Sensor Datasets

Lecture Overview

- Sensor Dataset Review
  - CrowdSignals.io
  - K-EmoCon
  - K-EmoPhone

- Colab for Sensor Data Processing
  - Accessing data through Google Drive
  - Using Pandas for data pre-processing

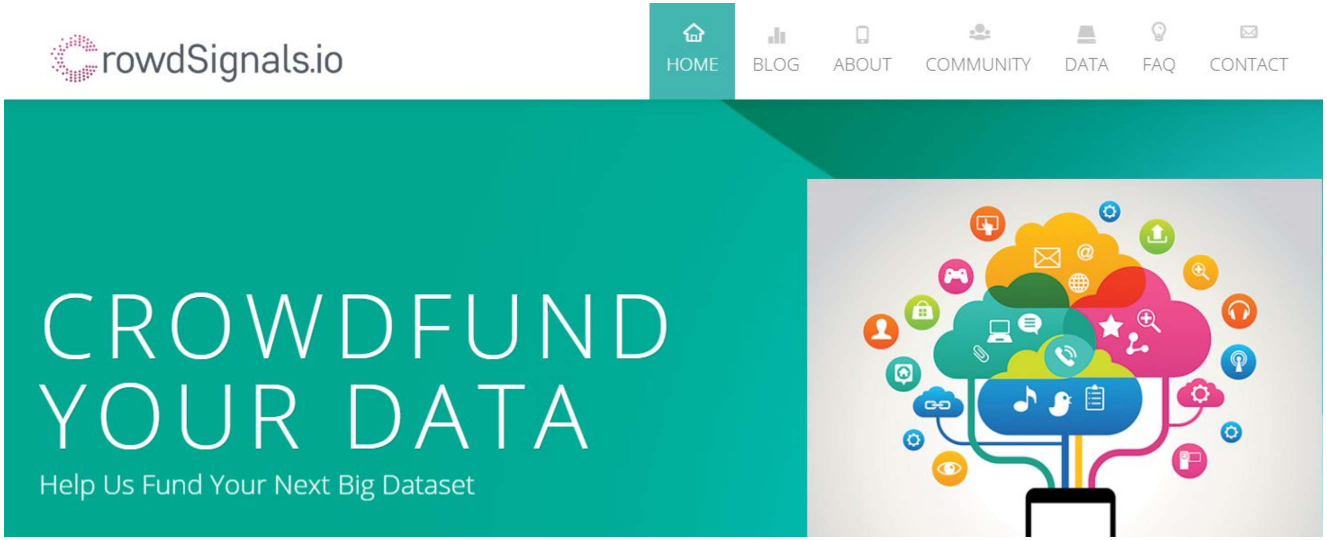
CrowdSignals: a call to crowdfund the community's largest mobile dataset

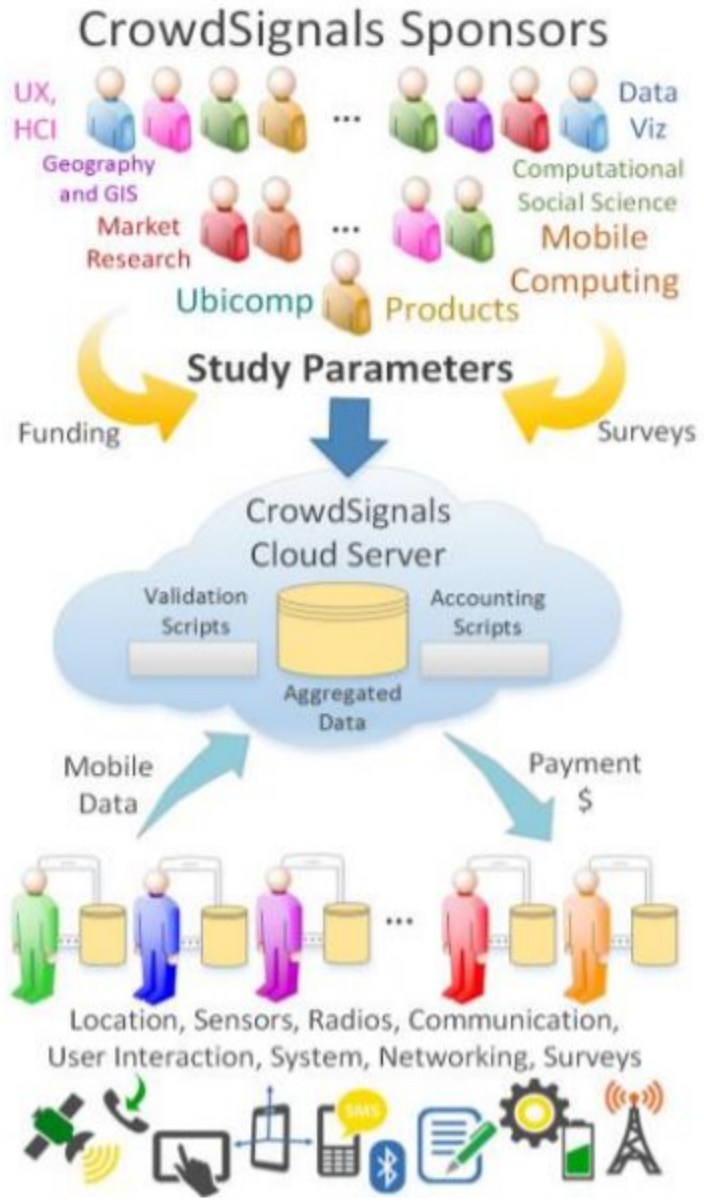
Evan Welbourne, Emmanuel Munguia Tapia

ACM Ubicomp EA 2014

Datasets: ***CrowdSignals.io***

- During the course we will use a running example provided by CrowdSignals.io
- People share their mobile sensors data (smart phone and smart watch) and get paid for annotating their data with activities





CrowdSignals: a call to crowdfund the community's largest mobile dataset, Evan Welbourne, Emmanuel Munguia Tapia, ACM Ubicomp EA 2014
https://dl.acm.org/citation.cfm?id=2641309

Data Collection is the ***Most Challenging Task*** in Sensor Data Science

CrowdSignals: A Call to Crowdfund the Community's Largest Mobile Dataset

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Abstract
Researchers from diverse backgrounds critically depend on mobile datasets. From training and testing activity recognition models, to verifying hypotheses in social science, mobile data is indispensable. Unfortunately, mobile data collection requires significant time and budget for infrastructure as well as subject recruiting, screening, training, legal agreements, equipment, and compensation. We estimate up to 70% of the resources in a study may be spent on data collection. Moreover, this massive investment can combine with institutional, legal, and political issues to create a disincentive to sharing with the community. In this paper, we propose and justify a crowdfunded and crowdsourced methodology for longitudinal mobile data collection that cuts researcher costs by orders of magnitude, removes barriers to data sharing, and boosts data value for all stakeholders. We also present CrowdSignals, a first instantiation which will generate the largest labeled mobile dataset available to the community.

