

# Mobile Health: Introduction

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Assessment and Practical Classes Team:

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# About Me

- Professor of Mobile Systems
- Work on mobile and sensing systems and wearable devices
  - Devising new ways to use sensors to measure behaviour
  - Making these systems efficient given resource constraints
  - Wearable data analysis and machine learning
  - Applications related to health and diagnostics

# What is Mobile Health

Mobile Health tries to make use of digital wearable devices and sensors to proxy information about human behaviour and health, including diagnostics and progression.

We will see example of use of these techniques in a variety of health settings and making use of a variety of sensing methods.



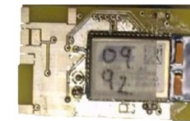
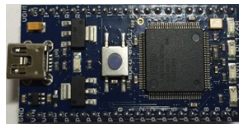
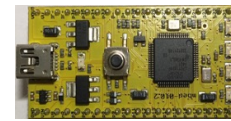
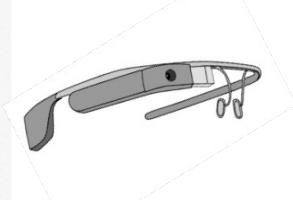
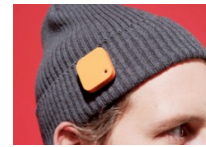
# Why

- Affordable
- Scalable
- Continuous
- Non invasive
- Sustainable

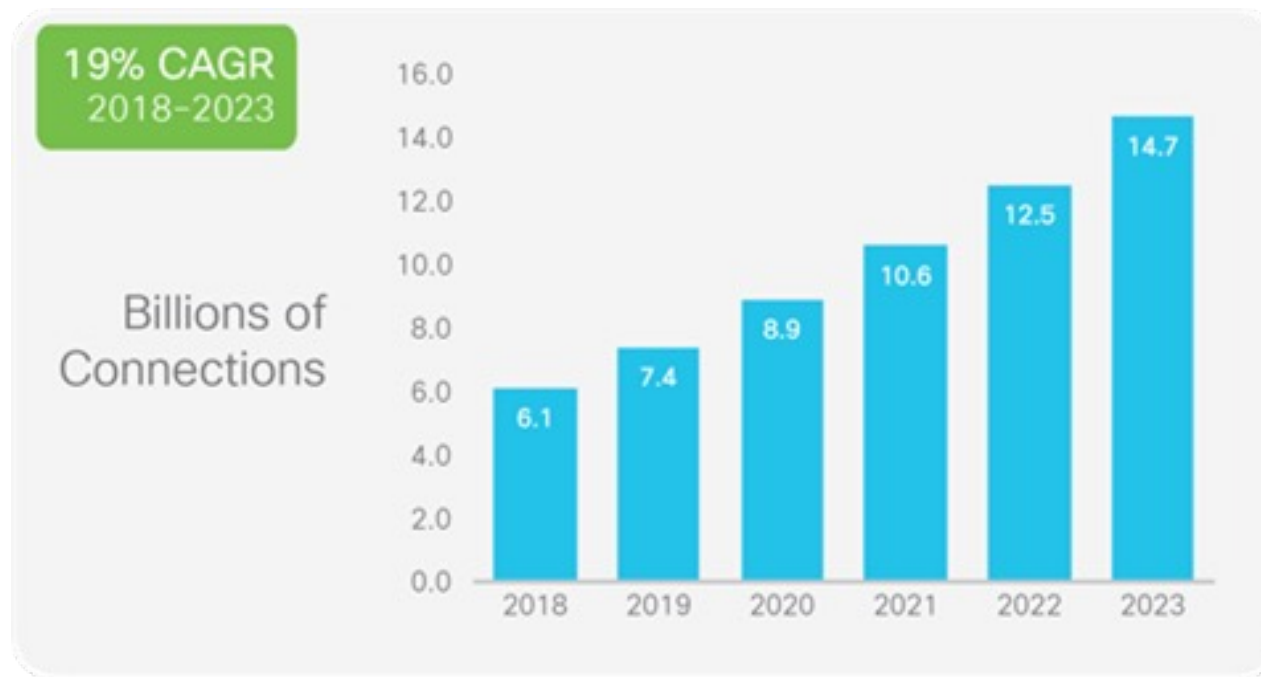
# Challenges

- Type of Sensors
- Resource constraints
- Frequency of data harvesting (sampling)
- Location of (pre)processing of data
- Data labelling
- Data sparsity
- Signal Processing/Machine learning for this data
- Data Privacy
- Linking data to clinical outcomes

