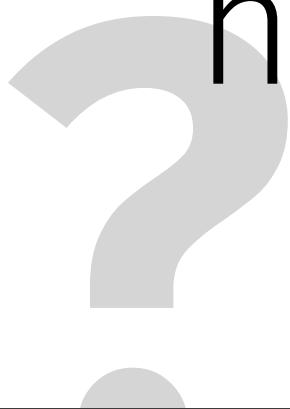


Mobile Health & Activity Monitoring

spring term 2023 | ETH Zürich
prof. christian holz



healthcare



digital health

3

healthcare

diagnostics

patients

4

healthcare

4 billion people in the world have no access
technology has the opportunity to be part of
the solution to create more equitable access

[<https://www.unicef.org/press-releases/almost-2-billion-people-depend-health-care-facilities-without-basic-water-services>]

5

healthcare

\$7.5 trillion business world-wide
\$1 trillion is going to waste in the US/year

physician activities

- spend 2x as much time entering clinical documentation
- for each patient visit

not a normal business

- people don't shop on price
- accidents: look for best possible care

6

healthcare

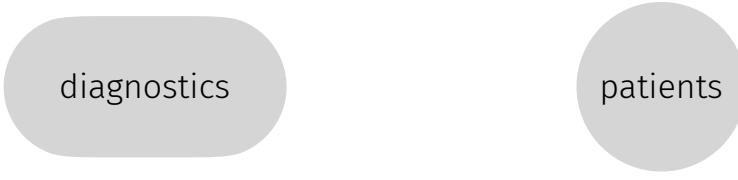
digital services as an opportunity

- data and services move to central systems
- data, computation, processing to make use of data

change in *care*

- away from fee-for-service to **value-based care**
- doctors and clinics are being reimbursed on quality of the outcomes

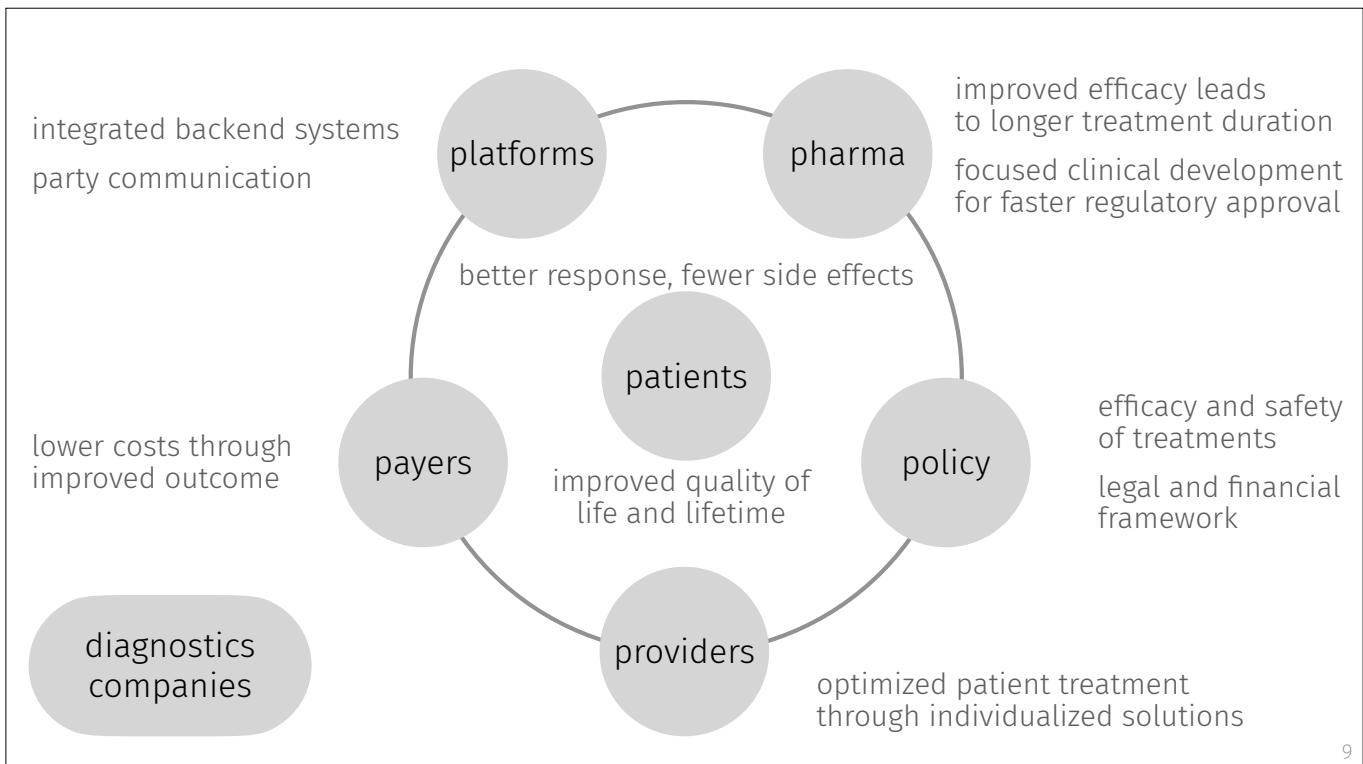
7



diagnostics

patients

8



9

healthcare digitization

digitization process

- HITECH Act (2009) requires healthcare organizations to digitize healthcare records over the past 20 years
- massive digitization of healthcare and medicine since
- past 10 years: from 15% of health records digital to today: > 98% records digital

medical devices and processes

- from analog to digital+connected
- analyses of biomarkers, records, genome, proteome

now: what can or should we do with all that data? and is it good enough?

10



mobile health

11

data-driven insights require **representative data capture**
it's the key requirement to advance personalized healthcare
capturing real-world settings is crucial, yet **non-trivial**
intervention needs to happen **in the moment**

12

clinical environments

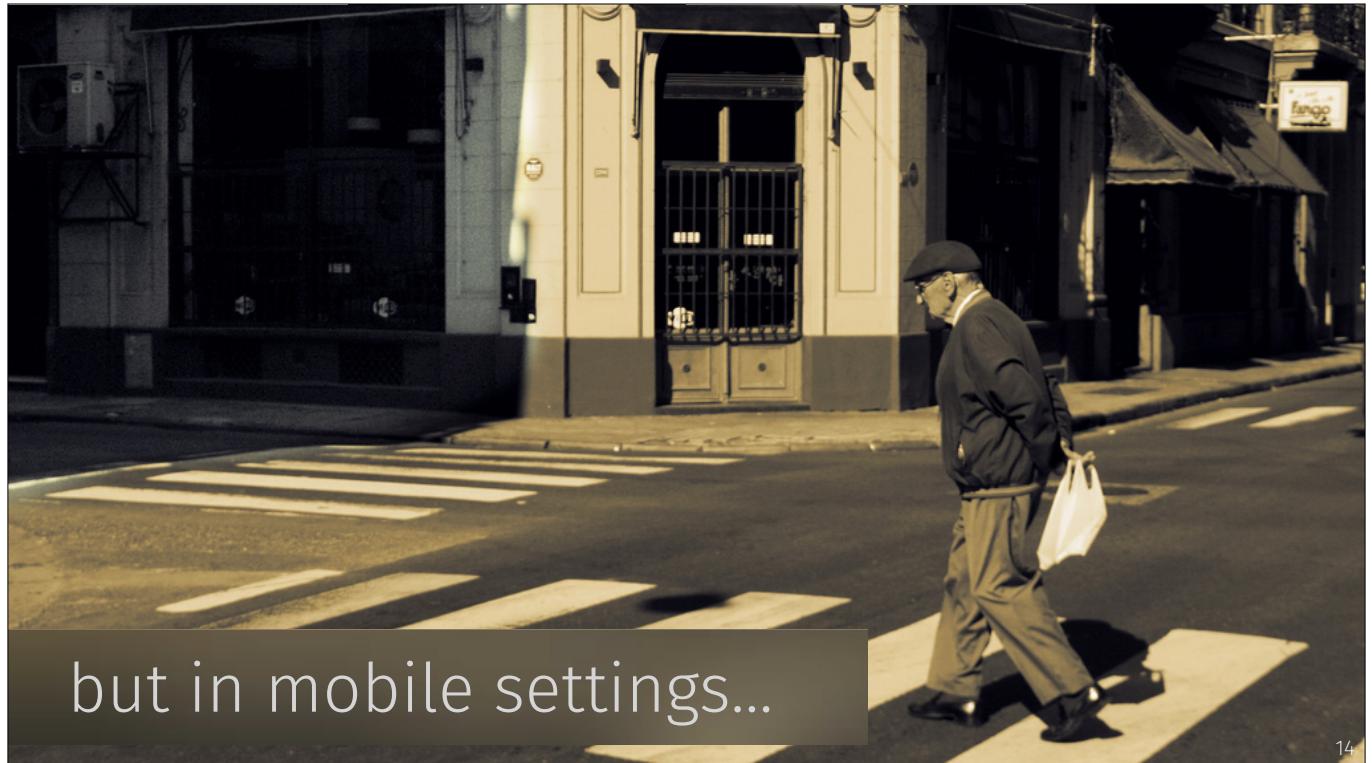
continuously measures
physiological signals

representative of
direct and indirect needs
treatment and **outcomes**



13

but in mobile settings...



14

before designing interventions,
we need data that is

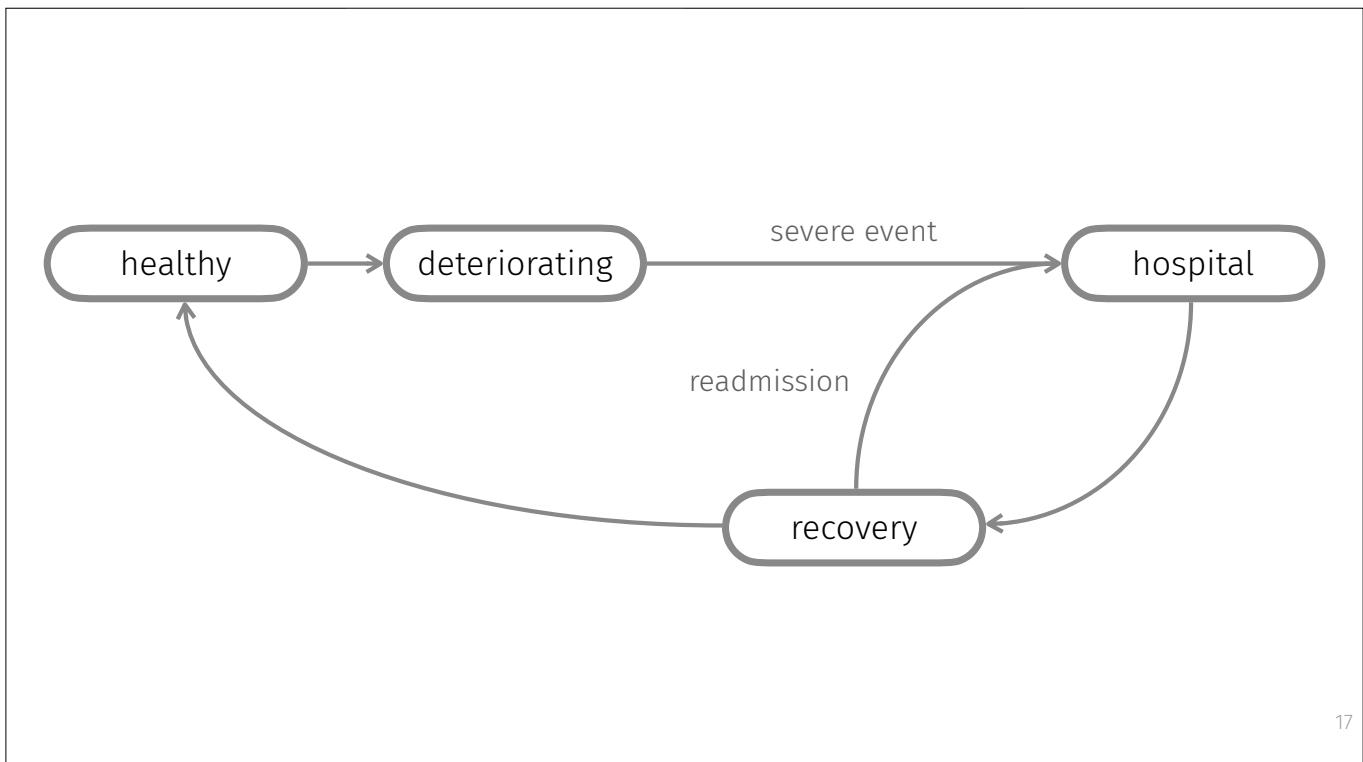
representative, continuous and high-resolution
'easy' to measure, at each and every moment in time
⇒ **unobtrusive**, a key challenge

15

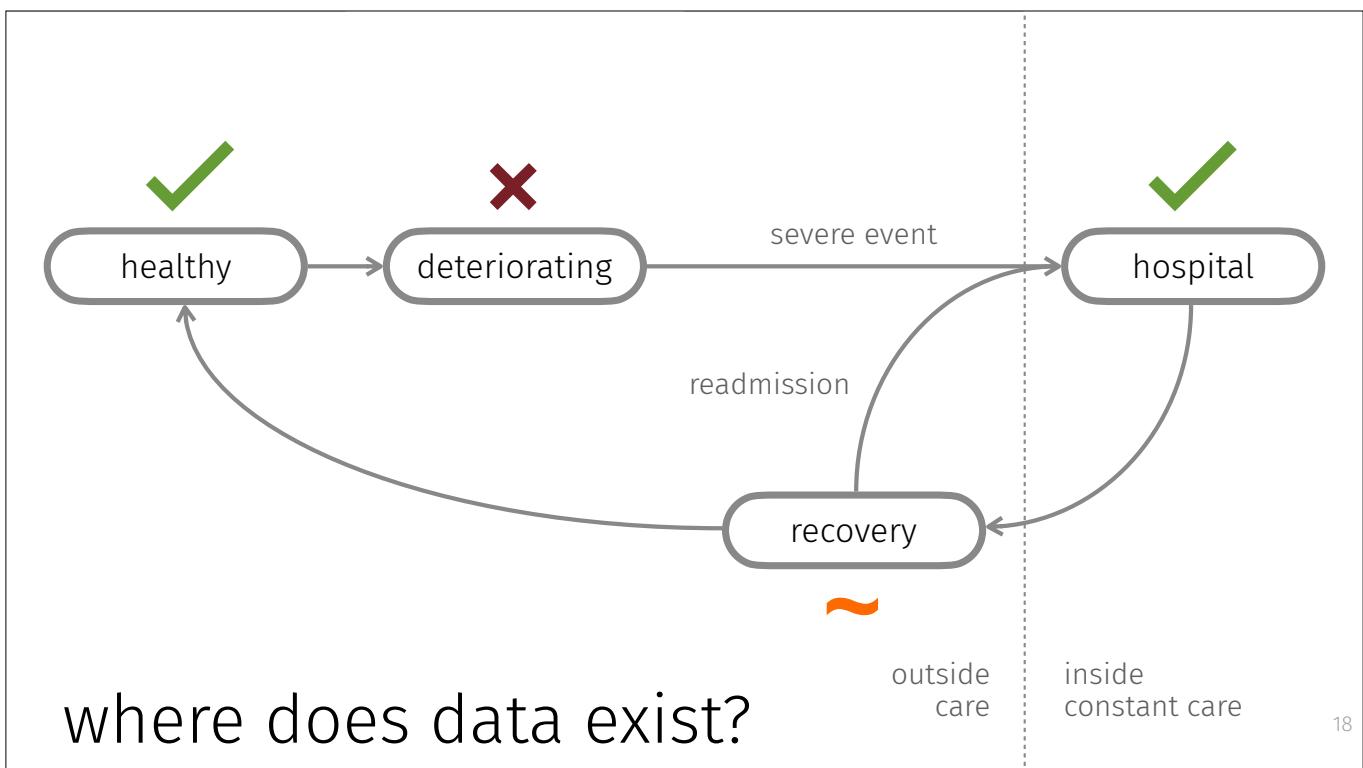
we have a lot of data...

I argue: we need more data.
⇒ but not of the **same kind!**
there's an unmet need for data that matters!

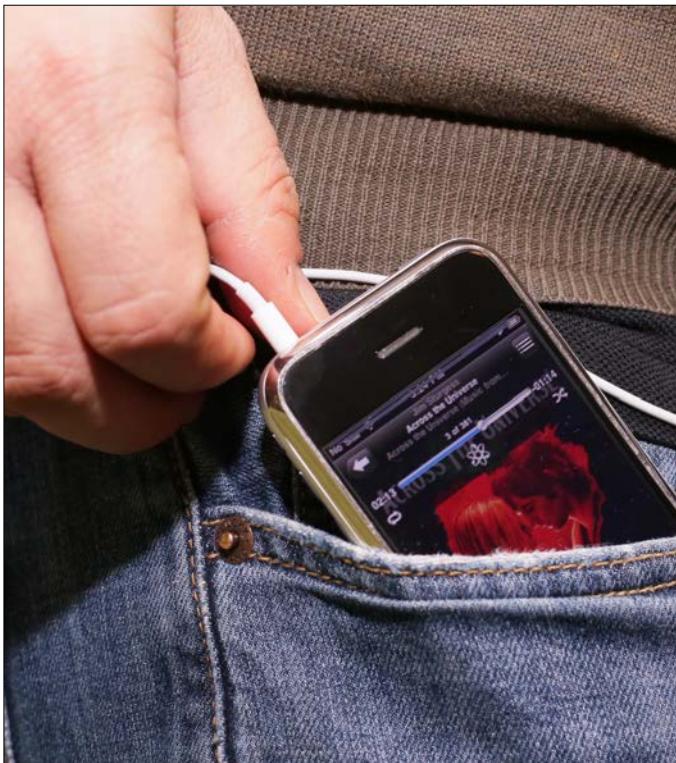
16



17



18



what we need

continuous physiologically accurate signals
on convenient and mobile form factors that are socially acceptable

⇒ carryable or wearable

19

categories of mobile health

1. education, reminders, and data management
2. population health
3. physiological signals
4. momentary state assessment
5. continuous health monitoring through data-driven insights

20



why are you
taking this course?

21



what are your
intended outcomes?

