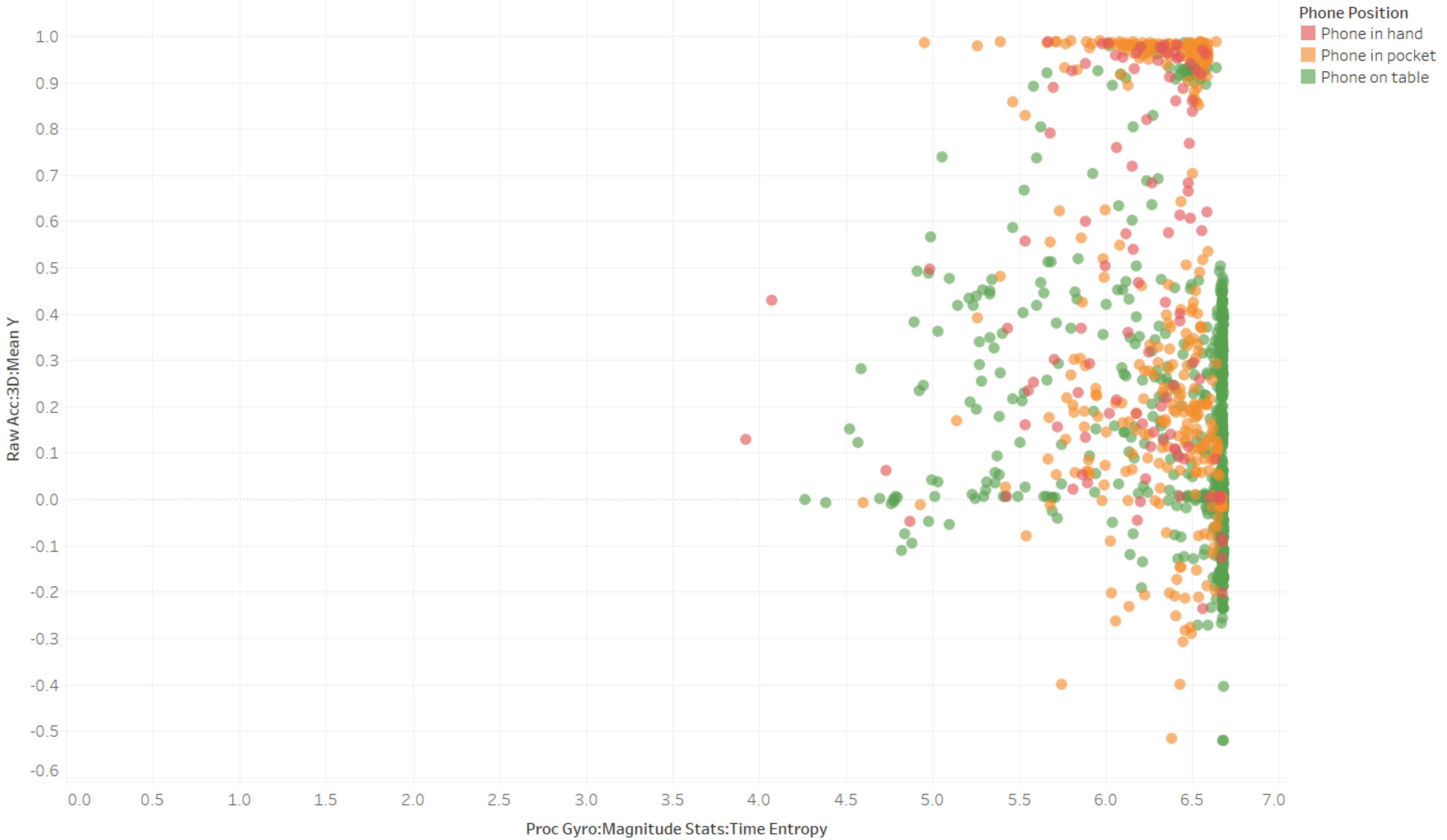
Where the activities took place (co-occurrence)?