Data Collection Methods

- Local administration (LA)
  - Researchers painstakingly recruit, on-board, and manage subjects in person, compensating them with smartphones and a mobile data plan
  - Examples: MIT, Nokia, UB, and SMU campaigns
- App store-based (AS)
  - An app is distributed to 1,000s of users via an app store (e.g., CenseMe project)
- Crowdsourced (CS)
  - Remote subjects are rapidly recruited, managed, and paid with a crowdsourcing service, but they install a data collection app on their own phone

Data Collection Methods

	Software	Hardware	Admin	Comp
Local Admin	$2000 x 4 months x # developers	$300-$600 x # subjects	$2000 x # months x # assistants	$50-$100 x # months x # subjects
App Store	$2000 x 8 months x # developers	N/A	$N/A	N/A
Crowd-source	$2000 x 4 months x # developers	N/A	$500 x # months x # assistants	$20-$50 x # months x # subjects

Table 2. Estimated US$ cost for methodologies, including: Software Development (grad students), Hardware (phones), Compensation (cash, data plan), and Admin (grad students).

CrowdSignals.io
Data collection app

- The Android app has a background service, configurable surveys, and basic controls.
  - All sensitive data (e.g., SMS content) is hashed to protect subjects
  - The service securely uploads encrypted, compressed data when the subject’s phone connects to WLAN

- Experience sampling (labeling)
  - Sponsors may solicit ground truth from subjects with a survey framework that offers **(1) lockscreen surveys and (2) experience sampling method (ESM) surveys**
  - The lockscreen solicits frequent, lightweight feedback with a multiple choice question (e.g., “How do you feel?”) every time subjects unlock their phone - about 19 times per day on average
  - ESM questionnaires use the Open Data Kit (ODK) [13] for configurable surveys and participatory sensing (e.g., audio, video, barcodes)
  - Top sponsors may specify custom ESM questionnaires using ODK’s JSON survey specifications; lockscreen surveys are specified as a combination of text and image files

lockscreen surveys

Smartphone & Tablet Sensors

	Samsung Galaxy S7 & Up	Apple iPhone X	Samsung Galaxy Tab S6	Apple iPad Pro 11
Accelerometer	O	O	O	O
Magnetometer (Digital Compass)	O	O	O	O
Gyroscope	O	O	O	O
Ambient Light	O	O	O	O
Proximity	O	O	O	O
Camera	O	O	O	O
Voice	O	O	O	O
Pressure (Barometer)	O	O		O
Humidity/IR/Temperature**	(was used only in Galaxy S4)			
NFC	O	O		
HR	O	O		
Fingerprint Scanner	O	O	O	O

*** Battery temperature sensors could be used to infer ambient temperature*

CrowdSignals.io Dataset

Sensor	Purpose	Device(s)	Values	Time point / Interval	Used
			Sensors		
Accelerometer	The acceleration of the device	phone/ watch	x, y, and z acceleration	time point	yes
Gyroscope	The angular speed of the device	phone/ watch	x, y, and z angular speed	time point	yes
Magnetometer	The magnetometer value of the device	phone/ watch	x, y, and z magnetometer value	time point	yes
Heart rate	The heart rate of the user	watch	heart rate (beats per minute)	time point	yes
Temperature	Ambient temperature	phone/ watch	temperature (in ^{o}C)	time point	no
Light	The light intensity	phone/ watch	light intensity (in lux)	time point	yes
Pressure	The current pressure	phone/ watch	pressure (in mercury millibars)	time point	yes
Humidity	The current humidity	phone/ watch	relative humidity (%)	time point	no
Proximity	Distance of user from phone	phone	distance (meters)	time point	no
Audio record	Record of audio obtained via the microphone	phone	audio recording	time point	no
			User labels		
Activity label	Record of the activity a user is conducting	phone	label (walking, running, ...)	interval	yes

Raw data

- What does the raw CrowdSignals data look like?
  - Separate tables per measurement
  - Only use a single user dataset for in-class activities and homework

sensor_type	**device_type**	**timestamps**	**rate**
heartrate	smartwatch	1454956086325639687	175.000
heartrate	smartwatch	1454956086684549167	176.000
heartrate	smartwatch	1454956087523516770	175.000

Specific time point measurements

sensor_type	**device_type**	**label**	**label_start**	**label_end**
interval_label	smartphone	On Table	1454956132985999872	1454956366574000128
interval_label	smartphone	On Table	1454956393088000000	1454956578385999872
interval_label	smartphone	On Table	1454956608515000064	1454956813323000064
interval_label	smartphone	Sitting	1454956894057999872	1454957092968000000

Interval measurements

K-EmoCon: A Multimodal Sensor Dataset for Continuous Emotion Recognition in Naturalistic Conversations

Cheul Young Park
Interactive Computing Lab

08.08.2019

Overview of the dataset

- Dataset for continuous emotion recognition in naturalistic conversations (N=32)
- Collected both self-reported labels and perceived labels
- Multimodal data
  - Audio: speech
  - Visual: facial expressions and gestures
  - Physiological: acceleration, heart rate, inter-beat interval (IBI), electrodermal activity (EDA), skin temperature, electroencephalogram (EEG), and electrocardiogram (ECG)
- Used off-the-shelf grade sensors and equipments to collect data

Data collection setup and methods

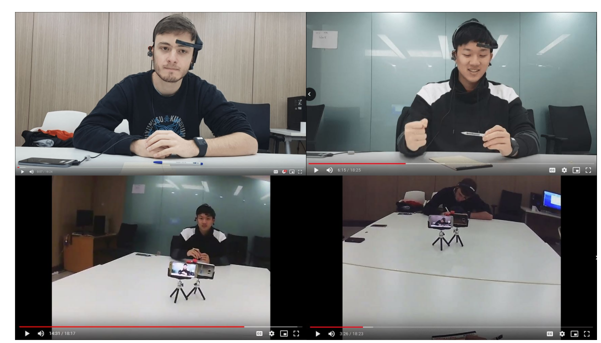
Devices for data collection:

1) NeuroSky MindWave headset for EEG
2) Samsung Galaxy S7 smartphones with tripods
3) Polar H7 chest band with ECG sensors
4) Empatica E4 wristbands
5) LookNTell head-mounted camera

A participant equipped with data collection devices. ECG sensor was worn underneath clothes to maintain contact with skin.