22

categories of mobile health

1. education, reminders, and data management
2. population health
3. physiological signals
4. momentary state assessment
5. continuous health monitoring through data-driven insights

focus
of this
course

23

activity monitoring

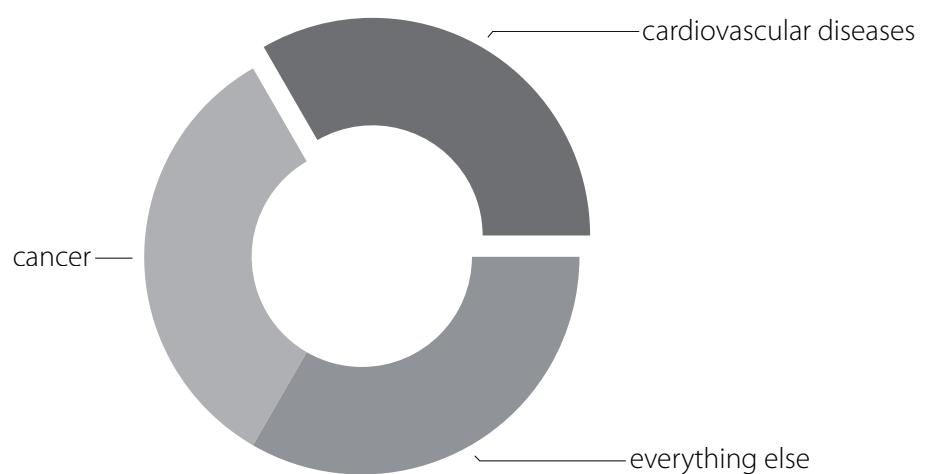


24





Project Glabella



causes of mortality

~108 million American adults have **high blood pressure** (45%)

high blood pressure was a primary cause of death
for more than 500,000 Americans in 2018

1 in 5 American adults is **unaware** of having high blood pressure

only 1 in 4 hypertensive people have their values under control

high blood pressure

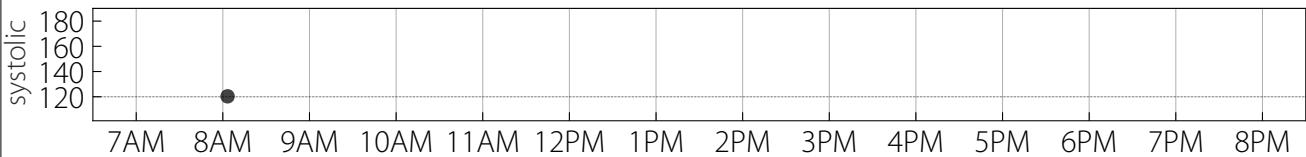
<https://www.cdc.gov/bloodpressure/facts.htm>

monitors are good for
long-term tracking



blood pressure measurements

monitors are good for
long-term tracking

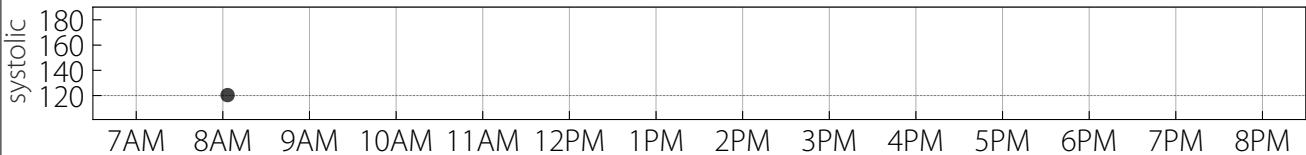


blood pressure measurements

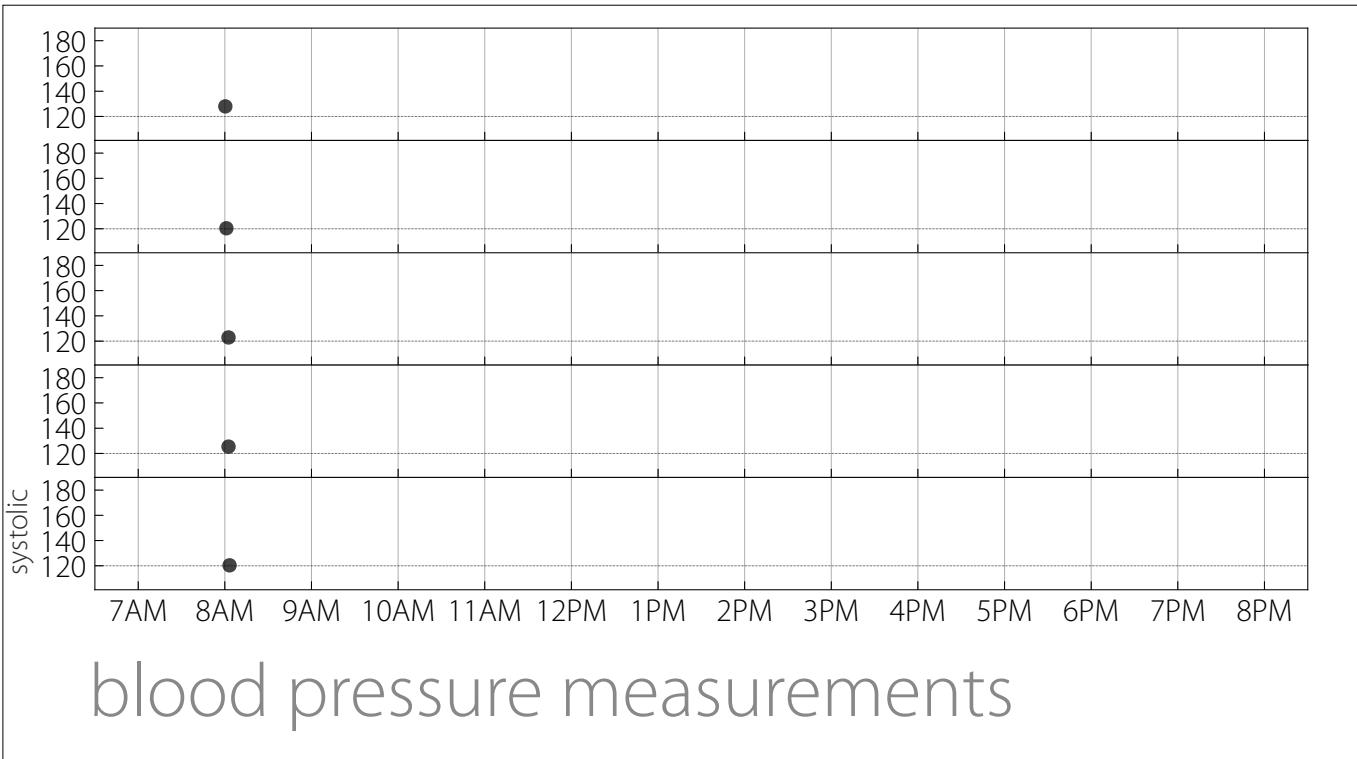
monitors are good for
long-term tracking

not so good in
mobile settings

needs correct attachment
takes time



blood pressure measurements



blood pressure during the day

additionally influenced by **short-term events**

eating and drinking

Smith et al., *Physiology & Behavior* 1997

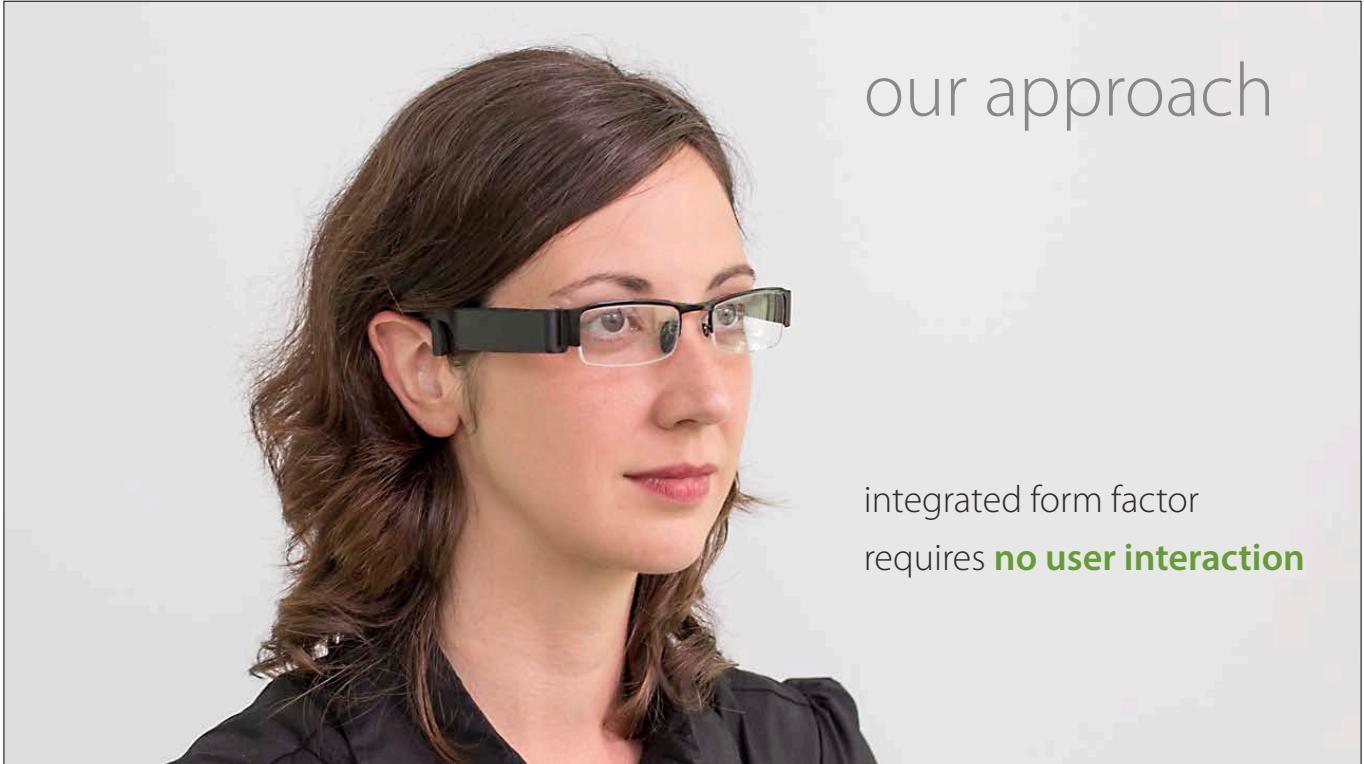
events at work

Lindquist et al., *Hypertension* 1997

exercise or postural changes

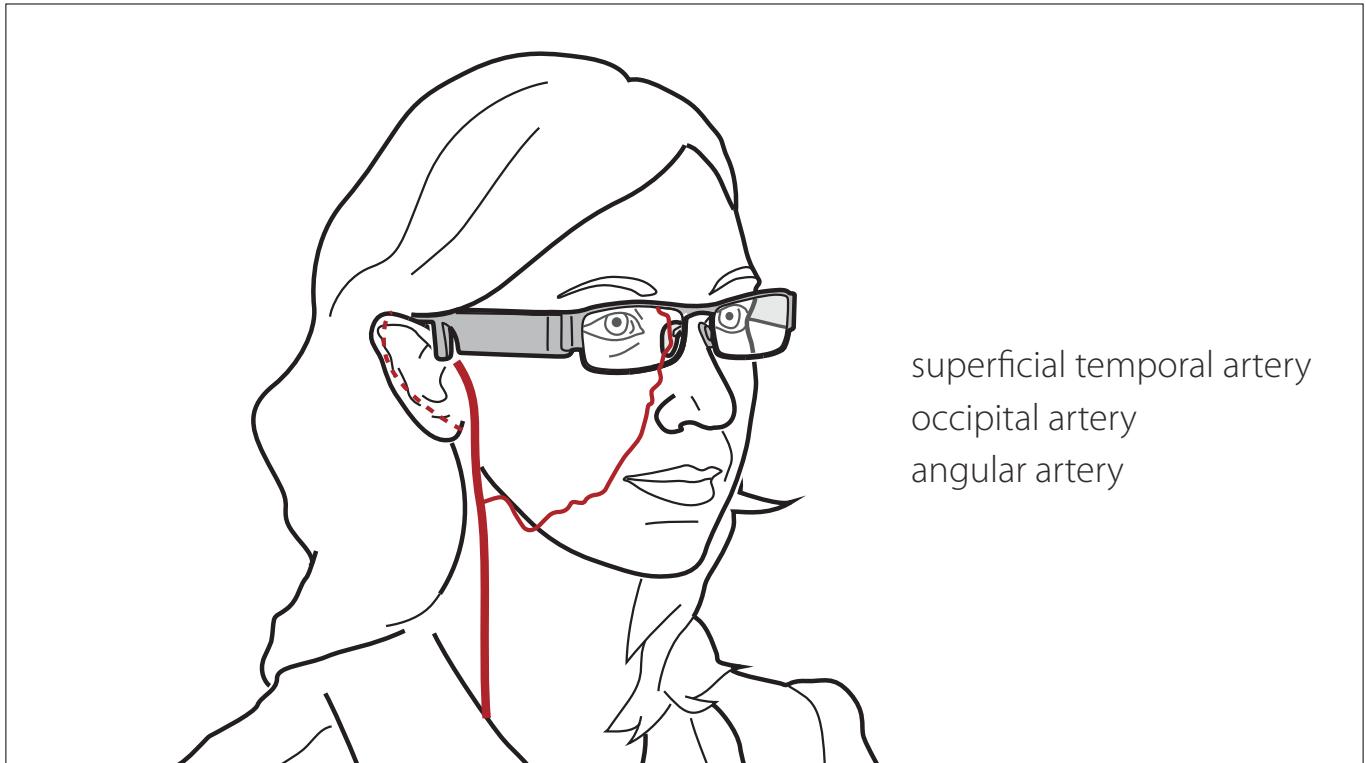
Imholz et al., *Cardiovascular Research* 1990

medication intake



our approach

integrated form factor
requires **no user interaction**

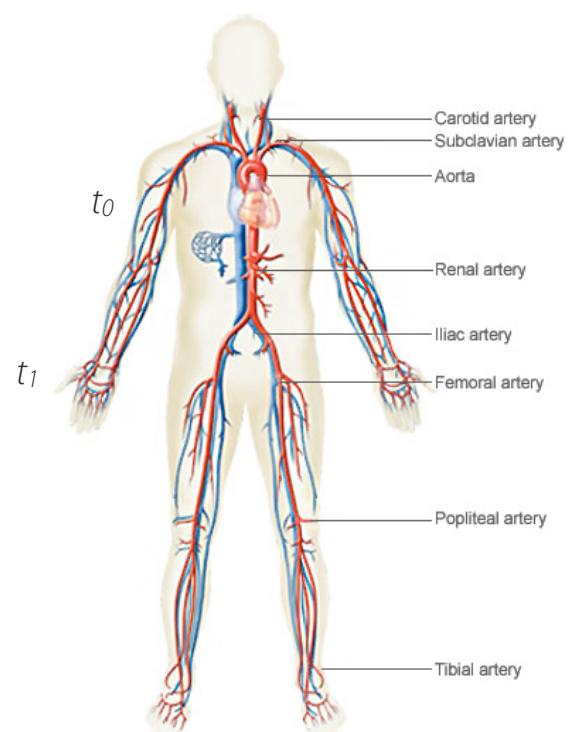


pulse transit time

- the time it takes a pulse wave to travel between two sites of the body

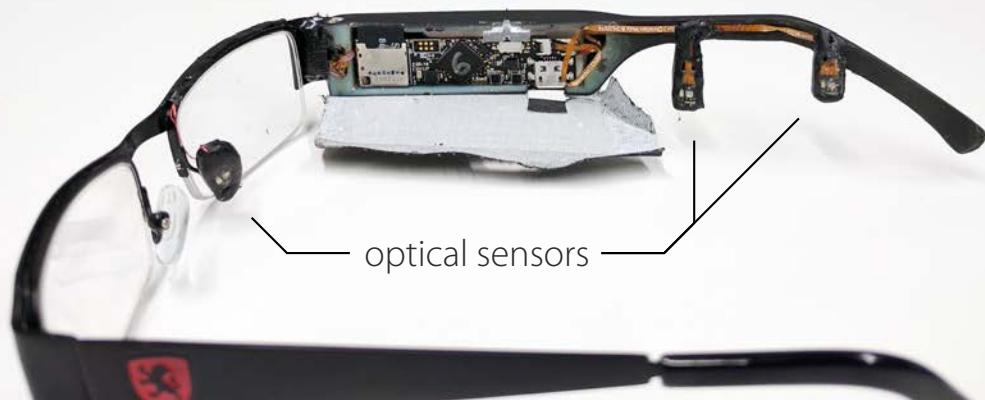
requires no cuff and can be measured during **each beat**