	At home	At school	At main workpla..	At the gym	At a bar	At a party	At a resturant	At the beach	In a meeting	In class	In a car
Bicycling	36.32%	59.45%	4.23%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Cleaning	78.33%	1.82%	19.86%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Computer Work	31.98%	25.88%	41.27%	0.00%	0.00%	0.00%	0.00%	0.00%	0.38%	0.49%	0.00%
Cooking	98.28%	0.09%	1.63%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Doing Laundry	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Dressing	99.72%	0.00%	0.28%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Drinking Alcohol	25.45%	0.00%	0.00%	0.00%	10.54%	47.61%	16.40%	0.00%	0.00%	0.00%	0.00%
Running	16.53%	23.35%	0.00%	59.09%	0.00%	0.00%	0.00%	1.03%	0.00%	0.00%	0.00%
Watching TV	96.47%	0.61%	2.66%	0.00%	0.00%	0.00%	0.10%	0.16%	0.00%	0.00%	0.00%
Washing Dishes	99.91%	0.00%	0.09%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Toilet	84.47%	5.04%	9.70%	0.00%	0.00%	0.00%	0.79%	0.00%	0.00%	0.00%	0.00%
Talking	41.62%	30.16%	18.14%	0.00%	1.13%	1.91%	1.79%	0.04%	0.62%	0.85%	3.72%
Strolling	31.90%	50.92%	7.98%	0.00%	0.00%	0.00%	9.20%	0.00%	0.00%	0.00%	0.00%
Standing	52.16%	12.66%	25.47%	2.99%	0.18%	4.08%	0.60%	0.10%	0.95%	0.09%	0.73%
Stairs-Going Up	18.45%	74.00%	6.92%	0.00%	0.00%	0.00%	0.00%	0.00%	0.63%	0.00%	0.00%
Stairs-Going Down	20.04%	72.07%	7.25%	0.00%	0.00%	0.00%	0.00%	0.00%	0.64%	0.00%	0.00%
Sleeping	98.55%	1.05%	0.41%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Sitting	43.81%	23.71%	20.90%	0.00%	0.51%	0.03%	1.64%	0.30%	1.19%	2.48%	5.43%
Singing	51.43%	18.29%	24.86%	0.00%	0.00%	0.00%	0.00%	0.00%	5.14%	0.00%	0.29%
Shopping	94.83%	3.45%	1.72%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Walking	32.18%	46.51%	18.22%	0.83%	0.01%	0.35%	0.61%	0.42%	0.80%	0.07%	0.00%