A data collection session. Two participants sat across a table and two smartphones were placed in the middle facing each participant. All debates were in English.

Devices	Collected data	Sampling rate	Signal range [min, max]
Empatica E4 Wristband	3-axis acceleration	32 Hz	[−2g, 2g]
	BVP (PPG)	64 Hz	n/a
	EDA	4 Hz	[0.01 μS, 100 μS]
	Heart rate (from BVP)	1 Hz	n/a
	IBI (from BVP)	n/a	n/a
	Body temperature	4 Hz	[−40 °C, 115 °C]
NeuroSky MindWave Headset	Brainwave (fp1 channel EEG)	125 Hz	n/a
	Attention & Meditation	1 Hz	[0, 100]
Polar H7 Heart Rate Sensor	HR (ECG)	1 Hz	n/a



1st-person POV video recordings (upper) and 3rd-person POV video recordings (lower) of a data collection session

Data collection protocol

Detailed steps for a data collection session. Each session lasted approximately two hours.

Step	Allocated time	Description
Read and sign consent forms	10 min	Experimenters provided consent forms to participants, and two written consents each for participation and the collection of privacy-sensitive data were obtained.
Choose sides and the order	5 min	Participants were assigned to either argue in favor of or against accepting refugees and decided on the first speaker.
Prepare debate	15 min	Participants were provided with supplementary materials to prepare their arguments.
Equip sensors	10 min	Experimenters explained wearable devices to participants and assisted them in wearing devices.
Measure baseline	2 min	A baseline corresponding to a neutral state was measured for each participant.
Overview debate	5 min	The moderator explained the debate rules and notified participants that they are allowed to intervene.
Debate	10 min	Participants could speak for two consecutive minutes during their turns and they were notified twice at 30 and 60 seconds before the end of the debate.
Annotate emotions	60 min	Participants annotated emotions at intervals of every 5 seconds, watching footage of themselves and their partners.

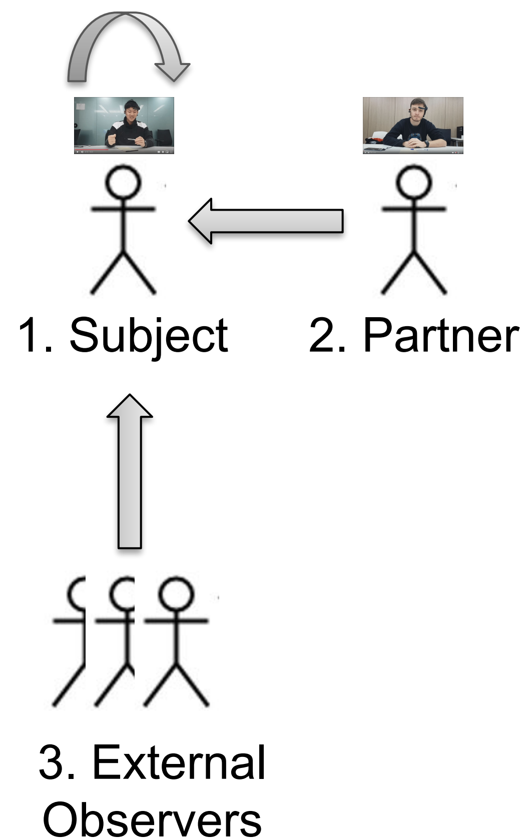
Data collection results – 3 Labels per 5s Segment

- Annotation via "retrospective affect judgment protocol"
    - Each participant watched one audiovisual recording of him/herself and another recording of his/her partner (both recordings from 2nd-person POV, including facial expressions, upper body movements, and speeches), to annotate emotions at intervals of every 5 seconds from the beginning to the end of a debate

Emotion annotation categories	Description	Measurement scale or method
Arousal/Valence	Two affective dimensions from Russell's circumplex model of affect[101]	1: very low - 2: low - 3: neutral - 4: high - 5: very high
Cheerful/Happy/Angry/Nervous/Sad	Emotion states describing a subjective stress state[102]	1: very low - 2: low - 3: high - 4: very high
Boredom/Confusion/Delight/Engaged concentration/Frustration/Surprise/None	Commonly used Baker Rodrigo Ocumpaugh Monitoring Protocol (BROMP) educationally relevant affective categories[103]	Choose one
Confrustion/Contempt/Dejection/Disgust/Eureka/Pride/Sorrow/None	Less commonly used BROMP educationally relevant affective categories[103]	Choose one

Data collection results – 3 Labels per 5s Segment

1. The subject – is the source who experiences emotions firsthand and produces self annotations, particularly the “felt sense” of the emotions
2. The partner – is the person who interacts with the subject, experiencing the subject’s emotions secondhand; thus, he or she has a contextual knowledge of the interaction that induced the subject’s emotions and produces partner annotations based on that
3. The external observers – are people who observe the subject’s emotions without the exact contextual knowledge of the interaction that induced the emotions, producing external observer annotations