# Mobile and Wearable Sensing

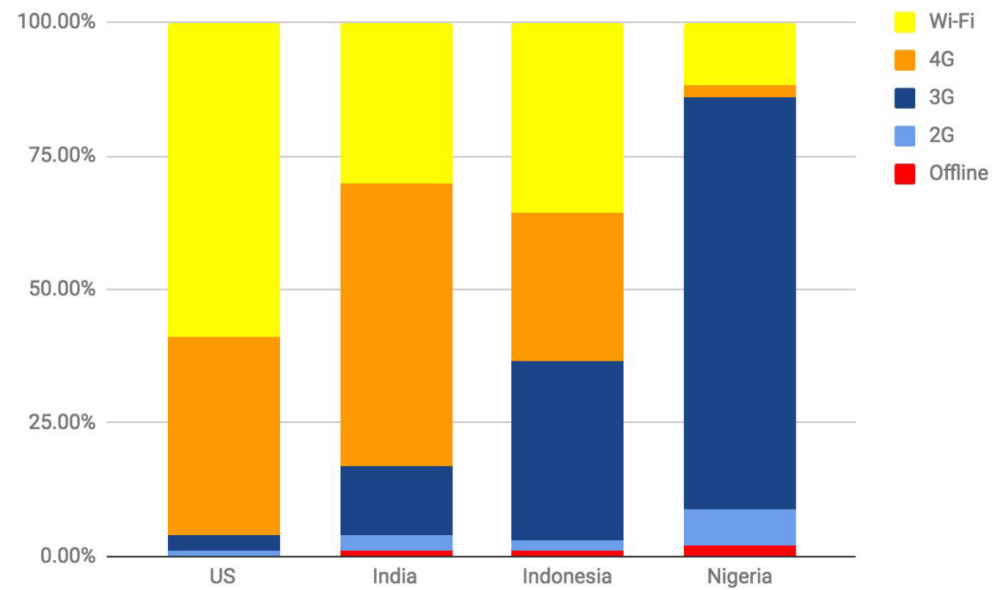


# Mobile Data



# Breakdown for some states of type of connectivity

Fraction of browsing sessions on each network technology



Source: Chrome logs



# Phone Sensors and Radios

Inertial Measurement Unit

Global Positioning System

Cameras

Proximity Sensors

Microphones

Radios: WiFi, BLE, Cellular...