hypothesis

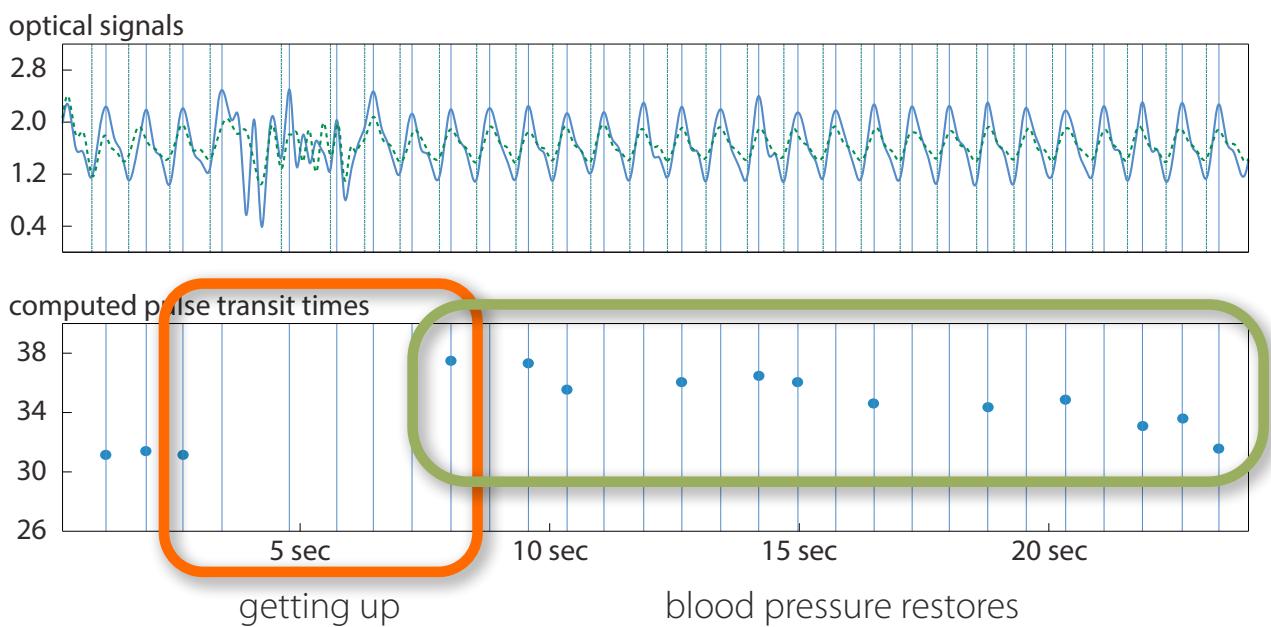


Glabella prototype

main board and battery



example: getting up after leaning back



Glabella prototype

continuously collects

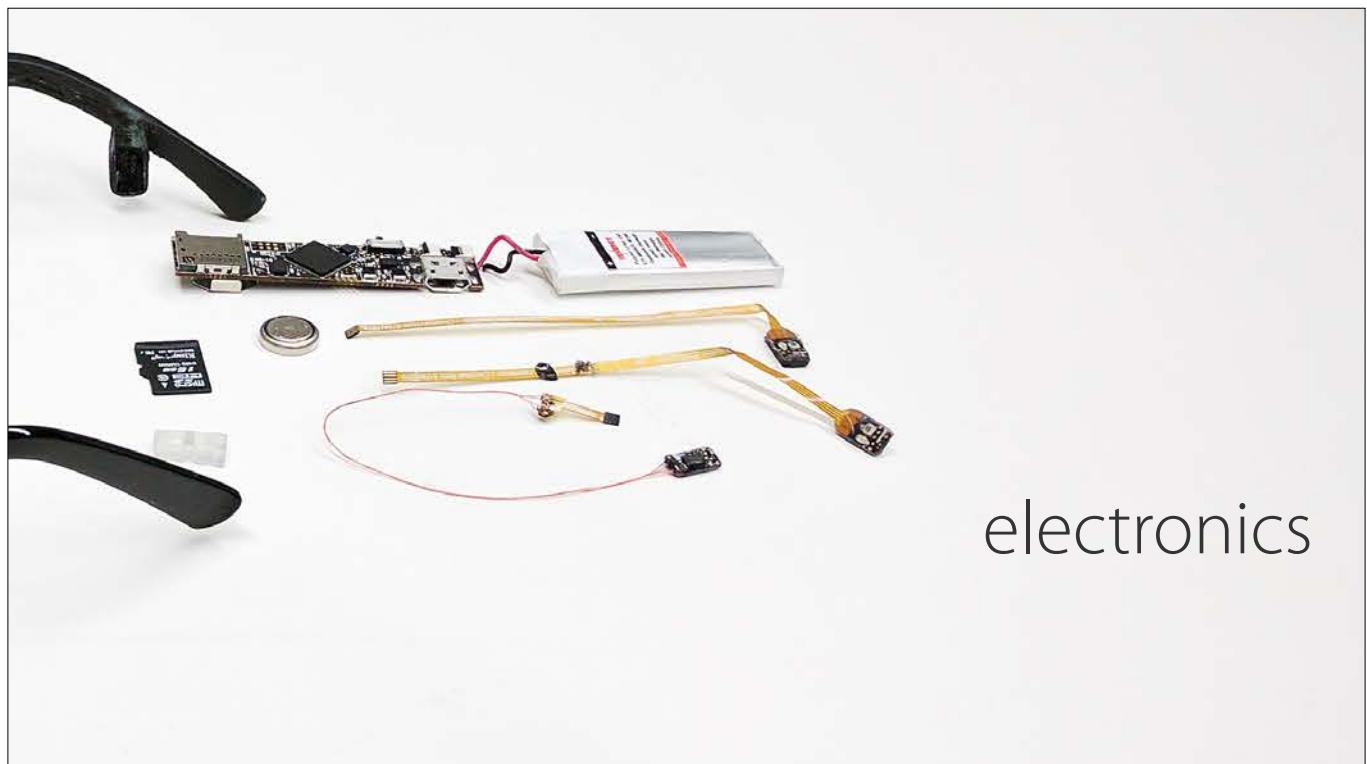
3 optical reflections (at up to 5 kHz)
for heart rate, oxymetry, blood pressure

3-DOF inertial motions (at 200 Hz)
for activity detection, step count, ...

24 hours runtime

45 grams in weight

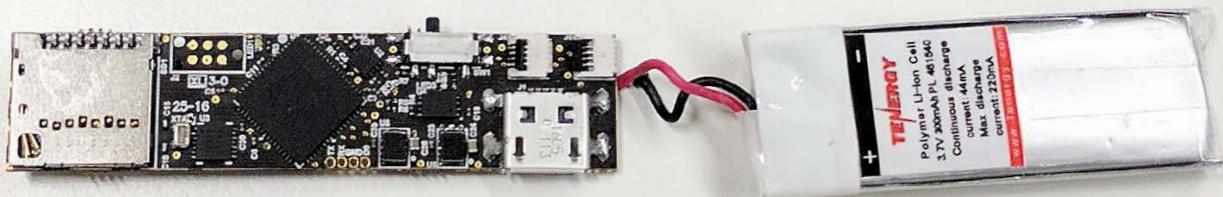




electronics

Gabella's main board

power switch FPC connectors



SD IMU PSoC USB

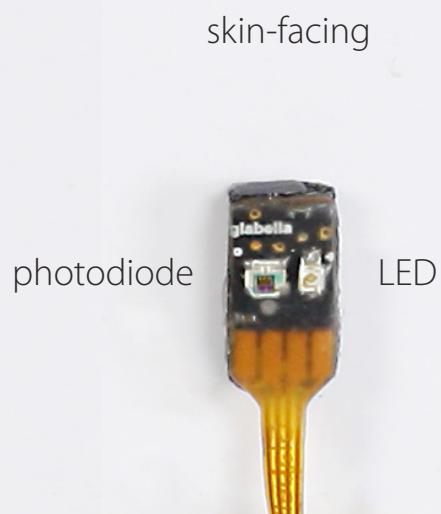
Gabella's main board



305 mAh LiPo battery

real-time clock

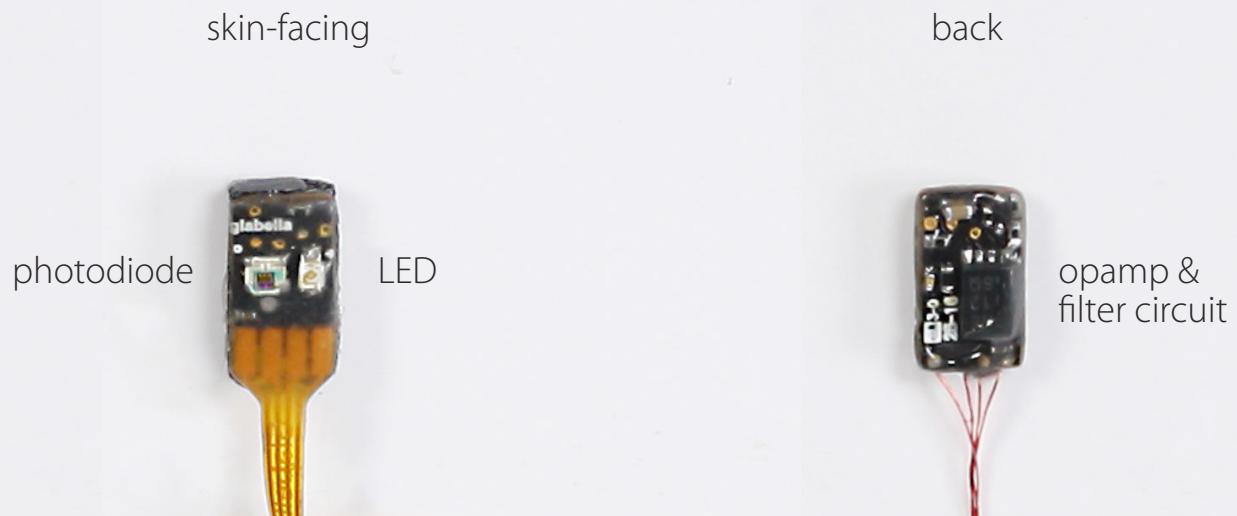
Gabella's optical pulse sensor board



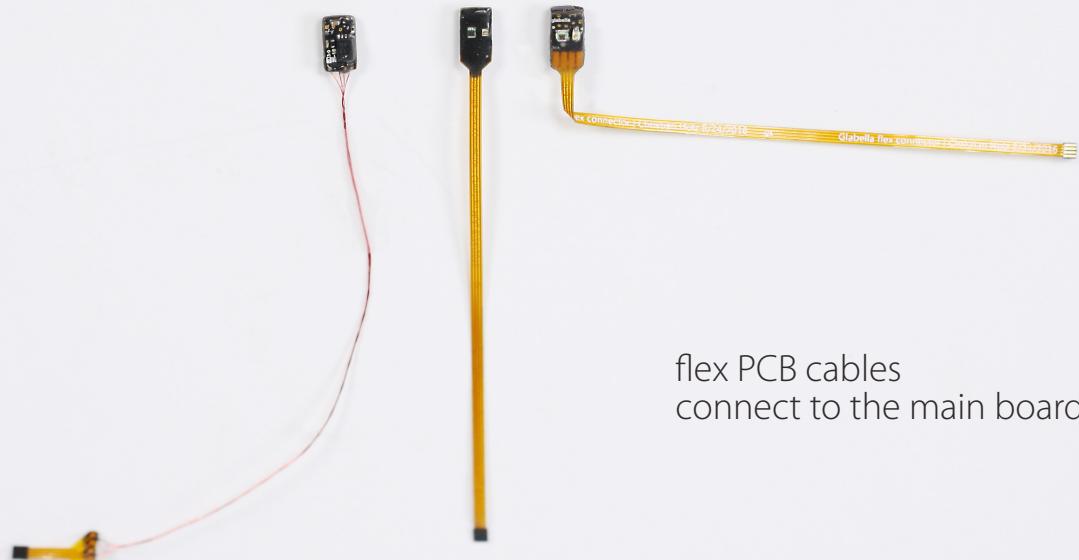
skin-facing

photodiode LED

Glabela's optical pulse sensor board



Glabela's optical pulse sensor board





mechanical design

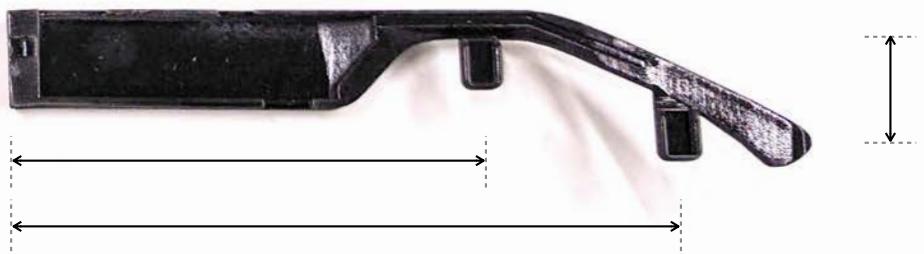
off-the-shelf metal-frame glasses

parametrized frame
3D printed with digital ABS



mechanical design

to fit a wearer's
head dimensions



to ensure
sensor contact

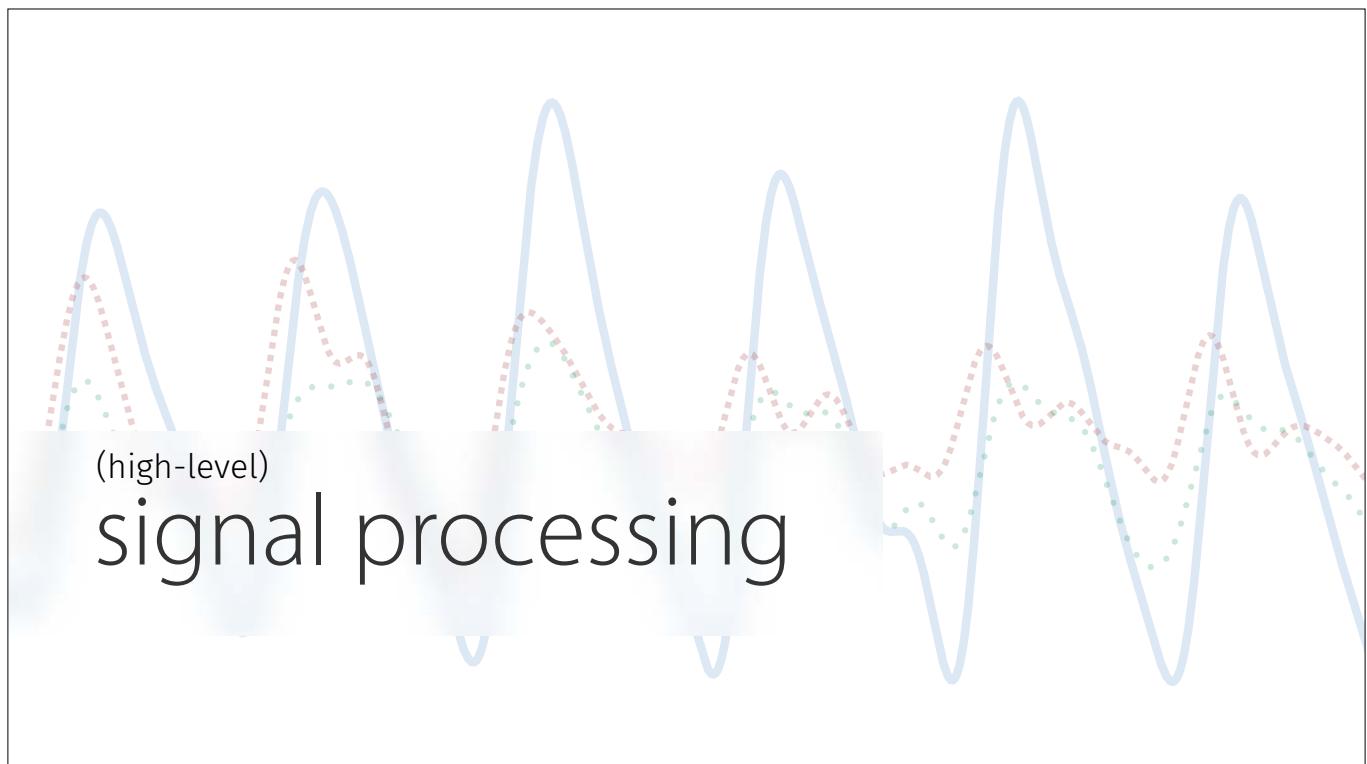


mechanical design parameters

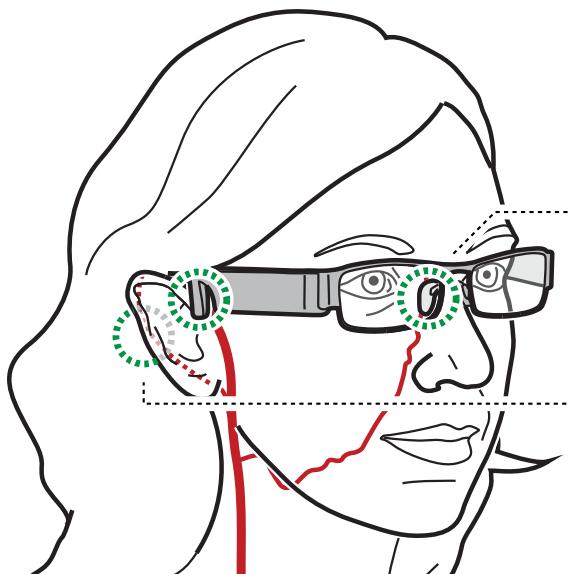


underfilled hot glue
to sustain constant skin contact

underfilled sensor



3 optical signals



angular artery (nose pad) s_{ang}

superficial temporal artery s_{sta}

occipital artery (behind ear) s_{occ}

1 filter optical signals

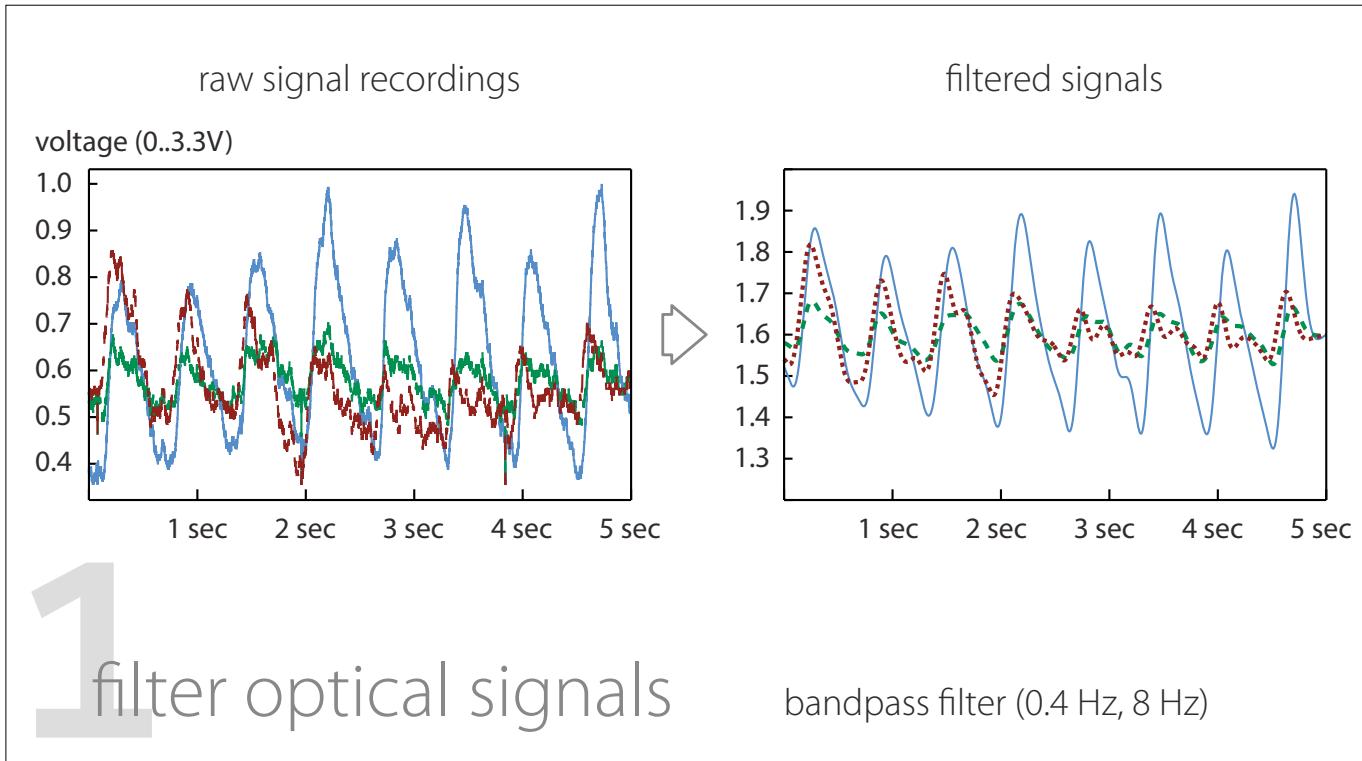
2 analyze the dominant frequency of each optical signal