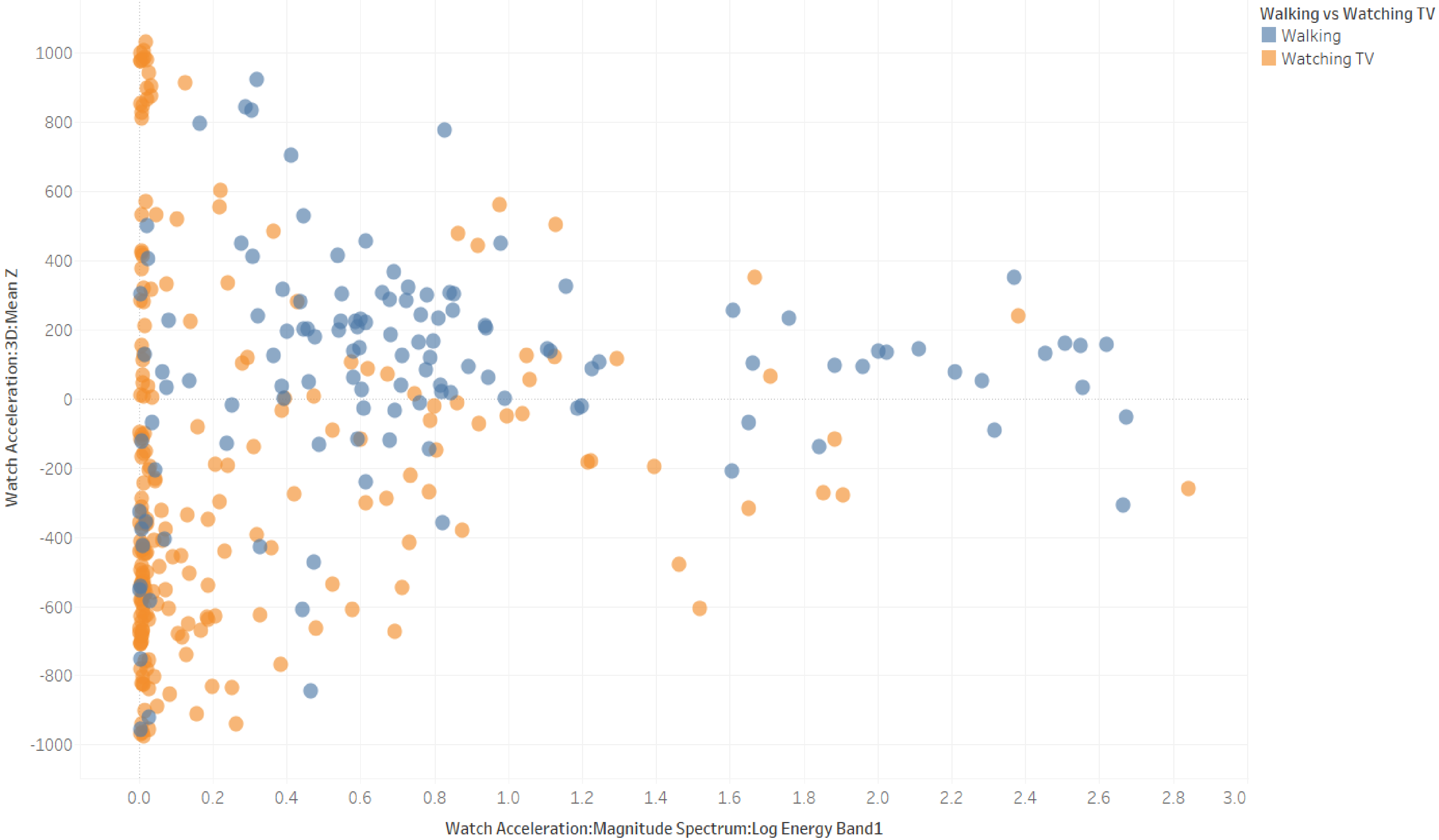
Sensor Features

- **The dataset contains 225 hand-crafted sensor and other features derived from the following sensors:**
    - Acc (Accelerometer): 26 features (smartphone) + 46 features (smartwatch)
    - Gyr (Gyroscope): 26 features
    - Magn (Magnetometer): 31 features
    - Loc (Location): 17 features
    - Aud (Audio): 26 features
    - Smartwatch compass: 9 features
    - PS (Phone State): 34 features
    - Time of the day: 8 features
- The sensor features contain information that is not provided from the raw signals and combined are being used to identify differences between activities and contexts
- For the extraction of the features various signal processing and statistical methods were applied. More detailed information on the feature extraction process and the calculations is provided in [3].