Processors: CPU, GPU, coprocessors



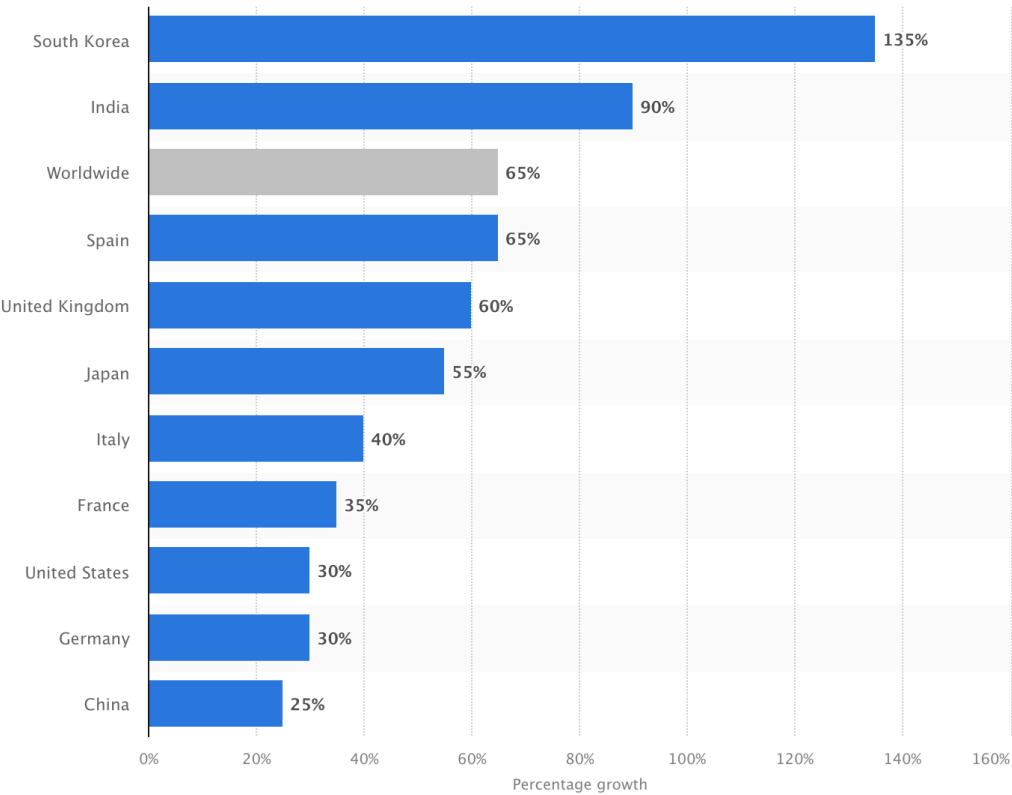


# “Basic” Mobile Health

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- Mobile questionnaires
- Feedback carefully tailored through messages or apps

# Growth in the number of medical apps downloaded during the COVID-19 pandemic by country in 2020\*



- ★
- 🔔
- ⚙️
- 🔗
- ”
- 🖨️

### DOWNLOAD

PDF + XLS + PNG + PPT +

### Sources

- [Show sources information](#)
- [Show publisher information](#)

### Release date

October 2020

### Region

Worldwide

### Survey time period

January to July 2020

### Supplementary notes

\* Based on downloads from the IOS and Google Play App stores. Data compare the number of medical app downloads in each country using its respective 'peak' month for the COVID-19 health crisis to the number of medical app downloads during January 2020.

# Wearables!





# Watch

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- Heart rate monitor
- Sleep monitor
- Activity monitor
- Blood Oxygen
- Electrocardiogram
  
- More coming...(Blood Pressure..)



# Future/Other Devices

- Many exist. Some more mobile than others.
  - Scales that measure body composition and pulse wave velocity
  - Earables have been defined as the “next computing platform after smartphone” [1]
  - Sensors in these devices could bring novel ways to monitor health [2]
- [1] Romit Roy Choudury <https://www.youtube.com/watch?v=1Qvu1G59JC0>
- [2] <https://cacm.acm.org/magazines/2021/8/254316-ebp/fulltext>

## COMMUNICATIONS OF THE ACM

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### RESEARCH HIGHLIGHTS

eBP: An Ear-Worn Device for Frequent and Comfortable  
Blood Pressure Monitoring



# Fabric...

## Sensors woven into a shirt can monitor vital signs

Comfortable, form-fitting garments could be used to remotely track patients' health.

[Watch Video](#)

Anne Trafton | MIT News Office  
April 23, 2020



“We can have electronic parts that we wear in our garments,” says Professor of  
Image: Court