3 detect pulses and extract temporal features

4 validate candidate features

5 compute pulse transit times

signal processing



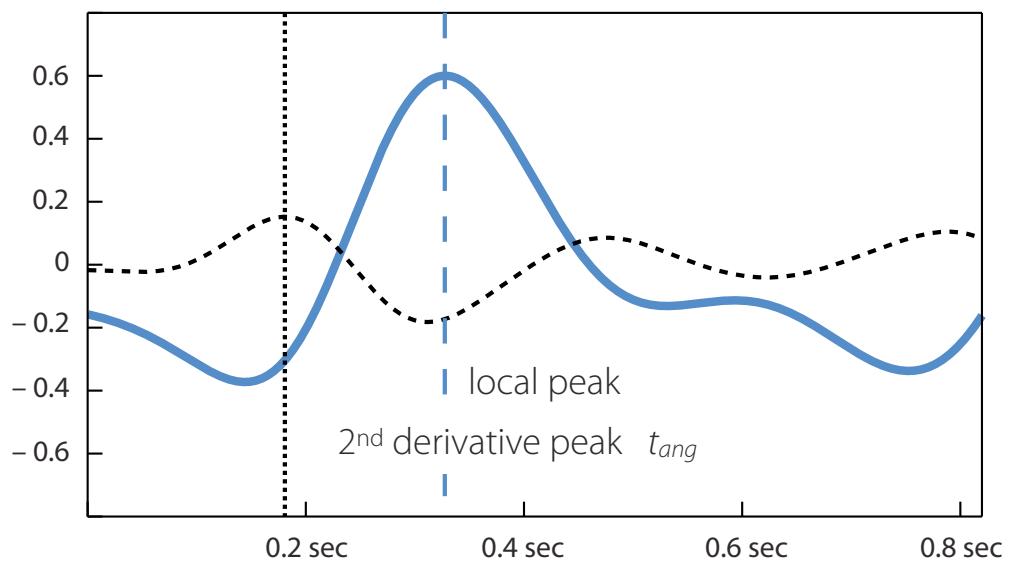
apply Fast Fourier transform to each 15-second window
to extract dominant frequencies $f_{ang}, f_{sta}, f_{occ}$

derive heart rate if $|f_{ang} - f_{sta}| < \epsilon$ and $|f_{ang} - f_{occ}| < \epsilon$
otherwise discard this window for feature extraction

2 derive the dominant frequencies

3

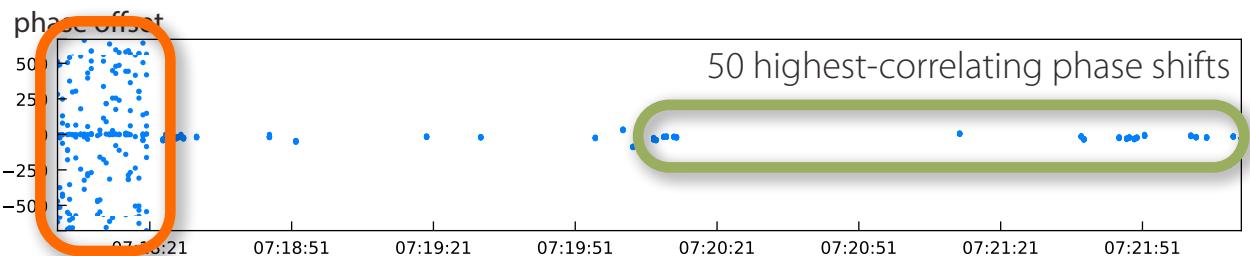
detect pulses, extract temporal features



discard if IMU variance exceeds a threshold

4

validate candidate features



4 validate candidate features

pulse transit time between the sensors on

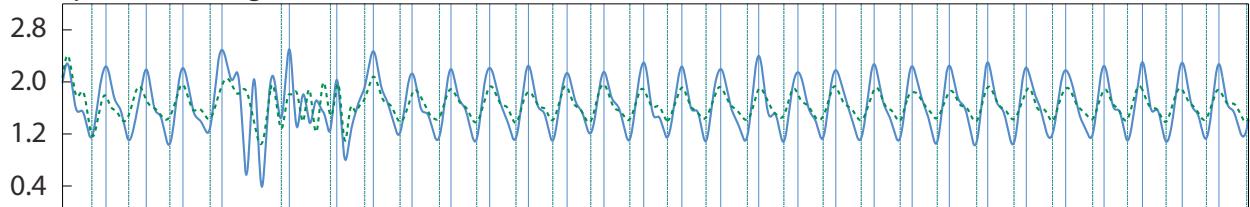
superficial temporal artery & angular artery $PTT_{ang-sta} := t_{ang} - t_{sta}$

occipital artery & angular artery $PTT_{ang-occ} := t_{ang} - t_{occ}$

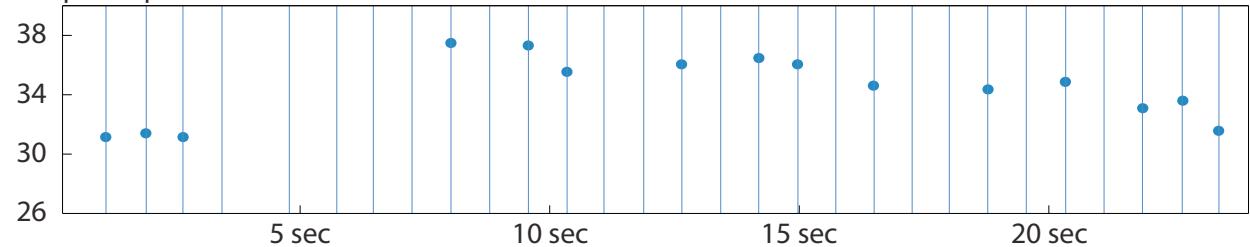
5 compute pulse transit times

example: getting up after leaning back

bandpass filtered signals



computed pulse transit times



in-the-wild evaluation

sustain operation and capture useful data
during everyday wear and **regular activities**

determine the correlation between the
pulse transit times recorded by our prototype and
systolic blood pressure values measured by a cuff-based monitor

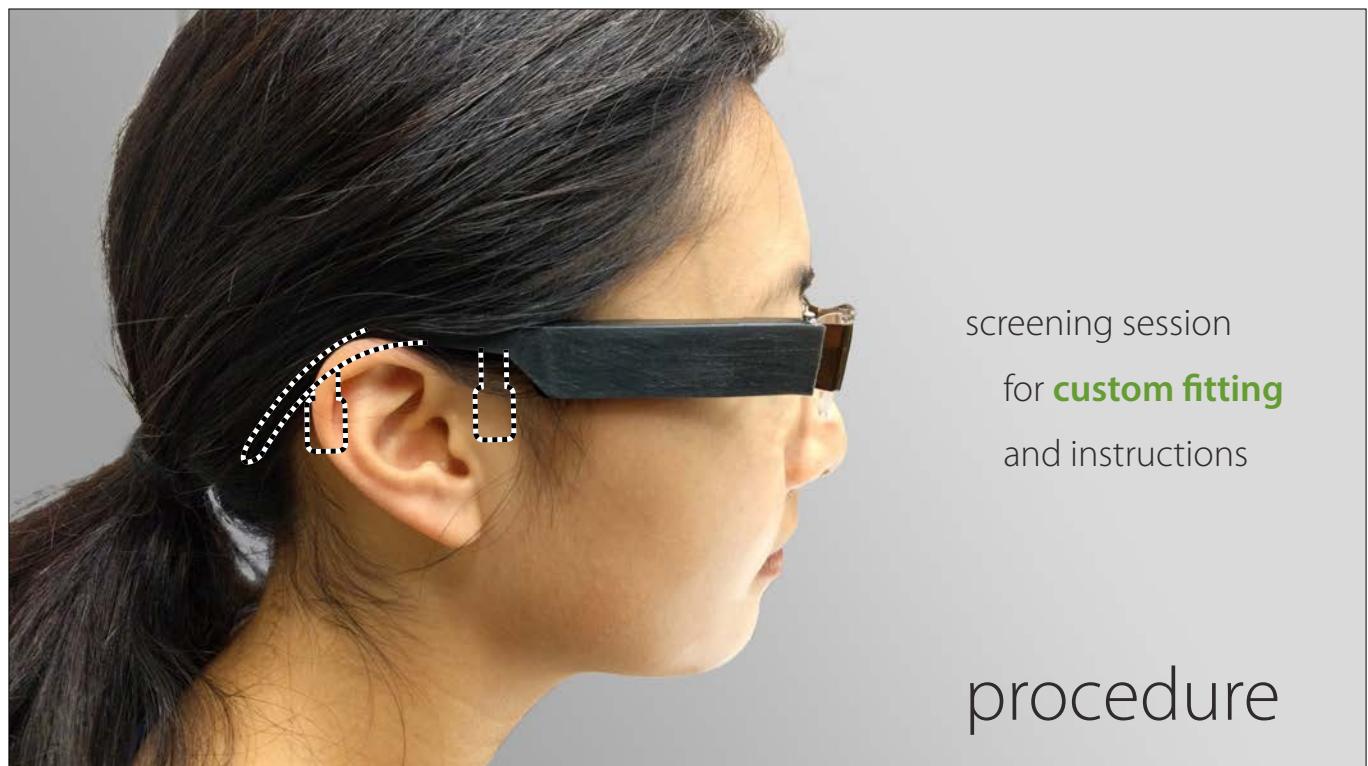
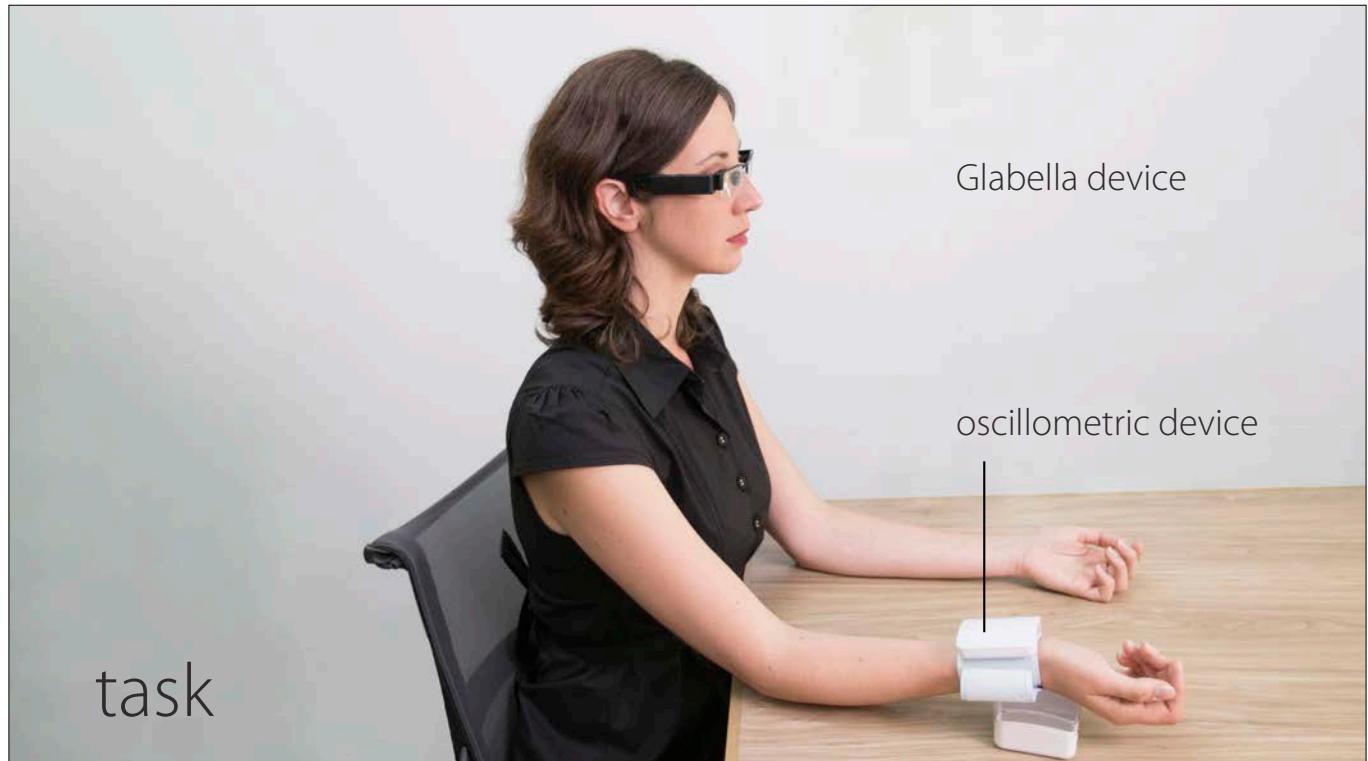
goals

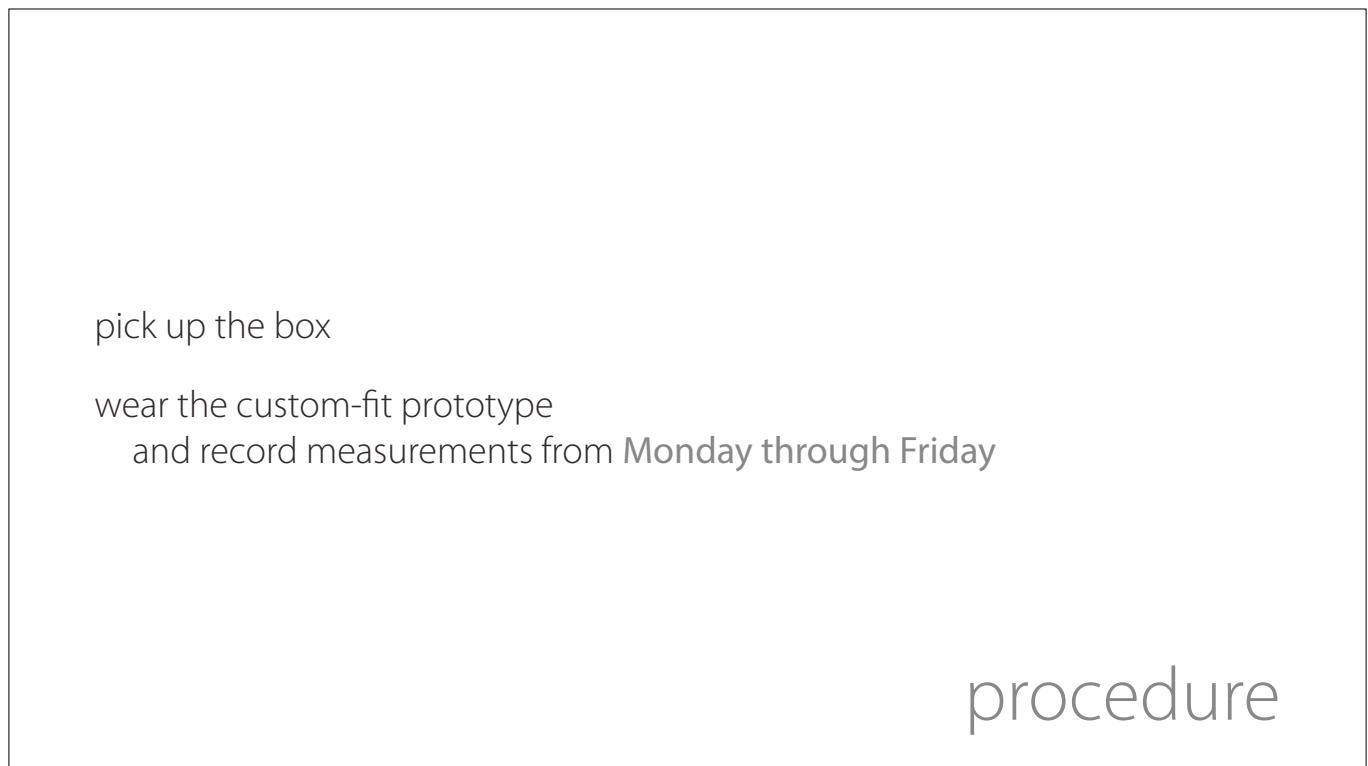
wear the custom-fit prototype glasses
at least **12 hours** per day

record blood pressure values three times an hour
at least **30 measurements** per day