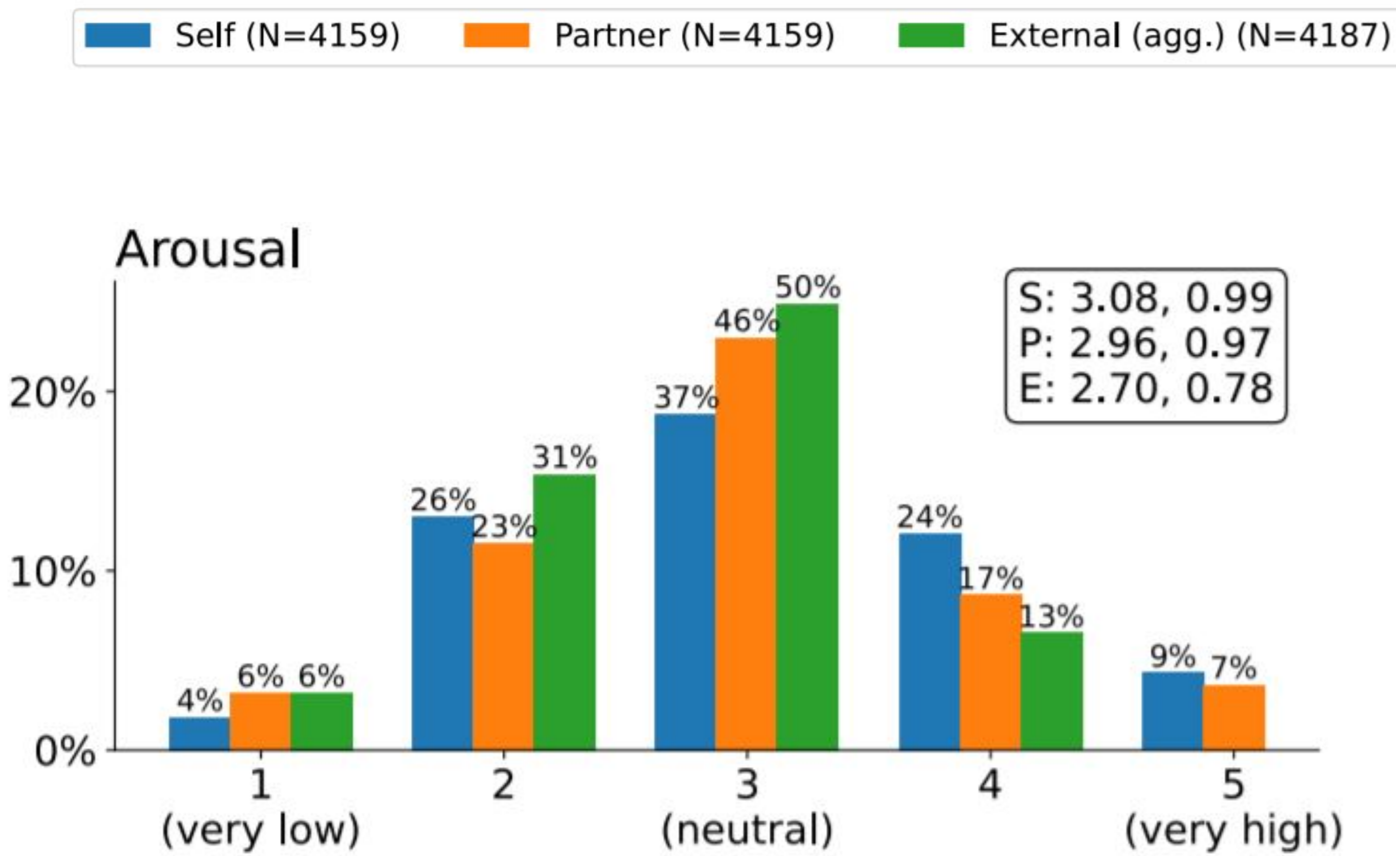
Comparison with other datasets

Name (year)	Size	Modalities	Spon. vs. posed	Natural vs. induced	Annotation method	Annotation type	Context
IEMOCAP (2008)[51]	10	Videos, face motion capture, gesture, speech (audio & transcribed)	Both	Both†	Per dialog turn	S, E	Dyadic
SEMAINE (2011)[52]	150	Videos, FAUs, speech (audio & transcribed)	Spon.	Induced	Trace-style continuous	E	Dyadic
MAHNOB-HCI (2011)[23]	27	Videos (face and body), eye gaze, audio, biosignals (EEG, GSR, ECG, respiration, skin temp.)	Spon.	Induced	Per stimuli	S	Individual
DEAP (2012)[24]	32	Face videos, biosignals (EEG, GSR, BVP, respiration, skin temp., EMG & EOG)	Spon.	Induced	Per stimuli	S	Individual
DECAF (2015)[25]	30	NIR face videos, biosignals (MEG, hEOG, ECG, tEMG)	Spon.	Induced	Per stimuli	S	Individual
ASCERTAIN (2016)[26]	58	Facial motion units (EMO), biosignals (ECG, GSR, EEG)	Spon.	Induced	Per stimuli	S	Individual
MSP-IMPROV (2016)[53]	12	Face videos, speech audio	Both	Both†	Per dialog turn	E	Dyadic
DREAMER (2017)[27]	23	Biosignals (EEG, ECG)	Spon.	Induced	Per stimuli	S	Individual
AMIGOS (2018)[28]	40	Vidoes (face & body), biosignals (EEG, ECG, GSR)	Spon.	Induced	Per stimuli	S, E	Individual, Group
MELD (2019)[38]	7	Videos, speech (audio & transcribed)	Both	Both†	Turn-based	E	Dyadic, Group
CASE (2019)[29]	30	Biosignals (ECG, respiration, BVP, GSR, skin temp., EMG)	Spon.	Induced	Trace-style continuous	S	Individual
CLAS (2020)[100]	64	Biosignals (ECG, PPG, EDA), accelerometer	Spon.	Induced	Per stimuli/task	Predefined‡	Individual
K-EmoCon (2020)	*32*	*Videos (face, gesture), speech audio, accelerometer, biosignals (EEG, ECG, BVP, EDA, skin temp.)*	*Spon.*	*Natural*	*Interval-based continuous*	*S, P, E*	*Dyadic*