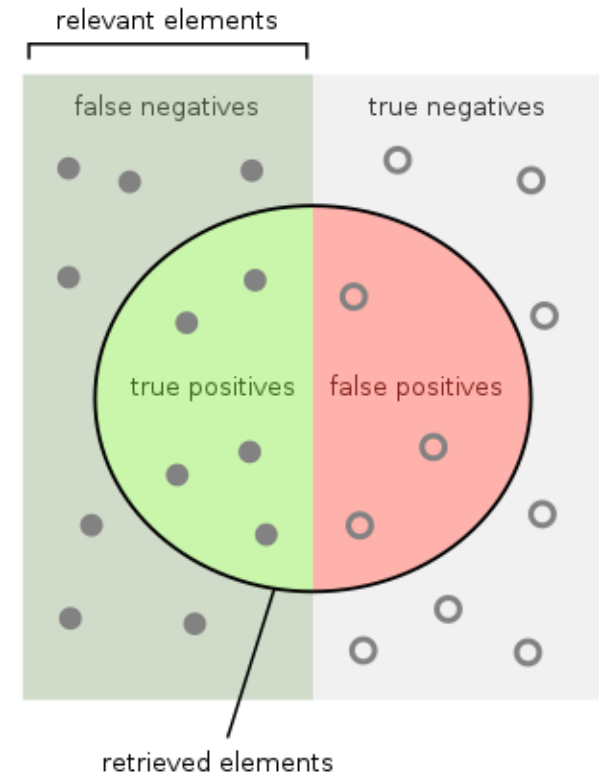
How we we measure performance of these systems?





# Machine Learning Metrics

- Classification tasks (trying to understand if a point is of a certain class)
- You are familiar with precision and recall and F1 score (which is a combination of precision and recall)



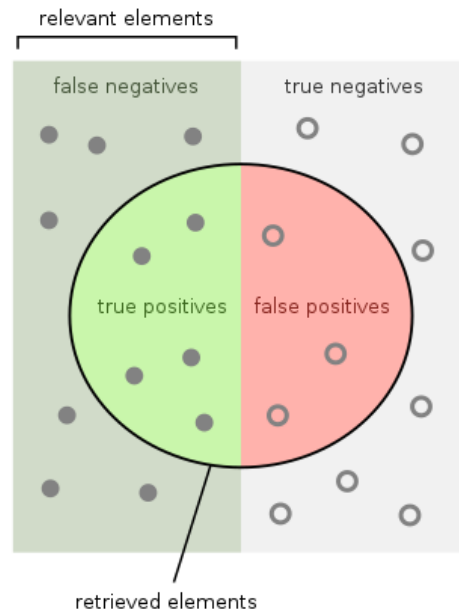
How many retrieved items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are retrieved?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

# Metrics meaningful to Health Applications

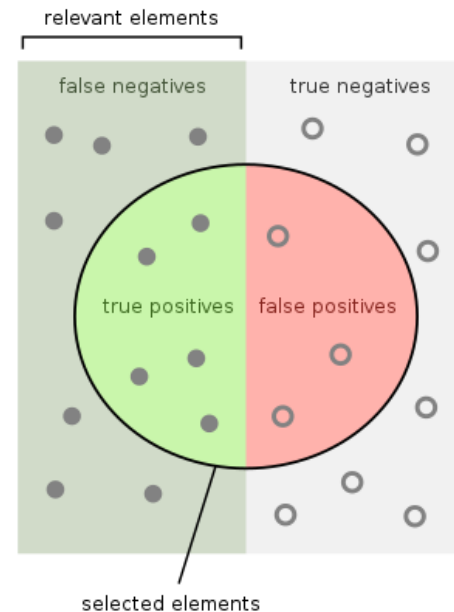


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How many relevant items are retrieved?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$



How many relevant items are selected?  
e.g. How many sick people are correctly identified as having the condition.

$$\text{Sensitivity} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

How many negative selected elements are truly negative?  
e.g. How many healthy people are identified as not having the condition.

$$\text{Specificity} = \frac{\text{true negatives}}{\text{true negatives} + \text{false positives}}$$

# Example of why sensitivity matters

- Let us assume that a COVID-19 test has a **sensitivity** of 70%.
- Let us assume that we test 10 people that we know have COVID-19. How many would the test correctly identify (in average)?
  - 7 would be identified. 3 would be false negatives.
- If the sensitivity was 80% we would identify 8.
- A **specificity** of 70% indicates that if we test 10 individuals who do not have COVID-19, the test would correctly identify 7 as healthy and 3 as affected by COVID-19 (wrongly).



# Disease Prevalence

- When trying to find if someone has a specific disease in a population often the distribution of the disease in the population is not “50-50” for this binary task...
- Prevalence indicates the amount of “diseased” people in the population in the “test set”.