5 days of participation

task





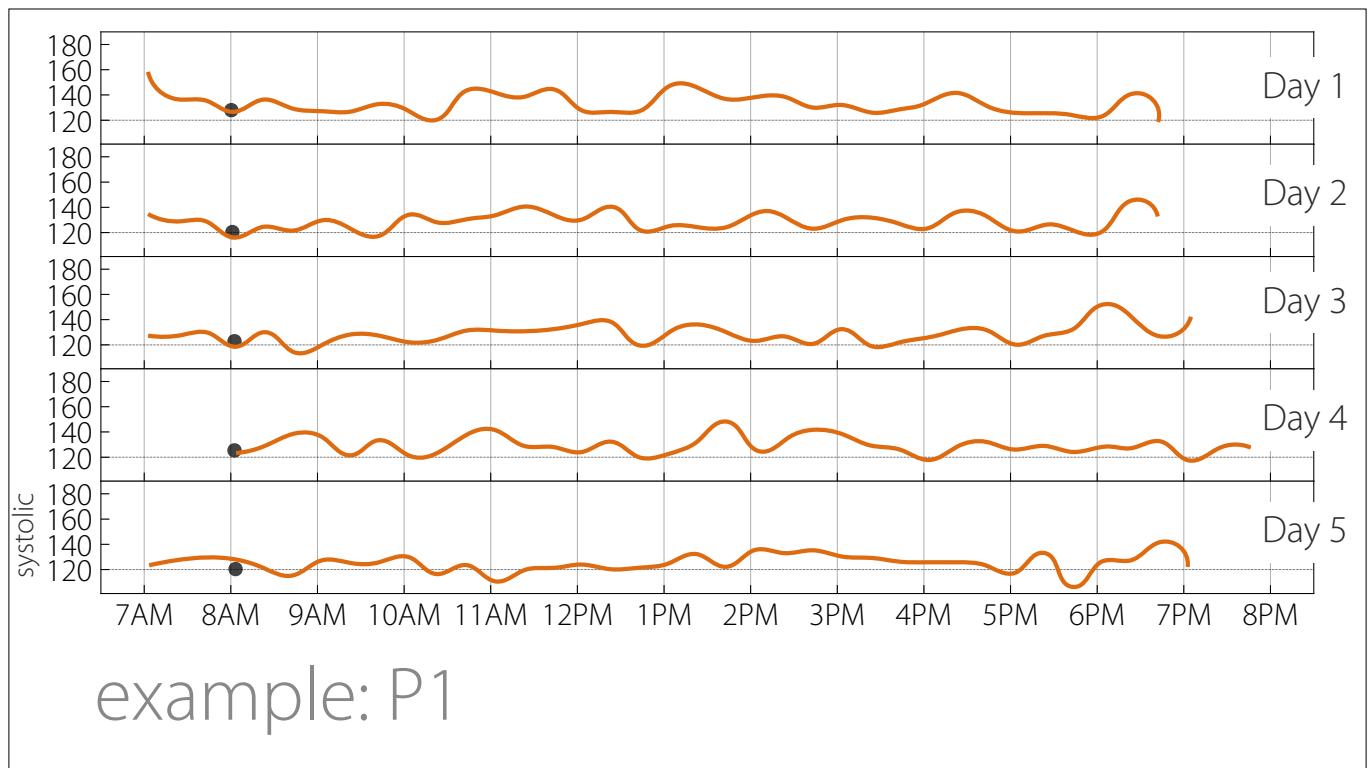
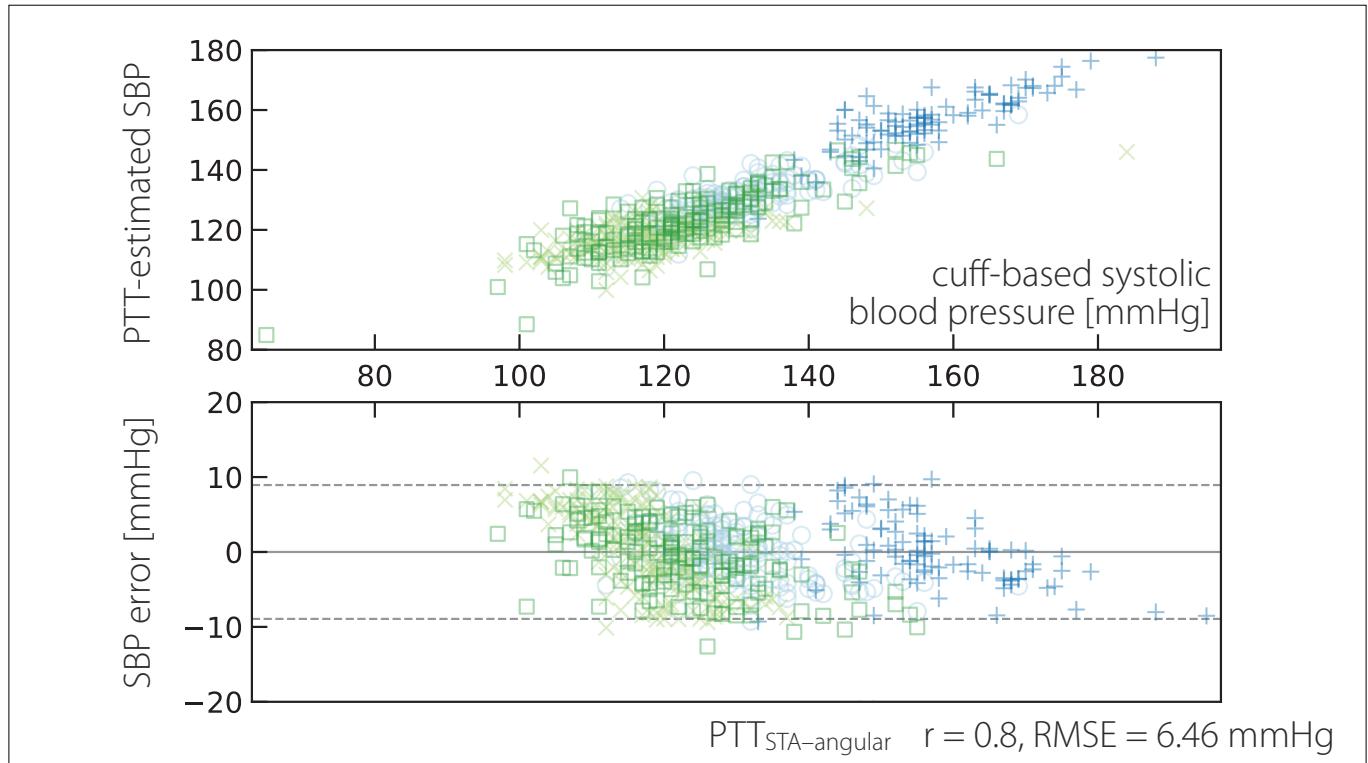
all participants had Fitzpatrick Skin Type II
no known related medical conditions (e.g., hypertension)
\$400 gratuity depending on compliance

participants

analyzed surrounding ± 2 minutes
of each blood pressure measurement

to predict the wearer's
heart rate
systolic blood pressure

results

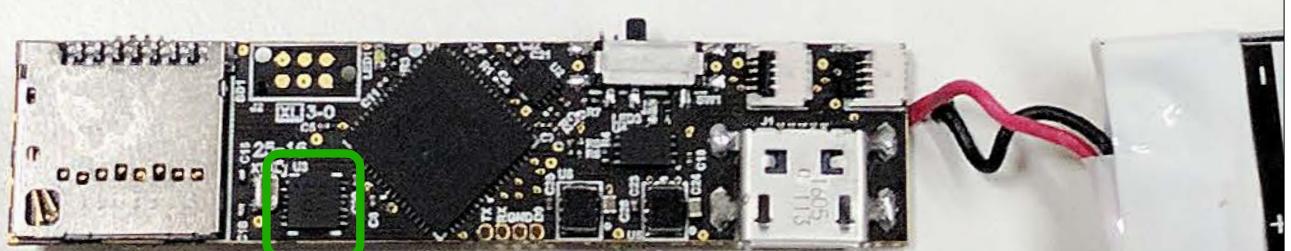


continuously tracks heart rates and blood pressure
lightweight, convenient, and integrated
without requiring any input from the user
all throughout the day and regular activities



where's the activity part?

Glabela's main board.



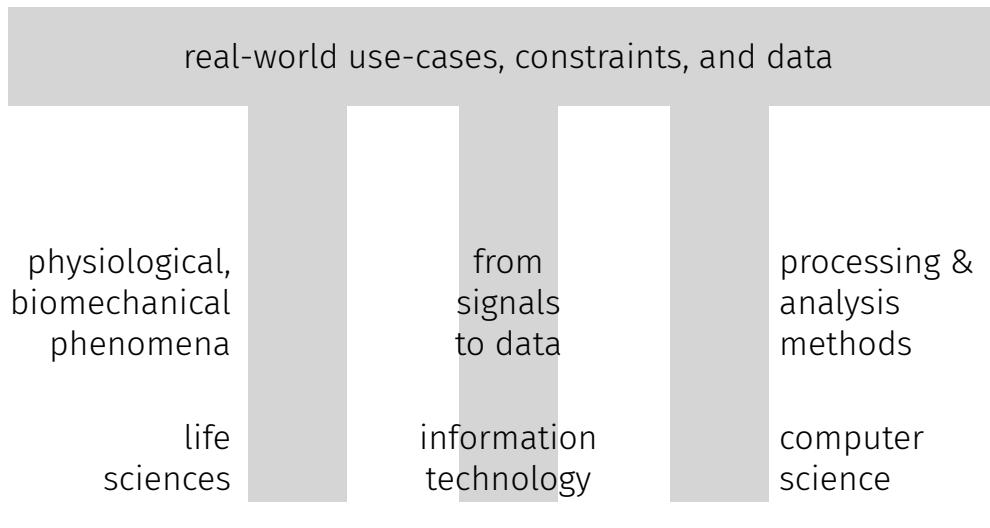
IMU



Course goals

Mobile Health & Activity Monitoring

the three pillars of this course



79

questions we will aim to answer

for mobile health,

- What is the data that you have?
- What's the type of **data you need?**
- How do you get the type of data you need but don't have?

more methodologically,

- How do you devise methods to get it?
- And how do you evaluate them in representative (**ecologically valid**) ways?

finally, what's the human component in this process?

- Where, when, and how to measure to get to the what?
- Relevance and acceptance, human factors such as **compliance**

80

outcomes

by the end of the term, you will

- understand the wider ecosystem of mobile health
- get an overview of human physiology (focus on vital signs)
- understand how health diagnostics devices work,
including concept, sensing method, device implementation, and application
- be able to dissect them
- learn physiological signal characteristics and processing methods
- learn how to evaluate interfaces in *representative environments* ("in the wild")

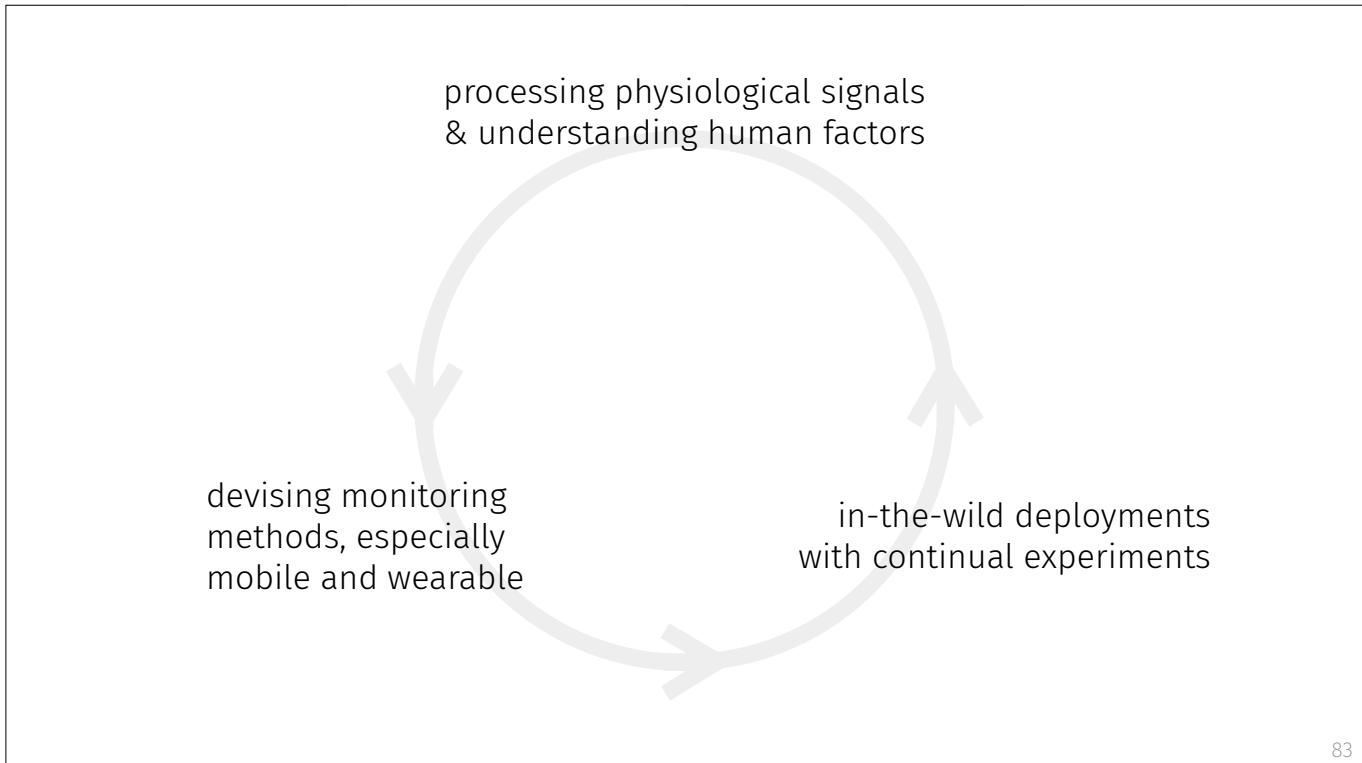
through the exercise, you will

- get first-hand experience with cross-modal data processing (time series!)
- develop processing methods for real-world (vs. applying ML to benchmarks)

81

⇒ mobile health falls into the **empirical sciences**

82



83

this course is necessarily **applied**

real-world problems and constraints

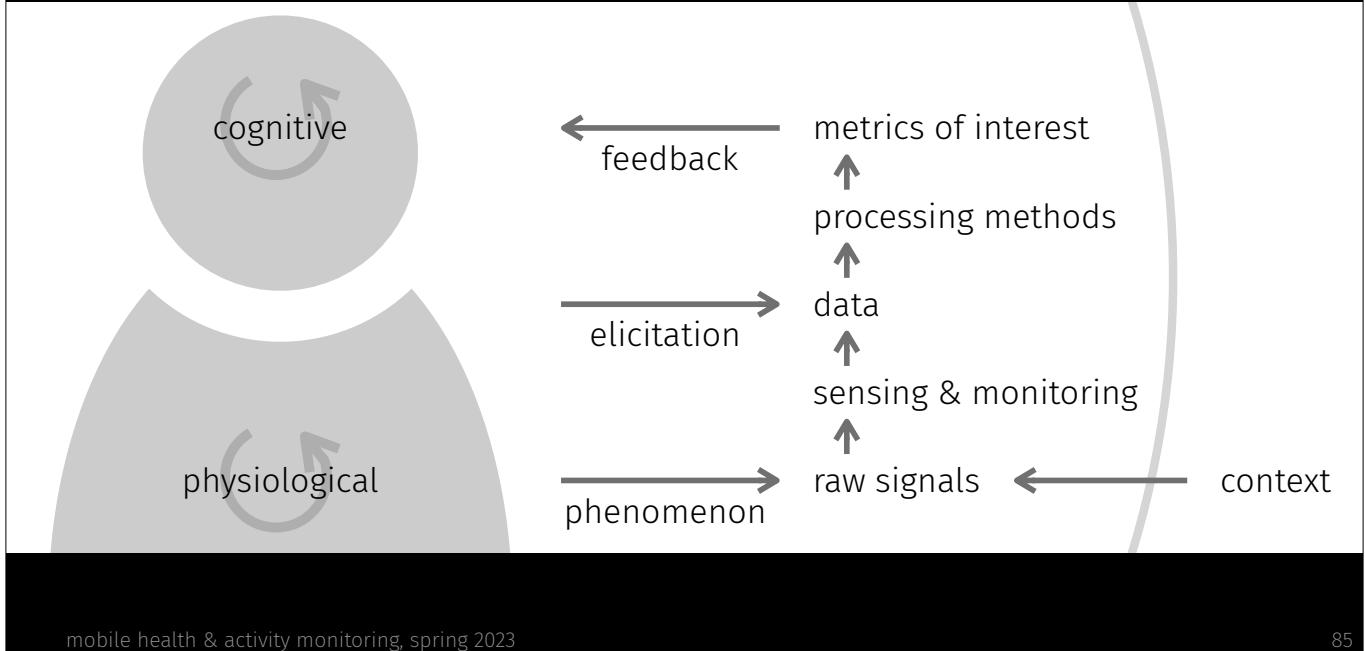
cross-disciplinary

- health sciences
- engineering
- human factors/social sciences

- ▷ think of this as a refresher of concepts from each domain, allowing you to dive into the domain of mobile health, where the total is more than the sum of the parts

84

this course



mobile health & activity monitoring, spring 2023

85

what this course is **not**

theoretical

- no proofs, no elaborate method design (if interested \Rightarrow thesis)
- instead: overview over existing methods

hardware engineering

- won't build, assemble, or innovate in hardware (if interested \Rightarrow thesis)
- won't dive into materials too much or expect detailed understanding

comprehensive medical curriculum

- instead: focus on vital signs and high-level cardiovascular processes
- application domain

86

#	DATE	WHO	TOPIC
1	Feb 20	Christian Holz	Introduction and course overview
2	Feb 27	Christian Holz	
3	Mar 6	Christian Holz	
4	Mar 13	Christian Holz	
5	Mar 20	Christian Holz	
6	Mar 27	Christian Holz	
7	Apr 3	Björn Braun	
-	Apr 10	-	<i>week after Easter</i>
-	Apr 17	-	<i>Sechseläuten</i>
8	Apr 24	Manuel Meier	
-	May 1	-	<i>first of May</i>
9	May 8	Christian Holz	
10	May 15	Shkurta Gashi	
11	May 22	Christian Holz	
-	May 29	-	<i>Whitsun</i>

...only 11 lectures

87

who we are

lecturers and TAs

88

lecturer



Prof. Christian Holz
Assistant Professor in Computer Science

“Human-Computer Interaction”
c (computational interaction
 u mixed reality
 u mobile health)
lots of research outside the lab

collaborations across D-HEST, D-ITET, D-MAVT

89

about me

background in software engineering/geography

PhD in human-computer interaction

2013 – 2015 research scientist at Yahoo Research, San Francisco, CA

2015 – 2019 research scientist at Microsoft Research, Seattle, WA

2019 – assistant professor at ETH Zürich, D-INFK
Sensing, Interaction & Perception Lab
<https://siplab.org>

90

teaching assistants



Max Moebus
M.Sc. Stats/Oxford
head TA



Kate Gadola
ongoing M.Sc.
ETH CS



Björn Braun
M.Sc. RSC
ETH



Paul Streli
M.Sc. EECS
Imperial



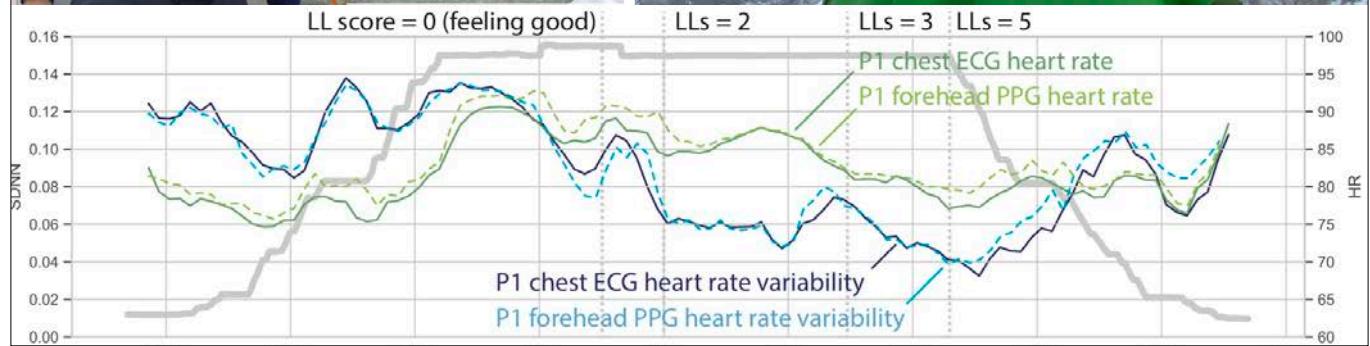
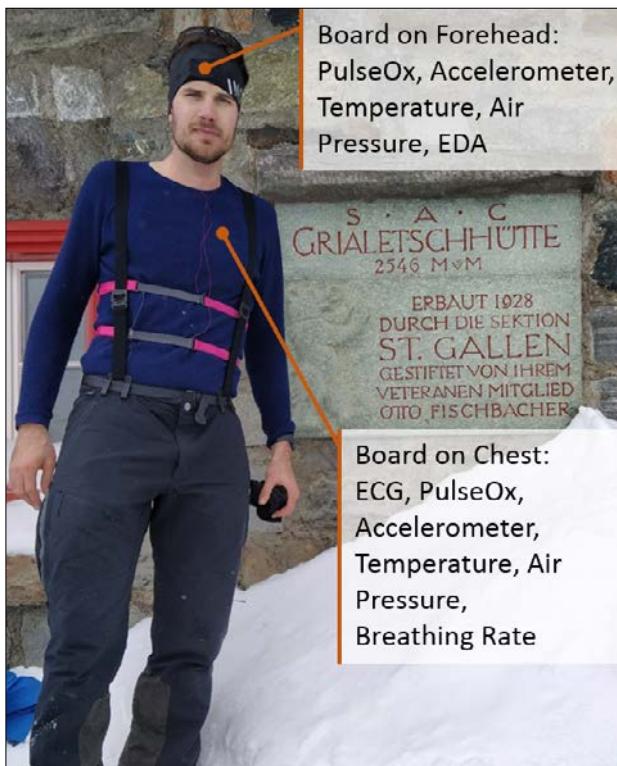
Manuel Meier
M.Sc. ITET
ETH