Dataset Summary

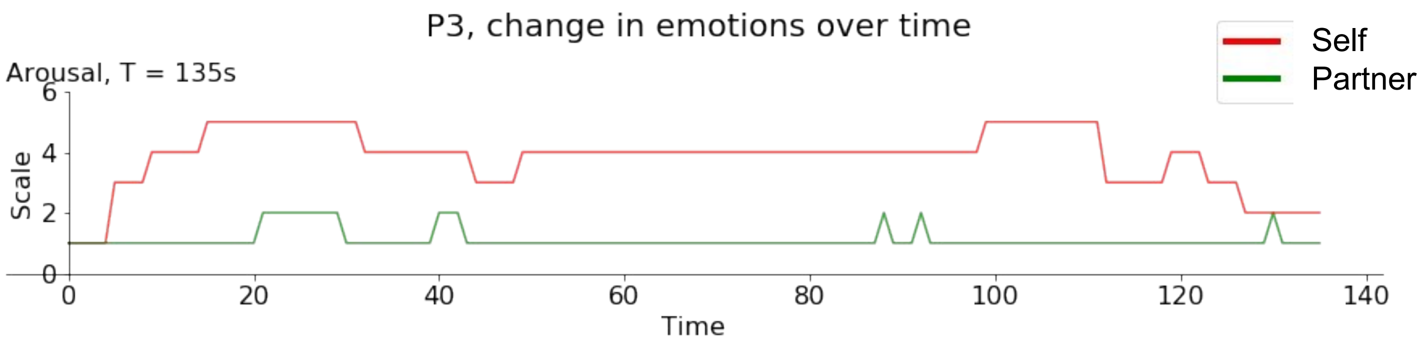
Data collection summary	
Number of participants	32 (20 males and 12 females)
Participants age	19 to 36 (mean = 23.8 years, stdev. = 3.3 years)
Session duration	Total 172.92 min, (mean = 10.8 min, stdev. = 1.04 min)
Emotion annotations categories	**1 - 5**: Arousal, Valence
	1 - 4: Cheerful, Happy, Angry, Nervous, Sad
	Choose one: Common BROMP affective categories + less common BROMP affective categories
Measured physiological signals	3-axis Acc. (32 Hz), BVP (64 Hz), EDA (4 Hz), heart rate (1 Hz), IBI (n/a), body temperature (4 Hz), EEG (8 band, 32 Hz), ECG (1 Hz)
Dataset contents	
Debate audios	172.92 min (from 16 debate sessions)
Debate footage	223.35 min (from 21 participants)
Physiological signals	Refer to *Dataset contents* subsection
Emotion annotations (# of 5-second intervals annotated)	**Self**: 4,159 **Partner**: 4,159 **5 external observers**: 20,803

Preliminary analysis results



Preliminary analysis results

- Mismatch in labels is highly variable across individuals.



K-EmoPhone: A Multimodal Mobile and Wearable Sensor Dataset for Emotion and Stress Recognition in the Wild

Soo Won Kang

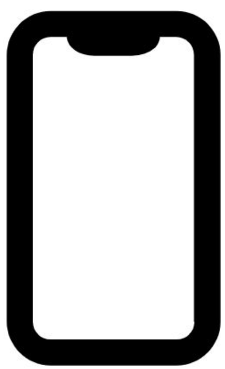
Interactive Computing Lab

Dataset Overview

- Data collection
  - # users: n =79
  - 1-week (84 hrs)
  - In-the-wild scenarios (everyday life scenarios)
- Devices
  - Wearable #1 Microsoft Band 2
  - Wearable #2 Polar HR
  - Smartphone
- Self-report data
  - Experience Sampling Method (ESM): 6,173 ESM responses in total
  - User characteristics
    - General health questionnaires (GHQ-12)
    - Stress (PSS-10)
    - Depression (PHQ-9)
    - Personality (BFI-15)
    - Self-esteem (RSE-10)

KAIST K-EmoPhone Dataset
"Emotion & Stress Tracking"

- Smartphone + wearable sensor data



Smartphone

Phone usage + Physical Activity/Location

Microsoft Band 2

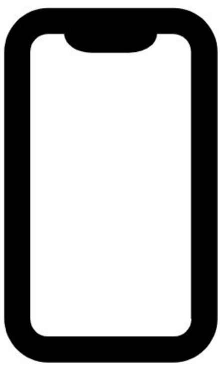
Activity + Physiological Signals (Heart Rate, Skin Temperature)

Polar H10

Physiological Signals (Heart Rate)

Smartphone + Wearable sensors

- Smartphone



Smartphone

Category	Collected Data Items								
Wifi	bssid	frequency	rssi	ssid					
Record	channelMask	duration	encoding	path	sampleRate				
Battery	level	plugged	status	temperature					
AppUsageStat	isSystemApp	isUpdatedSystemApp	name	packageName	startTime	endTime	lastTimeUsed	totalTimeForeground	
Location (GPS)	accuracy	altitude	latitude	longitude	speed				
InstalledApp	isSystemApp	isUpdatedSystemApp	name	packageName	firstInstallTime	lastUpdateTime			
AppUsage	isSystemApp	isUpdatedSystemApp	name	packageName	type				
DeviceEvent	type								
DataTraffic	duration	rxKiloBytes	txKiloBytes						
PhysicalActivity	confidence	type							
Connectivity	isConnected	type							
PhysicalActivity	transitionType								
Media	bucketDisplay	mimetype							
CallLog	contact	dataUsage	duration	isPinned	isStarred	number	presentation	timesContacted	type
Message	contact	isPinned	isStarred	messageBox	messageClass	number	timesContacted		

Smartphone + Wearable sensors

- Microsoft Band 2

Category	Collected Data Items				
Calories	Calories	CaloriesToday			
Accelerometer	X	Y	Z		
GSR	Resistance				
AmbientLight	Brightness				
HeartRate	HeartRate	Quality			
RRInterval	Interval				
Distance	TotalDistance	Pace	Speed	MotionType	DistanceToday
Pedometer	TotalSteps	StepsToday			
UV	UVIndexLevel	UVExposureToday			
SkinTemperature	Temperature				