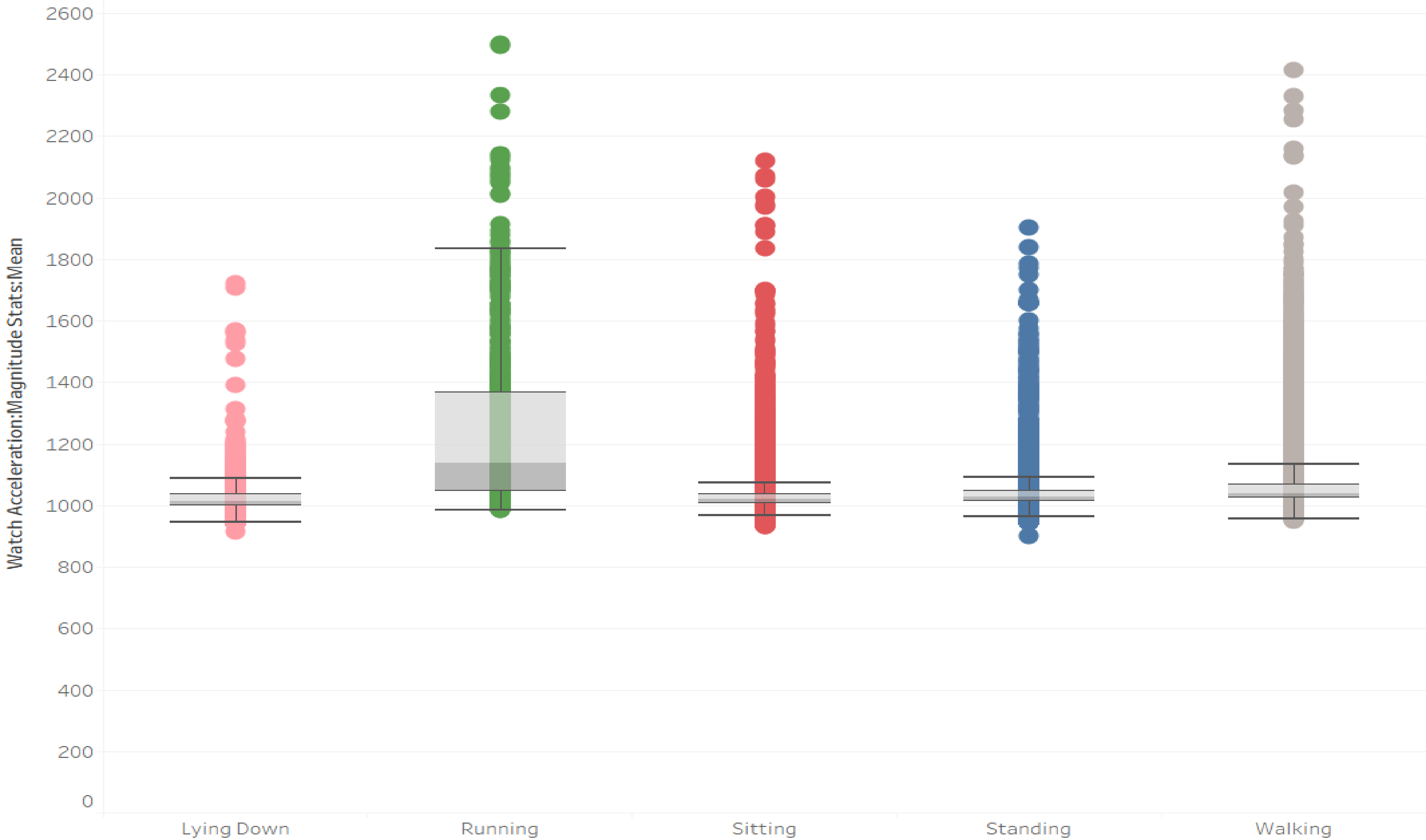
Phone Accelerometer and Gyroscope



Smartwatch Accelerometer: Walking – Watching TV



Smartwatch Accelerometer: Different Activities



Related Works on Extrasensory Dataset

Method	Labels Recognized	Sensors	Algorithm	Evaluation
Single-Label HAR/HCR [3]	25 labels	Acc (smartphone and smartwatch), Gyr, Loc, Aud, PS	Logistic Regression	Balanced Accuracy = 71.8%
Multi-Label HAR /HCR [4]	15 combined labels	Acc (smartphone)	Random Forest	Balanced Accuracy = 80%
Multi-Label HAR/HCR [5]	29 combined labels	Acc (smartphone and smartwatch) Gyr	Random Forest	Balanced Accuracy = 86.7%
Multi-Label HAR/HCR [2]	29 combined labels	Acc (smartphone and smartwatch)	Random Forest	Balanced Accuracy = 89.8%
Multi-Label HAR/HCR [6]	51 combined labels	Acc (smartphone and smartwatch), Gyr, Loc, Aud, PS	MLP	Balanced Accuracy = 77.3%

Next Steps

- Complete with EDA - Explore in more depth the sensor features
- Include mood labels and absolute locations that are available for some of the participants
- Define an appropriate approach and methodology for HAR
- Construct an accurate recognition model

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