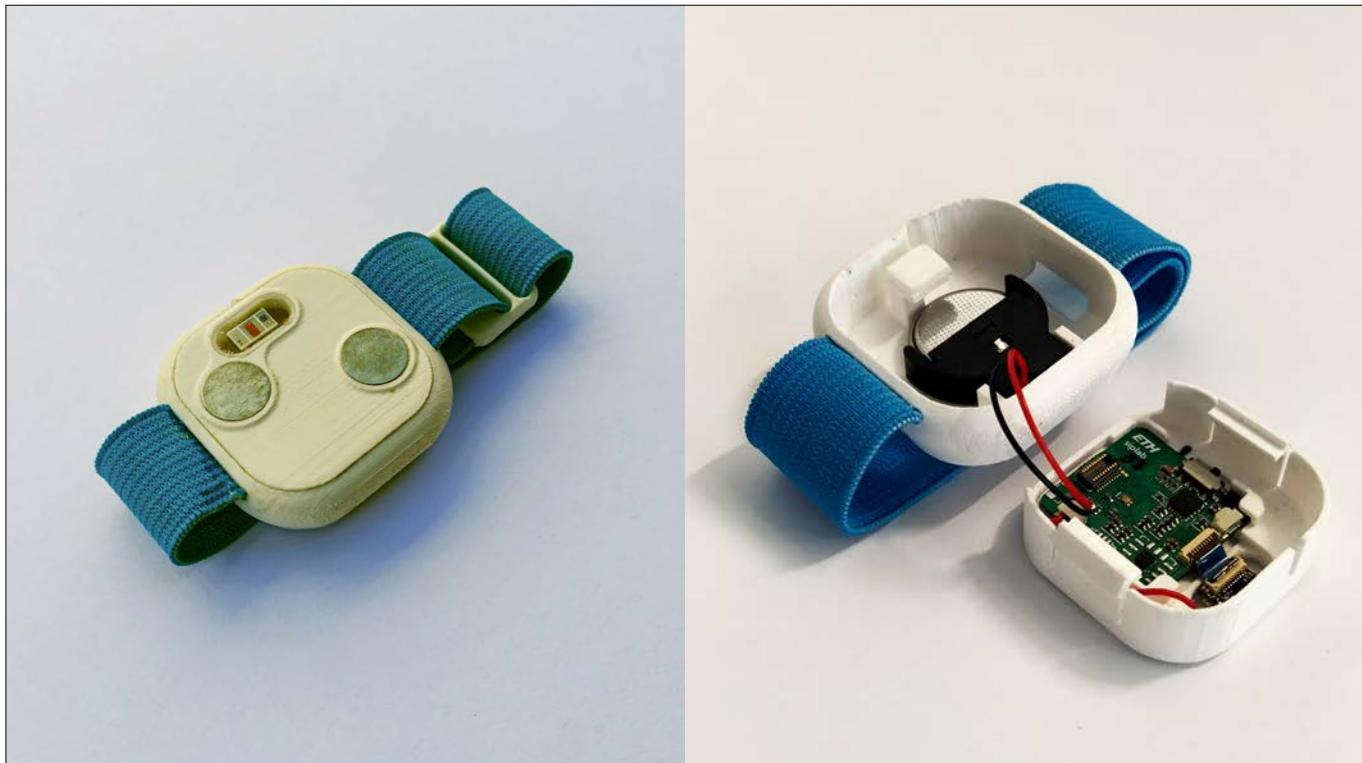
⇒ contact the TAs through Moodle

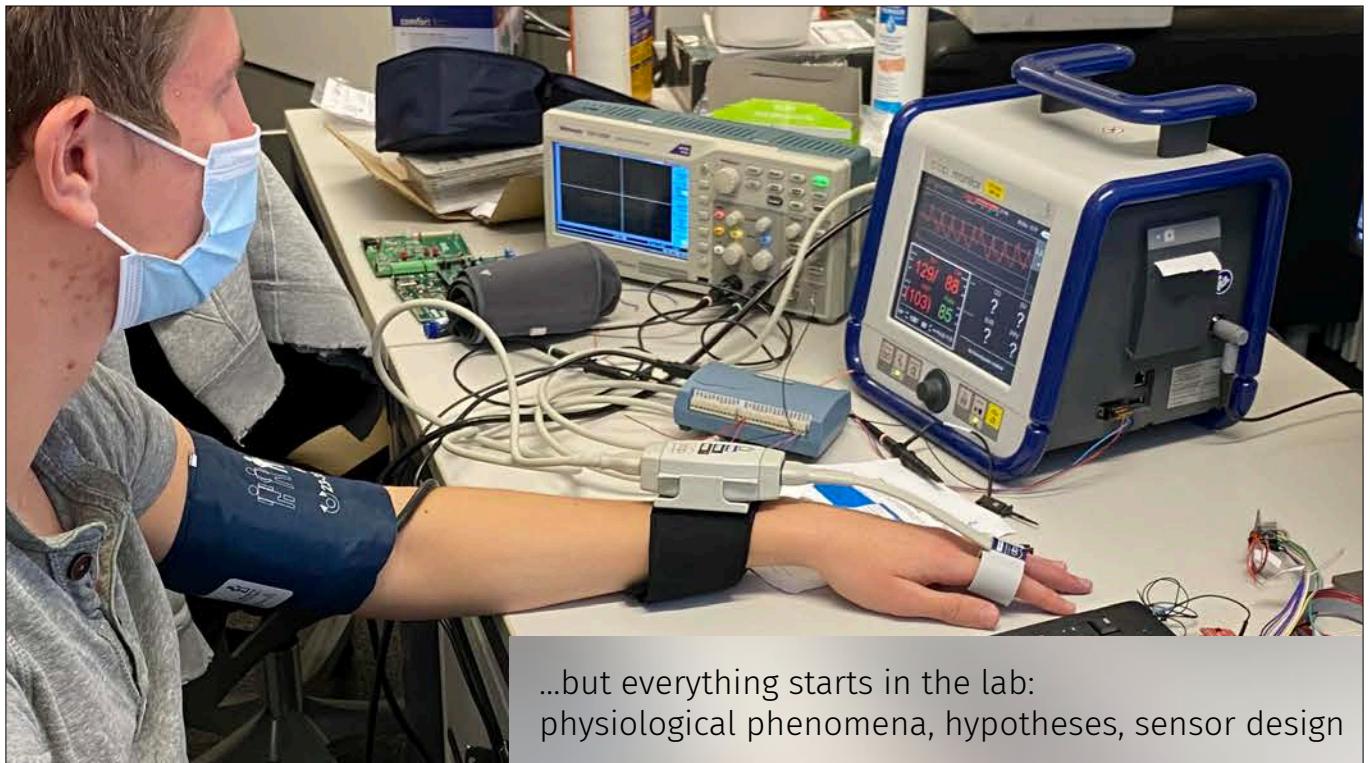
91

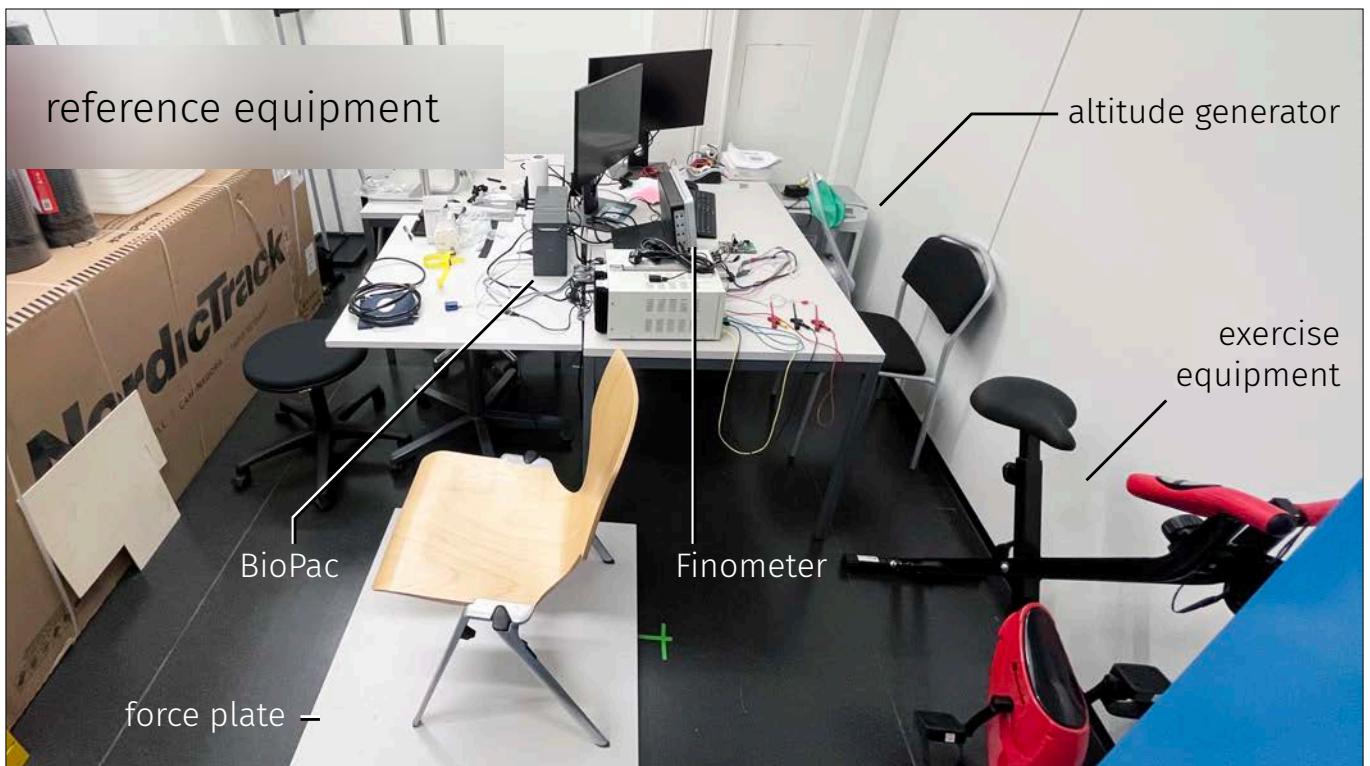
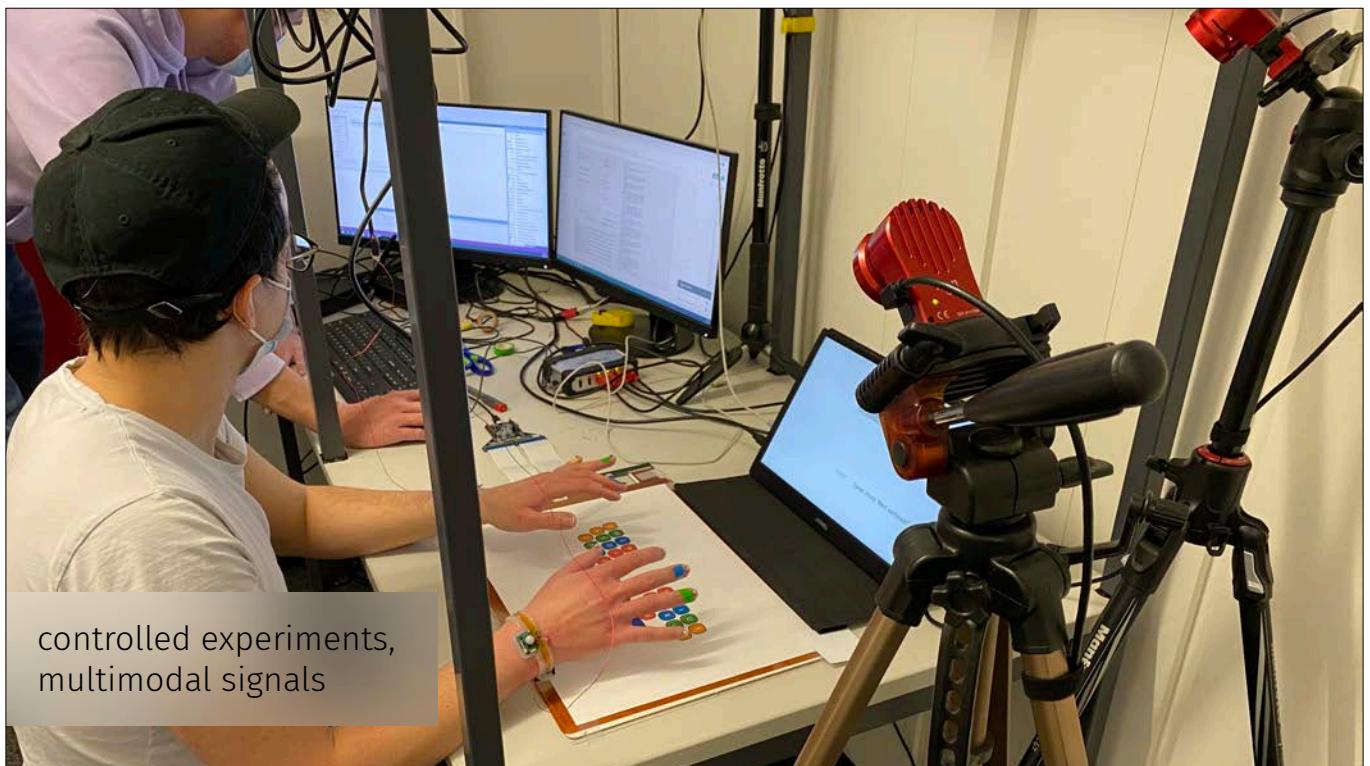


we care about **real-world** problems
(& data, measurements, generating insights)



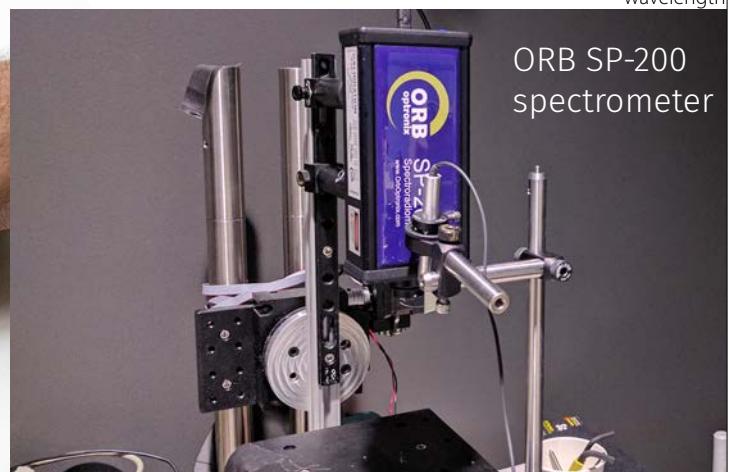
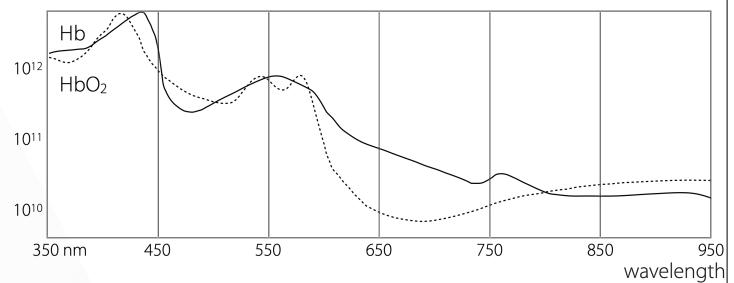








PulseOx (SpO_2) on a smartphone



MiBot

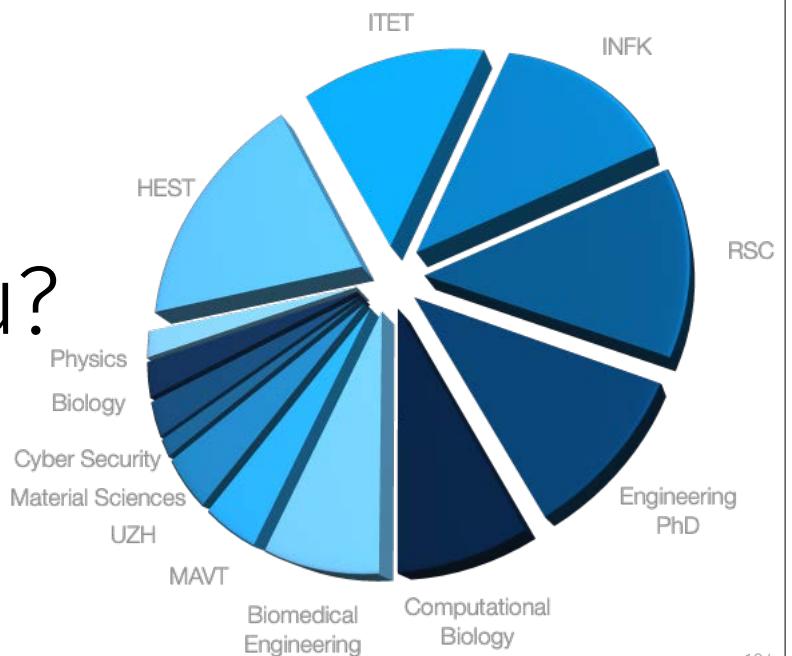
migraine mitigation
massage-based
prevention and
treatment