Smartphone + Wearable sensors

- Polar H10

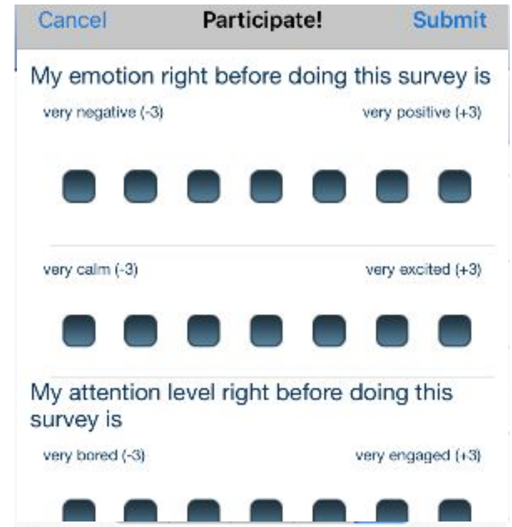
Polar H10

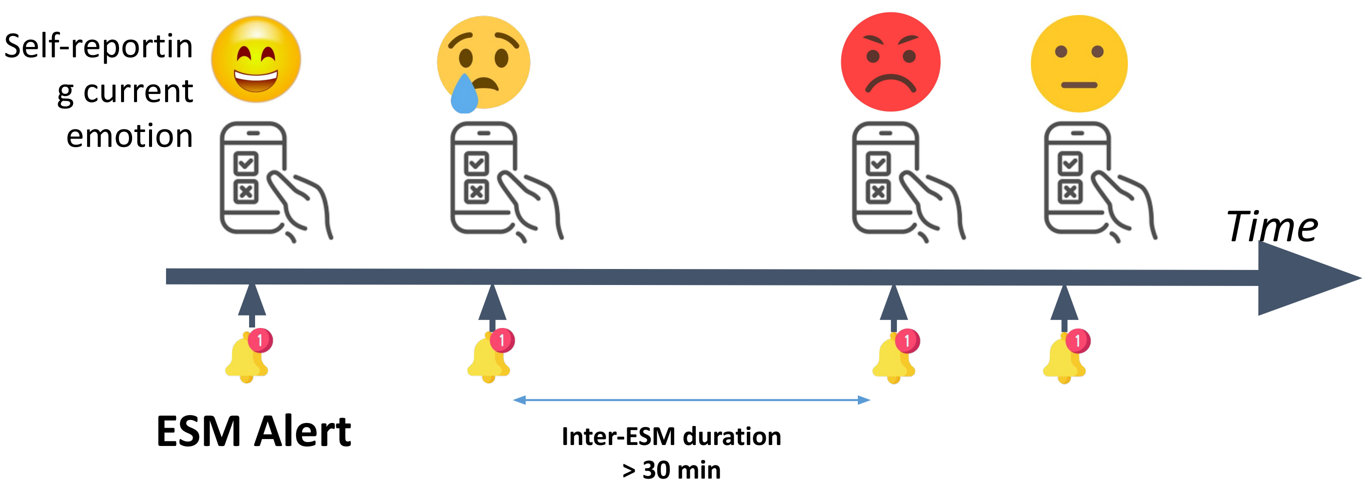
Physiological Signals
(Heart Rate)

Category	**Collected Data Items**
Heart Rate (bpm)	Heart Rate

Ground Truth Labeling
“Emotion & Stress Tracking”

- Experience sampling method (ESM):
  - In-situ self-reporting of a user’s current status (i.e., emotion, stress, interruption)
- ESM scheduling
  - Randomly send 16 ESM alerts per day (10 am ~ 10 pm)
  - ESM expiration: 10 min
  - Inter-ESM notification duration: at least 30 min





Ground Truth Labeling
“Emotion & Stress Tracking”

valence /arousal
- Q1&2. My **emotion** right before doing this survey was
  - very negative (-3) ~ very positive (+3)
  - very calm (-3) ~ very excited (+3)

attention level
- Q3. My **attention** level right before doing this survey could be rated as
  - very bored (-3) ~ very engaged (+3)

stress level
- Q4. My **stress** level right before doing this survey was
  - not stressed at all (-3) ~ very stressed (+3)

emotion duration
- Q5. My **emotion** that I answered above has **not changed** for recent ____ minutes.
  - 5 10 15 20 30 60 min / I am not sure

disturbance level
- Q6. Answering this survey **disturbed** my current activity
  - entirely disagree (-3) ~ entirely agree (+3)

valence change
- Q7. How did your **emotions change** while you are answering the survey now?
  - I felt more negative (-3) ~ I felt more positive (+3)

Dataset Usage

- Homework
  - Crowdsingals.io dataset
  - KAIST K-EmoPhone dataset
  - KAIST K-EmoCon dataset

Dataset Exploration: CrowdSignal.io

Machine Learning for the Quantified Self On the Art of Learning from Sensory Data

> **Basics of Sensory Data**

Mark Hoogendoorn, Burkhardt Funk

Raw Data Transformation

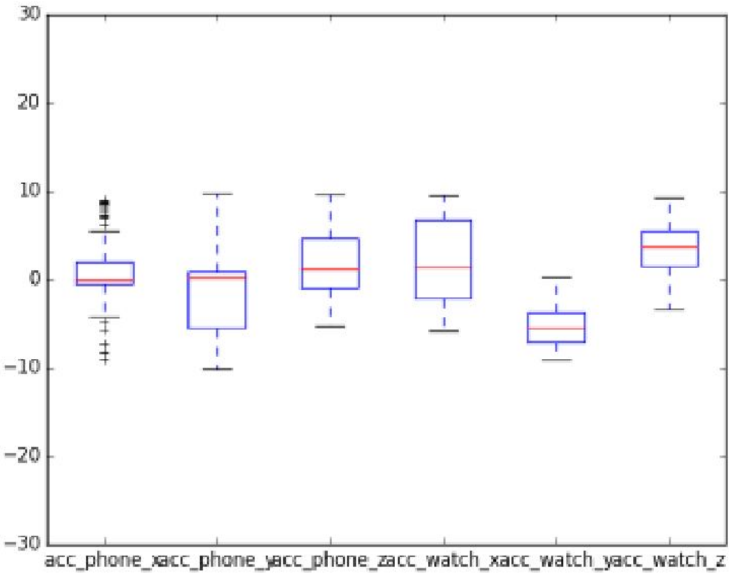
- Need to combine these table, but how? **Ans: windowing**
- Select a *step size* Δt you want to consider in the data
  - This will represent one discrete time step
  - Start at the earliest time point in the data
  - Find all measurements for each single attribute associated with each interval *[t, t+Δt]*
  - Consider categorical features (e.g. label) as a number of binary features
  - Combine their values (e.g. average for heart rate or accelerometer or sum for the label)

time	**heart_rate**	**label On Table**	**label Sitting**
2016-02-08 19:28:06	175.333	1	1
2016-02-09 19:28:06	-	0	0