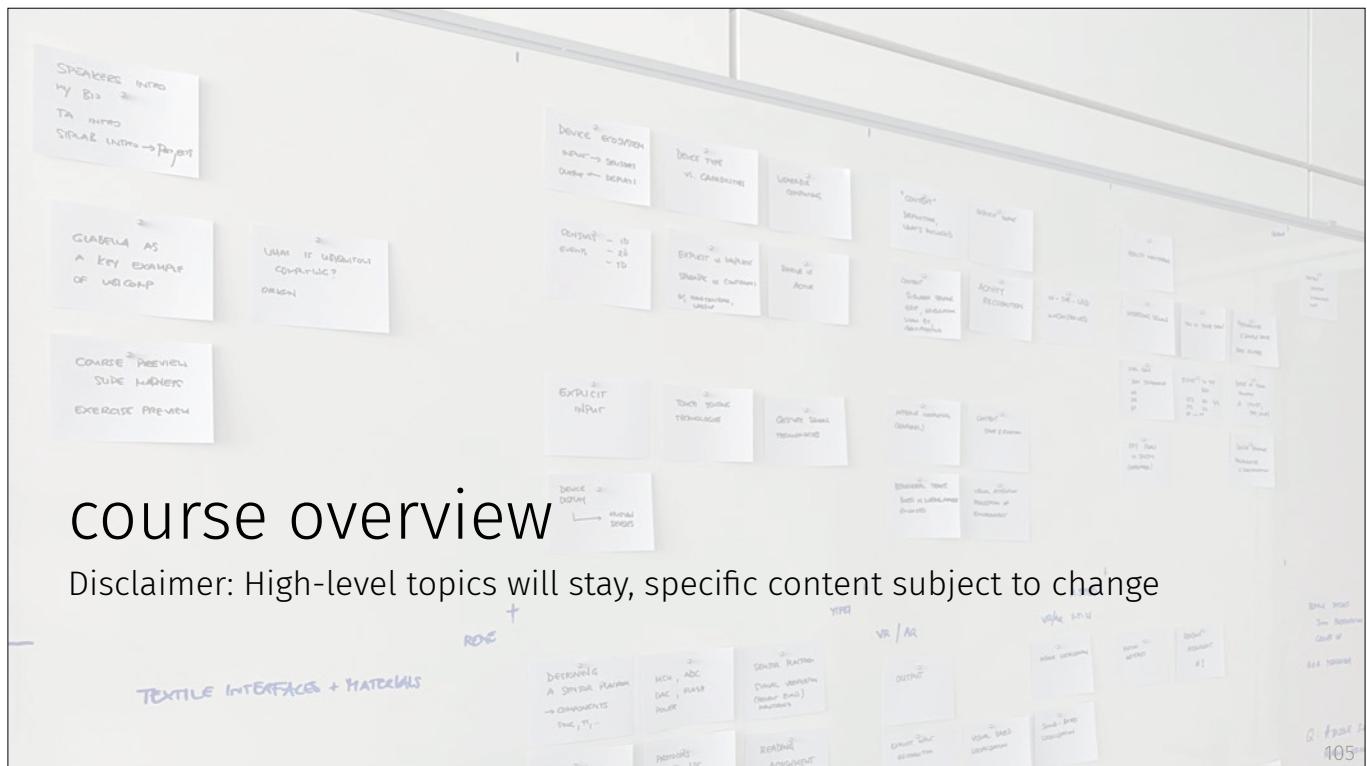
103

who are you?

program and aspirations
expectations of the course,
hopes, and wishes?



104



course overview

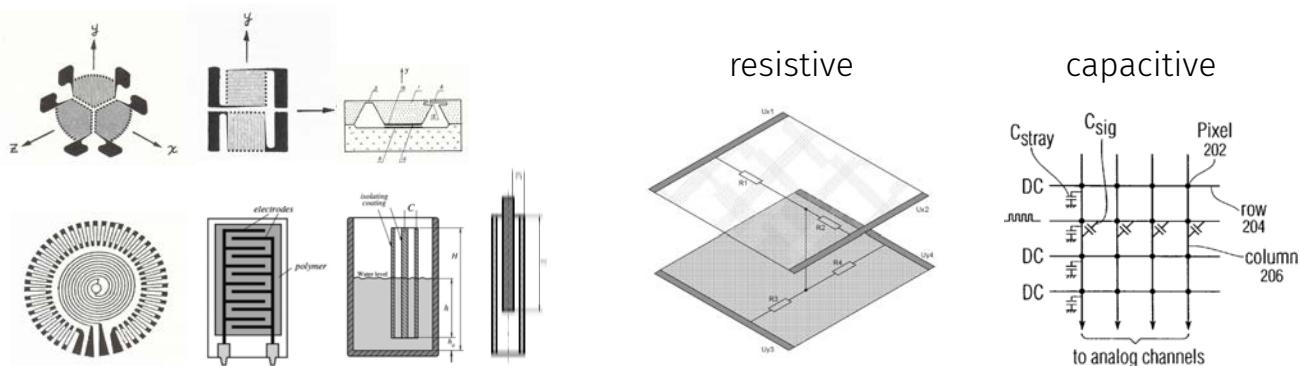
Disclaimer: High-level topics will stay, specific content subject to change



what makes a wearable health tracker (work)?



types of sensors
 physical phenomena & measurable modalities
 implicit vs. explicit sensing



devices, sensors, sensing principles

detecting activity



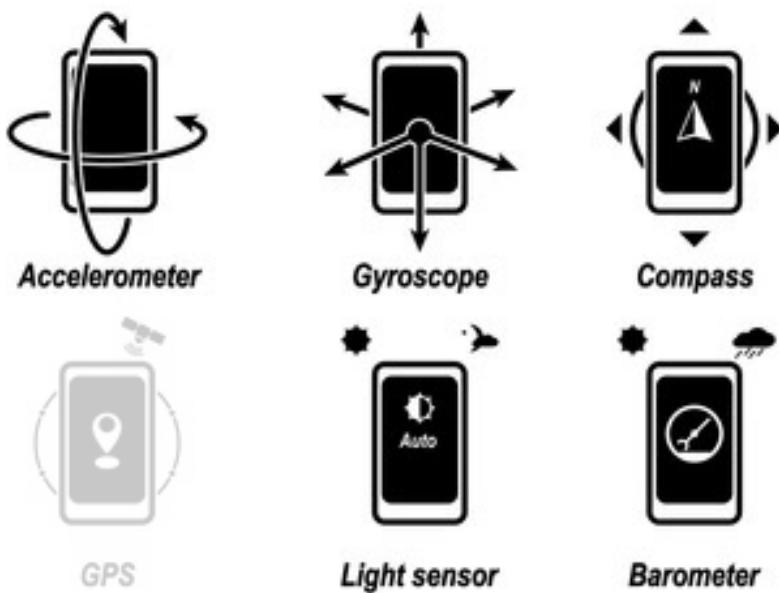
detecting hand-object interaction



detecting context of use



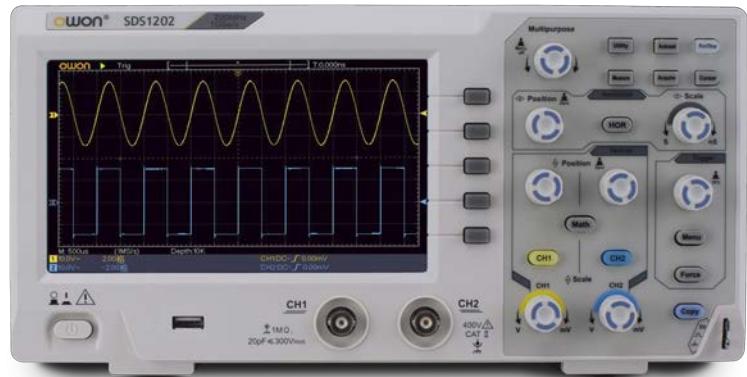
activity & context sensing



what are the signals,
where do they come from,
how to process them
to turn them into data
simple methods to
detect events

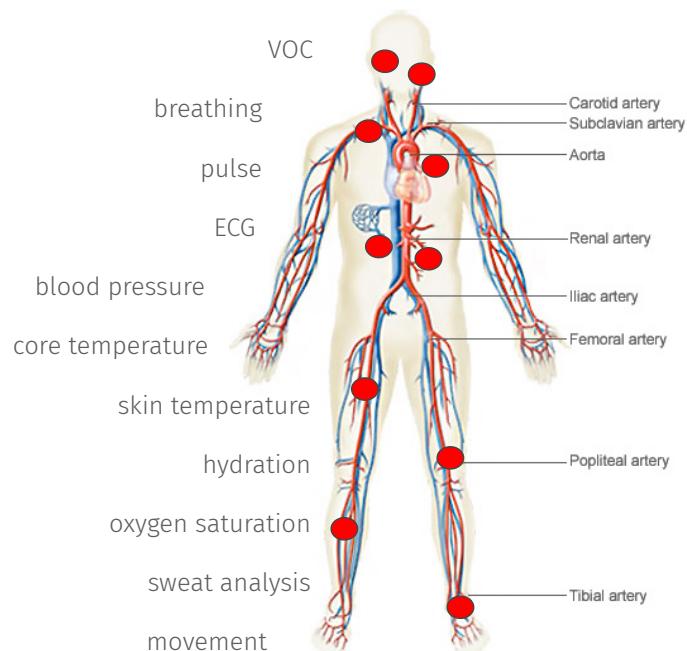
motion detection

signals (time & frequency domain)
analog vs. digital
sampling



“sensing”

vital signs and their meaning

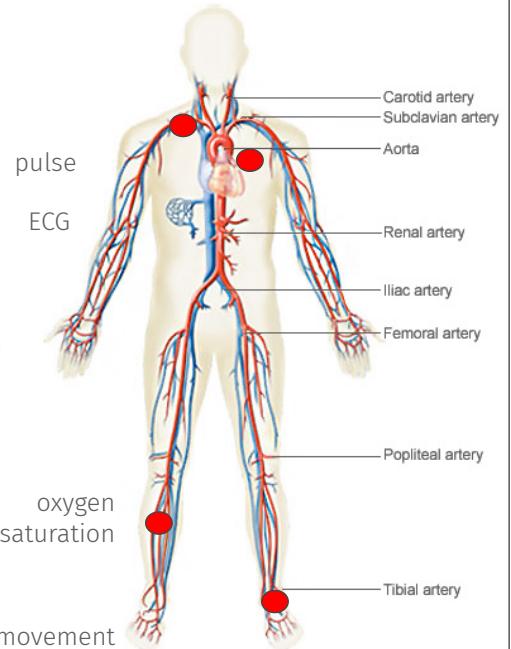
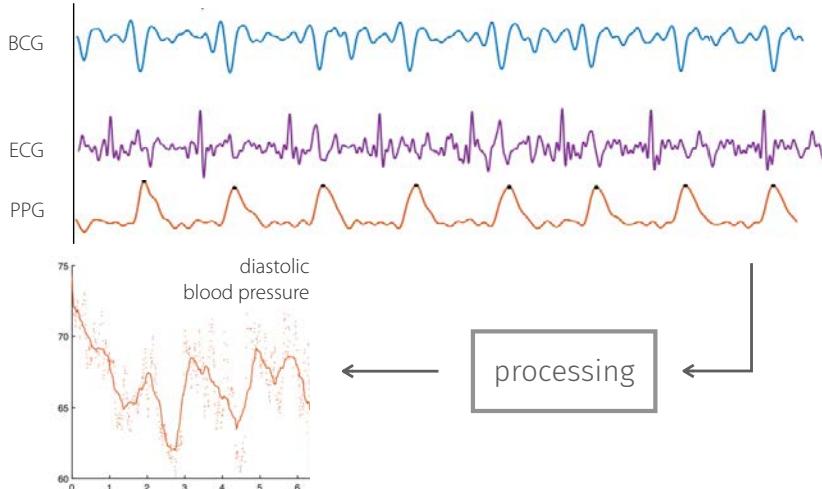


health monitoring: physiological processes

resulting signals

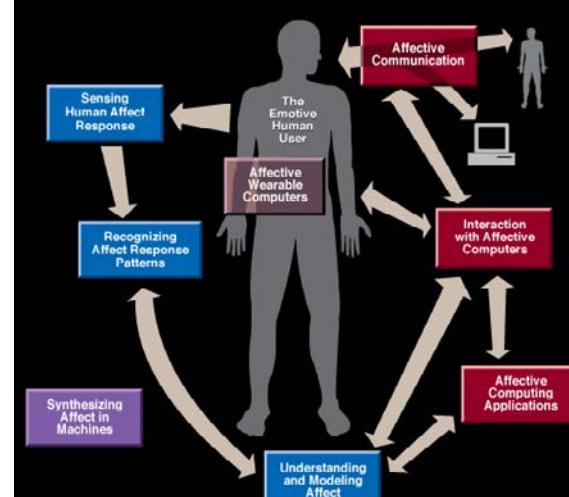
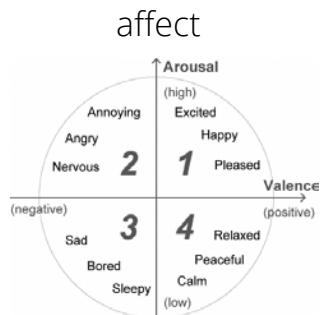
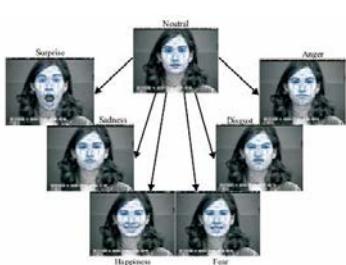
means to measure them

non-invasive vs. invasive monitoring



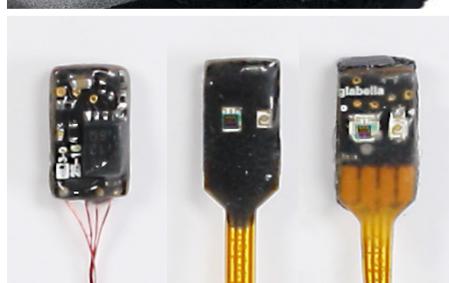
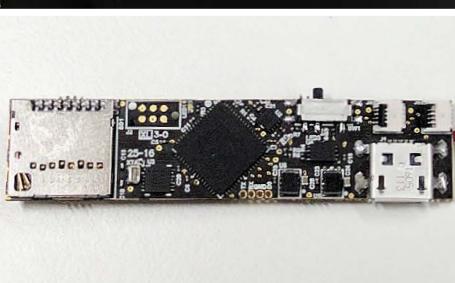
health monitoring: physiological signals & processing

emotion



affective computing

methods to estimate affect



synchronization, power
data storage, read out
MPUs, ADC, DAC
+ where to process?

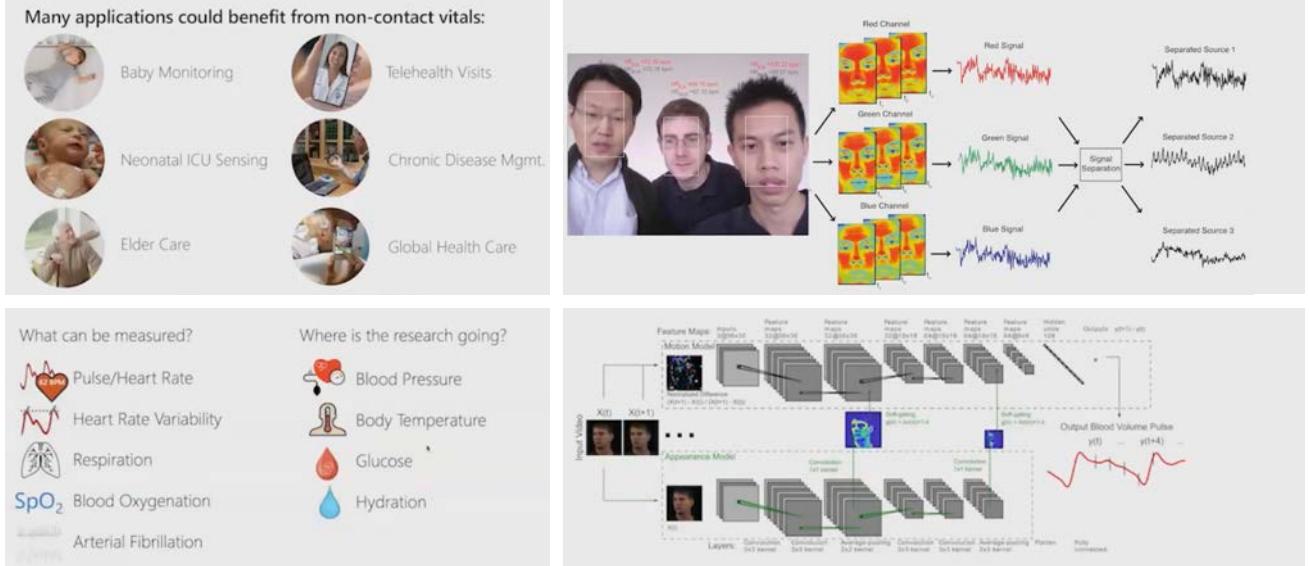
(conceptually) designing a wearable for health & activity sensing

from special-purpose sensing devices
to mobile phone apps

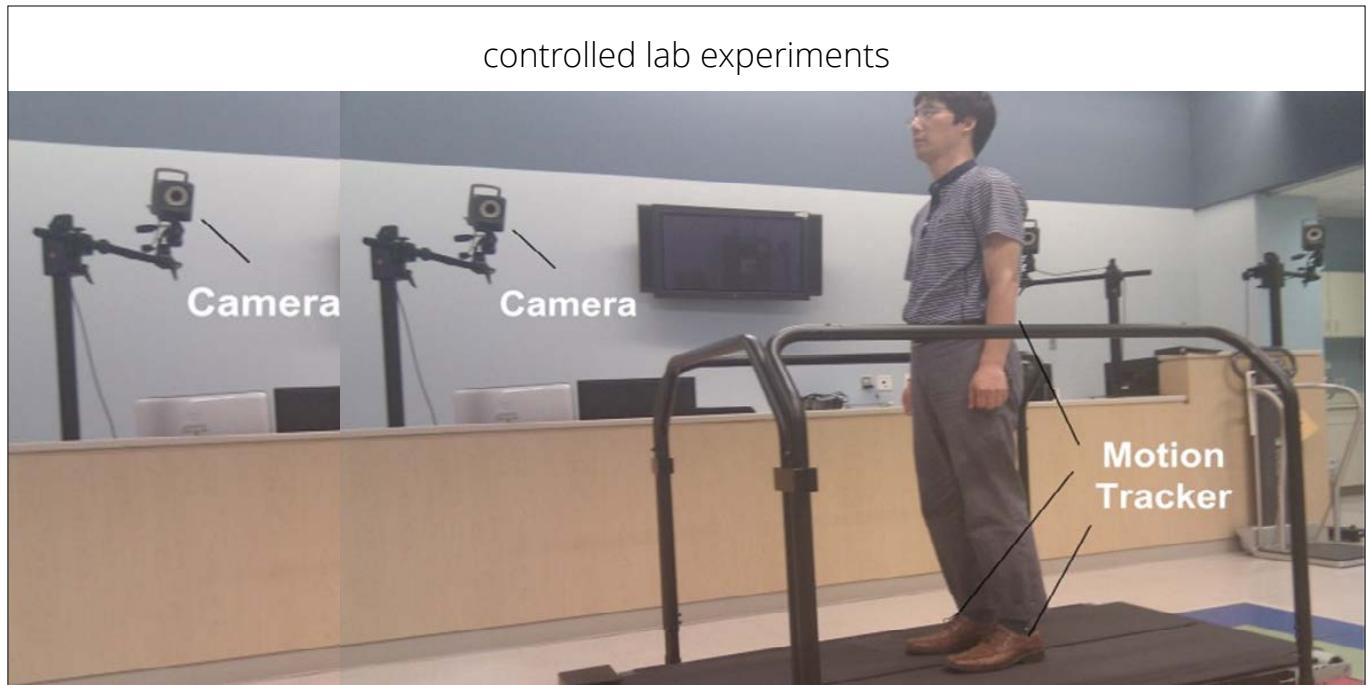
- complement or even take over data acquisition
- aid diagnostics through context

complementary mobile phones





camera-based non-contact health sensing



how to record data

controlled lab experiments

vs.

in the wild



logging & power
online vs. offline
processing
device reliability
state recovery

how to record data

...more than adding a battery

questionnaires

During the past week, I found that:

- My motivation is lower when I am fatigued.
- Exercises brings on my fatigue.
- I am easily fatigued.
- Fatigue interferes with my physical functioning.
- Fatigue causes frequent problems for me.
- My fatigue prevents sustained physical functioning.
- Fatigue interferes with carrying out certain duties and responsibilities.
- Fatigue is among my three most disabling symptoms.
- Fatigue interferes with my work, family, or social life.