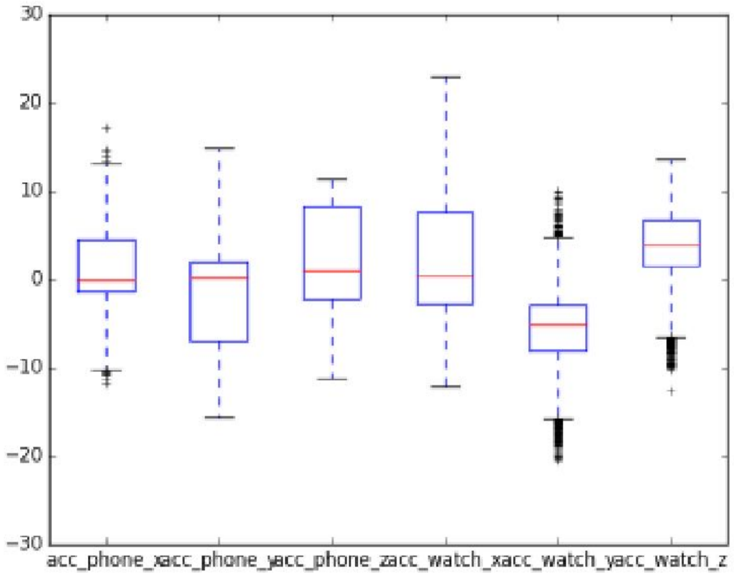
Data Exploration

- Let us consider a dataset from CrowdSignals which covers around 2 hours of data
- Imagine we take a step size of Δt = 1 minute and Δt = 250 milliseconds
- What difference would you expect in the spread of the data?
- What are the pros and cons of a higher value for Δt (less fine grained)?

Data Exploration

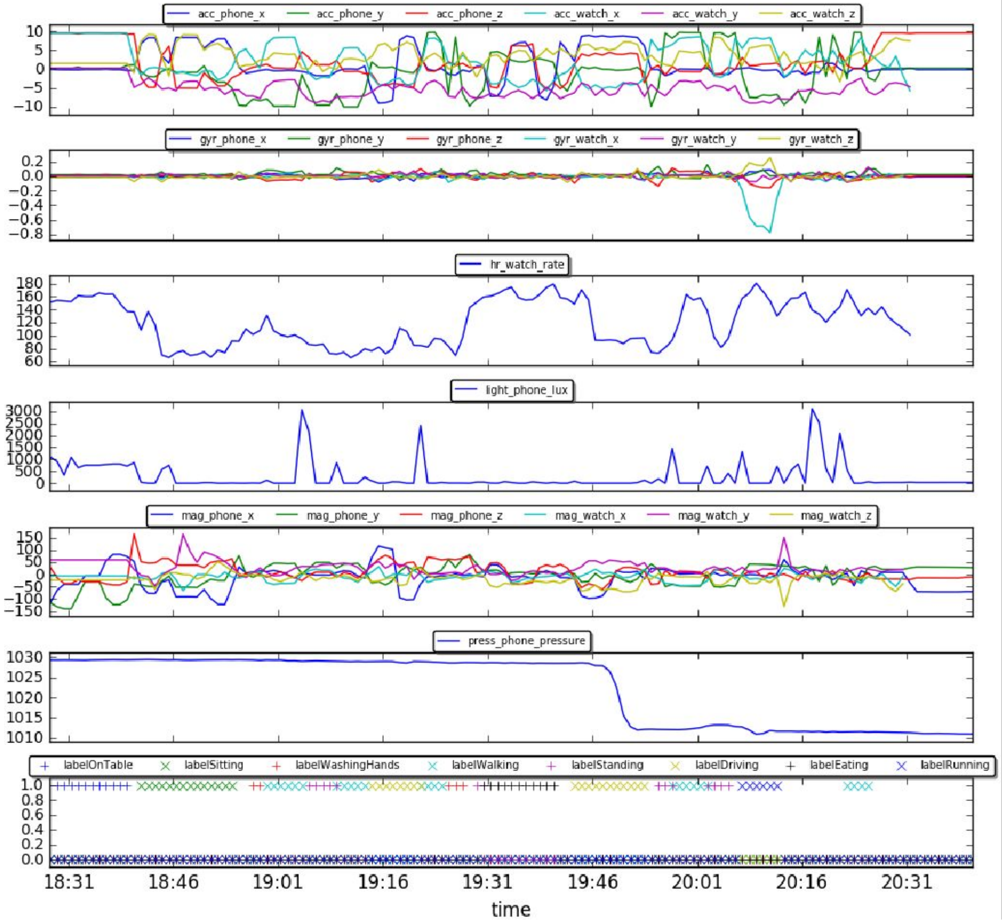


Δt = 60 seconds



Δt = 0.25 seconds

Data Exploration



Accelerometer

Gyroscope

Heart Rate (Watch)

Light

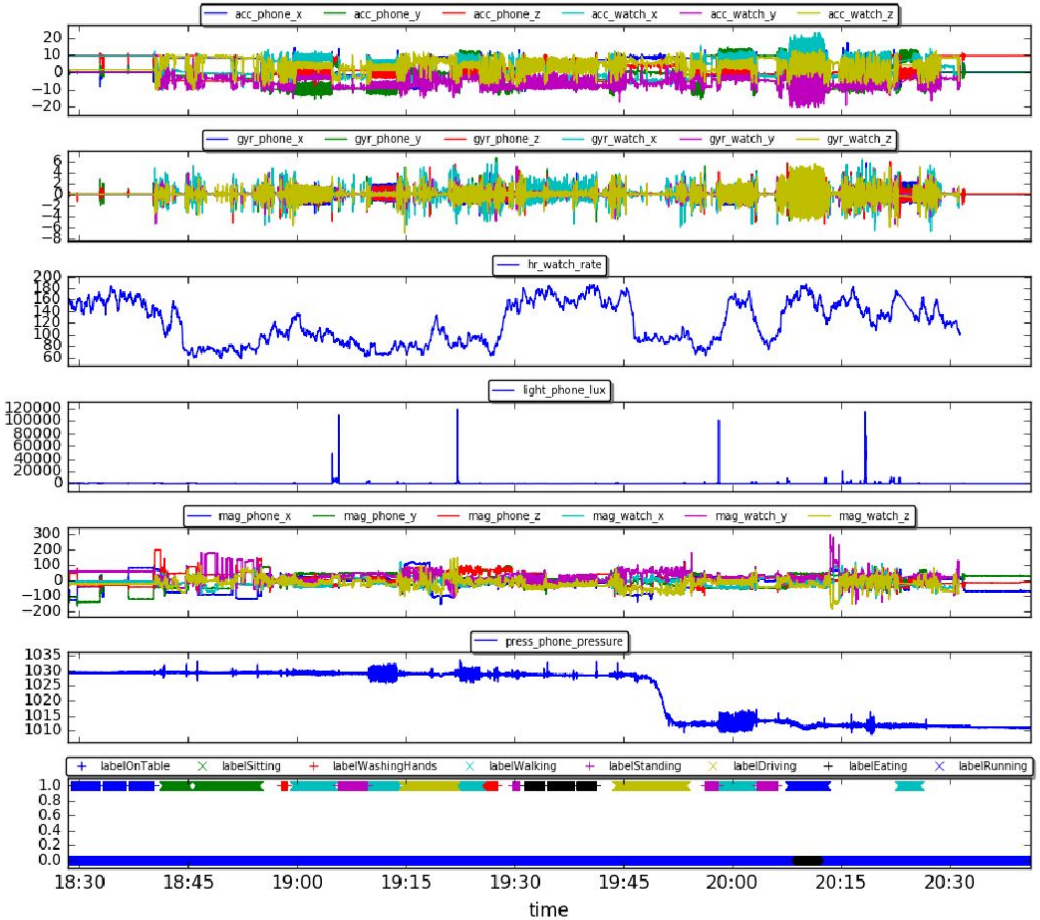
Magnetometer

Pressure (barometer)

Activity labels

Δt = 60 seconds

Data Exploration



Accelerometer

Gyroscope

Heart Rate (Watch)

Light

Magnetometer

Pressure (barometer)

Activity labels

$\Delta t = 0.25$ seconds

Data Exploration

Numerical					
attribute	**missing (%)**	**mean**	**standard deviation**	**minimum**	**maximum**
acc_phone_x	0.00% / 0.00%	1.09 / 1.10	4.19 / 4.67	-9.12 / -11.76	9.00 / 17.10
acc_phone_y	0.00% / 0.00%	-0.94 / -0.94	5.60 / 6.35	-10.08 / -15.60	9.78 / 14.87
acc_phone_z	0.00% / 0.00%	2.02 / 2.00	4.72 / 5.39	-5.29 / -11.30	9.63 / 11.38
acc_watch_x	7.52% / 8.78%	2.04 / 2.08	4.88 / 5.78	-5.82 / -12.18	9.55 / 22.94
acc_watch_y	7.52% / 8.78%	-5.15 / -5.18	2.43 / 3.52	-9.13 / -20.56	0.20 / 9.97
acc_watch_z	7.52% / 8.78%	3.64 / 3.60	2.72 / 4.01	-3.36 / -12.62	9.22 / 13.65
gyr_phone_x	0.00% / 0.00%	-0.00 / -0.00	0.03 / 0.57	-0.08 / -3.98	0.09 / 5.69
gyr_phone_y	0.00% / 0.00%	0.02 / 0.02	0.03 / 0.43	-0.06 / -4.95	0.16 / 6.50
gyr_phone_z	0.00% / 0.00%	-0.00 / -0.00	0.04 / 0.52	-0.16 / -5.39	0.11 / 5.92
gyr_watch_x	8.27% / 8.90%	-0.03 / -0.03	0.13 / 0.69	-0.77 / -6.66	0.06 / 6.32
gyr_watch_y	8.27% / 8.90%	0.00 / 0.00	0.03 / 0.55	-0.08 / -5.46	0.12 / 4.95
gyr_watch_z	8.27% / 8.90%	-0.00 / -0.00	0.04 / 0.80	-0.09 / -7.02	0.25 / 5.51
hr_watch_rate	7.52% / 76.41%	119.17 / 120.99	35.45 / 35.23	65.39 / 58.00	180.66 / 188.00
light_phone_lux	0.00% / 10.43%	278.35 / 281.51	596.30 / 2220.90	0.00 / 0.00	3109.34 / 118985.00
mag_phone_x	0.00% / 0.01%	-13.68 / -13.52	46.87 / 50.62	-121.76 / -156.36	115.52 / 126.55
mag_phone_y	0.00% / 0.01%	-3.72 / -3.80	44.87 / 47.92	-139.73 / -165.40	80.70 / 96.83
mag_phone_z	0.00% / 0.01%	7.53 / 7.57	35.19 / 40.01	-61.17 / -106.37	164.14 / 198.00
mag_watch_x	8.27% / 8.90%	-9.23 / -9.12	17.68 / 26.07	-66.03 / -137.96	31.67 / 122.83
mag_watch_y	8.27% / 8.90%	27.20 / 27.28	29.71 / 39.60	-47.61 / -151.27	163.57 / 297.44
mag_watch_z	8.27% / 8.90%	-19.97 / -20.01	24.17 / 31.62	-130.29 / -186.73	51.42 / 149.71
press_phone_pressure	0.00% / 10.34%	1022.34 / 1022.37	8.33 / 8.30	1010.96 / 1008.61	1029.38 / 1033.51

Categorical		
attribute	**value**	**percentage of cases**
label	OnTable	9.02% / 7.84%
label	Sitting	10.53% / 8.60%
label	WashingHands	3.75% / 1.98%
label	Walking	18.80% / 14.74%
label	Standing	10.53% / 7.27%
label	Driving	14.29% / 12.41%
label	Eating	8.27% / 6.80%
label	Running	4.51% / 3.79%

Summary

- Dataset collection methods (mobile) + challenges
- Dataset description
  - Crowdsignals.io
  - K-EmoCon
  - K-EmoPhone
- Dataset exploration
  - Windowing
  - Data visualization