	Strongly disagree	2	3	4	5	6	7	Strongly agree
1	2	3	4	5	6	7		
1	2	3	4	5	6	7		
1	2	3	4	5	6	7		
1	2	3	4	5	6	7		
1	2	3	4	5	6	7		
1	2	3	4	5	6	7		
1	2	3	4	5	6	7		
1	2	3	4	5	6	7		
1	2	3	4	5	6	7		

clinical equipment+supervision



clinical assessment

vs.

continual monitoring everywhere



a mobile health use-case: monitoring neurological conditions

lecture format

fully hybrid

- in person teaching
- recorded and posted online

interactive

- raise your hand anytime
- time management = my job

121

reading assignments



122

4 reading assignments

full papers or articles, published at Mobile Systems/Digital Health venues
mandatory reading assigned each ~3 weeks

two papers

- discussed in class
- relevant for exam

two papers

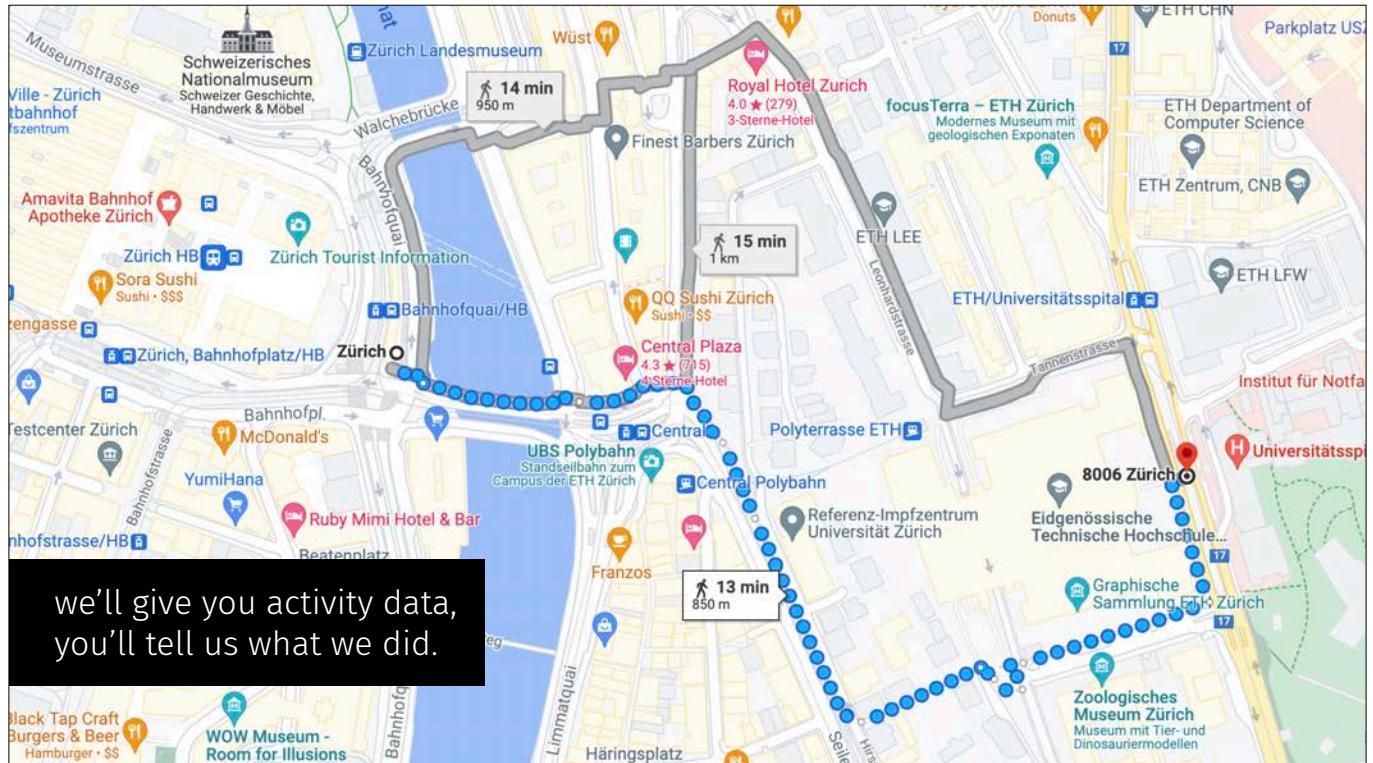
- useful for the exercise
- great overview and good start to solve tasks

123

exercise

(very applied)

124



LilyGo smart band

each group gets one
battery-operated wearable band
includes sensors

- 3-axis accelerometer
- 3-axis gyroscope
- 3-axis magnetometer
- (sensor) temperature



LilyGo smart band

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127

LilyGo smart band

each group gets one
battery-operated wearable band
includes sensors

- 3-axis accelerometer
- 3-axis gyroscope
- 3-axis magnetometer
- (sensor) temperature



128

pairs with your phone



additional sensors

- GPS
- barometer
- ...



129

smartphone app

connects to smartwatch through BLE,

logs additional data, including:

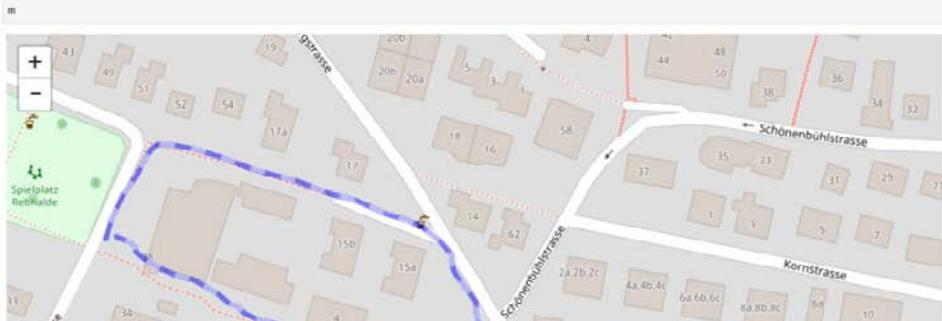
- GPS
- 3-axis phone accelerometer
- 3-axis phone gyro
- 3-axis phone magnetometer
- barometric altitude



130

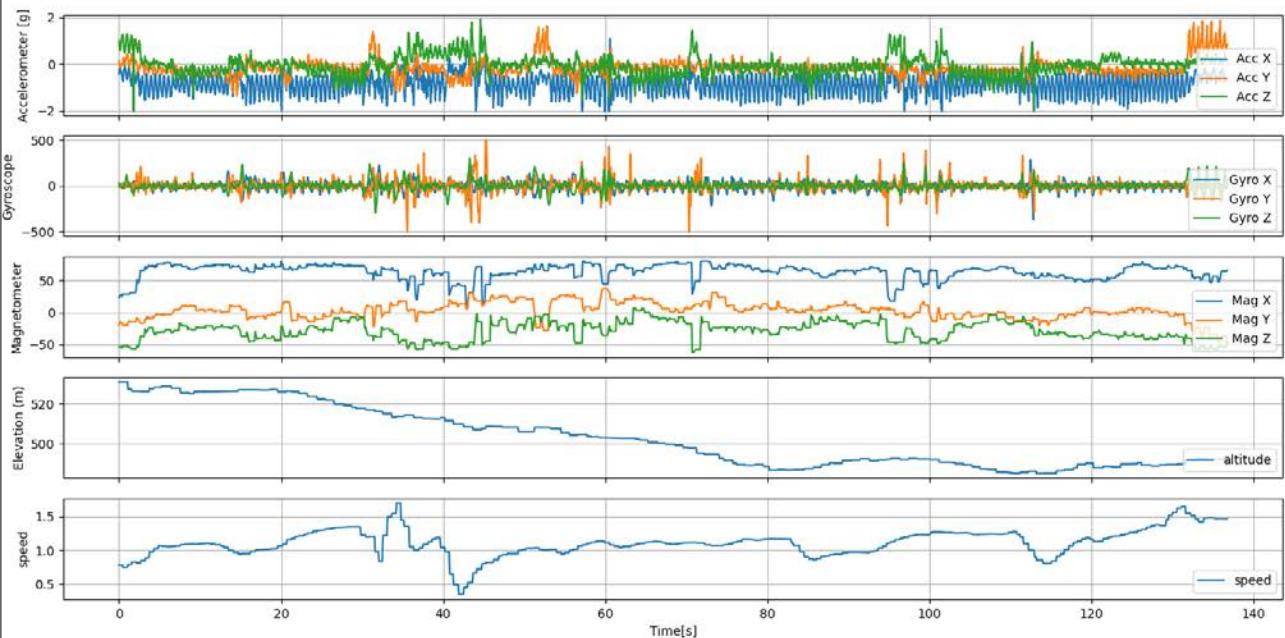
Python environment for loading+viz

```
coords = list(zip(trace.data['latitude'].values[100:-40], trace.data['longitude'].values[100:-40]))  
m = Map(center=coords[int(len(coords)/2)], max_zoom=22, zoom=18, basemap=basemaps.OpenStreetMap.Mapnik)  
m.layout.width='900px'  
m.layout.height='600px'  
ant_path = AntPath(locations=coords, delay=2000)  
m.add_layer(ant_path)  
  
# display directional speed if data available  
if 'speed' in trace.data:  
    for i in range(len(coords)):  
        if i % 20 == 0:  
            size = trace.data['speed'].values[i] * 20  
            middle = int(size/2)  
            icon = Icon(icon_url='img/arrow.png', icon_size=[size, size])  
            #marker = Marker(location=coords[i], draggable=False, rotation_angle=example.data['bearing'].values[i]-90, rotation_origin='middle center', icon=icon)  
            #m.add_layer(marker)
```



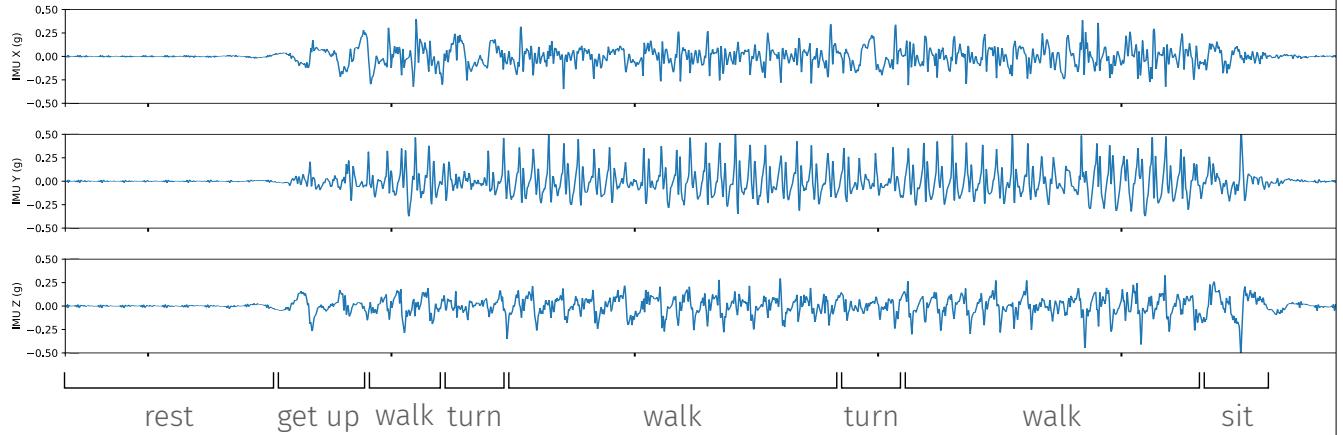
131

Python environment for loading+viz



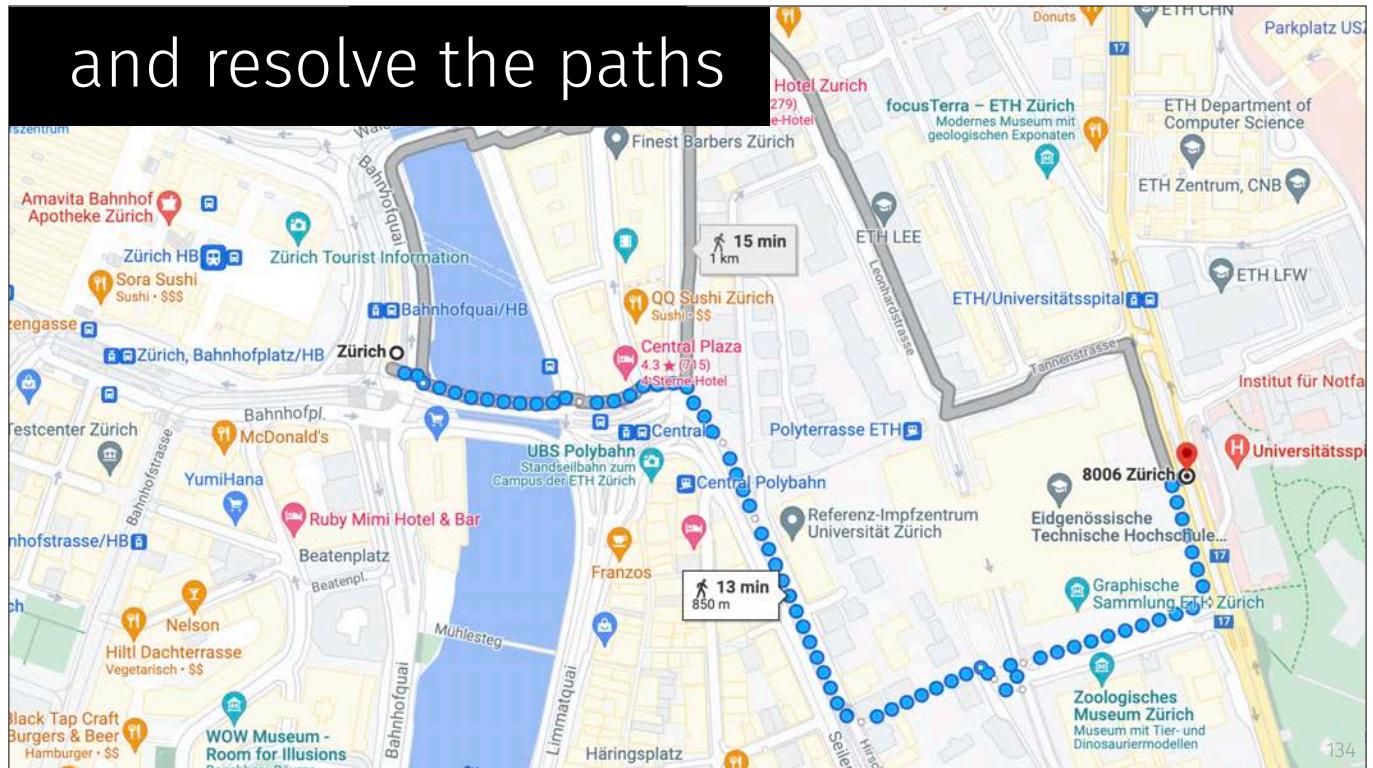
132

your job: classify activities...



133

and resolve the paths



134

sub tasks

step counting

detecting

- mode of transport (e.g., walk, cycle, tram, ...)
- path taken across city
- location of device on the body

detailed task description will be released by next week

135

formalities

exercise in groups

three deadlines for sub tasks (enough time for exam)

exercise accounts for 50% of total grade

136

formalities

weekly exercise Q&A sessions

- slot to be announced
- tutorials, intros, overview as needed (input appreciated)
- attendance **optional**
- starting Week 3

announcements and communication

- TAs will announce important bits on Moodle
- Q&A also through Moodle

137

exam

138

exam

end-of-term exam (Semesterendprüfung)

- presence exam, computer based
 - 90 minutes
- ⇒ counts 50% of the grade

in early June

139

office hours

140

Wednesdays 9–10am

in person:

- book 15 min slot through link
- STD G 29.2
- <https://siplab.org/contact>

Zoom:

- <https://ethz.zoom.us/my/christianholz>
- has waiting room



141

summary

142

summary

11 lectures	(not always 90 minutes)
2 weeks break	(1 week for Easter, Sechseläuten)
1 exercise	(accompanying the semester)
4 reading assignments	
1 end-of-term exam	(Semesterendprüfung)

course repository

- <https://go.siplab.org/mhealth2023>
- user: mhealth2023, password: PuntaNizuc

contact

- everything through Moodle
- <https://moodle-app2.let.ethz.ch/course/view.php?id=19753>

143



prof. christian holz
mobile health & activity monitoring, spring 2023



sensing,
interaction &
perception lab

optional reading

Christian Holz and Edward J. Wang. 2017. **Glabella: Continuously Sensing Blood Pressure Behavior using an Unobtrusive Wearable Device.** *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 58 (September 2017), 23 pages.
DOI:<https://doi.org/10.1145/3132024>

145

146