# Confounding

- Confounding factors:
  - A confounding variable (factor) which produces spurious associations which are not the underlying causal link of from your data to your result.
- Example: trying to find link between lack of exercise and weight gain.
  - You find that lack of exercise leads to weight gain.
    - But if you do not check how **much people eat** it might be that in your set, you have that all the people who exercise eat less and those who don't eat more.
  - Eating should be a "control variable"



# Data Bias

- Bias in the data collection can lead to wrong conclusions/predictions.
- If data on which you train your model contains data from a predominant group which means other groups are not able to be predicted well.
  - “models for cardiovascular disease that claim to predict heart attacks 5 years before they happen are trained in predominantly male datasets”.
    - Prediction in women may not be accurate as the disease has different expression in women!

# Prediction for COVID-19 with Audio

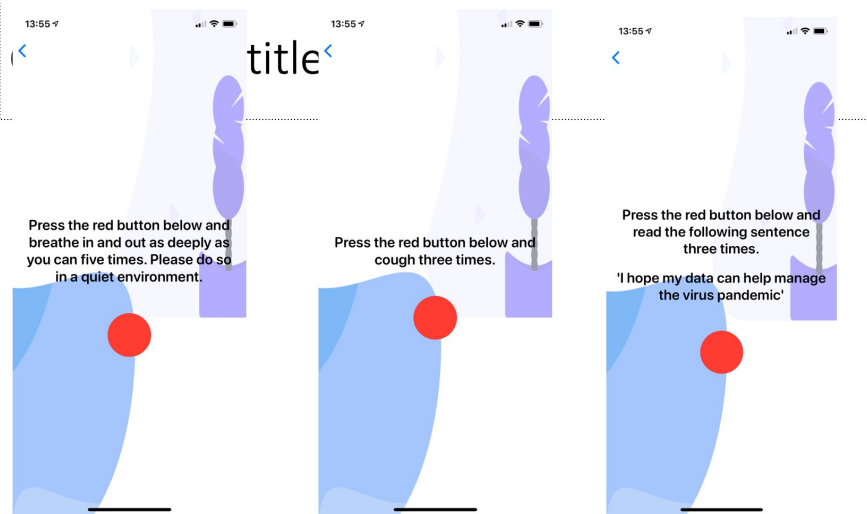


## COVID-19 Sounds App

Upload short recordings of cough and breathing and report symptoms to help researchers from the University of Cambridge detect if a person is suffering from COVID-19. Healthy and *non-healthy* participants welcome.



or use the online form



# Example of Confounding and Bias

- At some point our classifier was “too good”
- Bias:
  - Our training data was biased: Italians had COVID and English did not
  - Our model was learning if the people were speaking English or Italian 😊
  - The model was **biased by language: solution was to control for language**



# Ethics!

- Sensitive data: continuous nature, very personal, very revealing, easily collected, easily aggregated...
- What can be done?
  - On device approaches
  - Differential privacy
  - Federated learning
- Model development vs model deployment



# Outline

- 1 Introduction
- 2 Signal Processing Primer
- 3-4 PPG: Physiological and Sleep monitoring
- 5-6 Audio for Health Diagnostics and Physiology
- 7-8 Inertial Measurement Units and Human Activity
- 9-10 Bluetooth and GPS: Population Health and Contact/Location Tracing
- 11 Radios and Contactless Health Monitoring
- 12 Apps, Behaviour Intervention (and Applied Reinforcement Learning)
- 2 Practical Classes (8<sup>th</sup> February, 22<sup>nd</sup> February)
- 2 Guest Lectures

# Guest Lectures

- 29<sup>th</sup> February 2pm: Tong Xia, University of Cambridge
- 5<sup>th</sup> March 2pm: Dr Alessandro Montanari, Nokia Bell Labs



# Seminars on Mobile and Wearable Health

- Generally at 4pm on Tuesdays in FW26 (some online)

## Mobile and Wearable Health Seminar Series

[Add to your list\(s\)](#) [Halt your e-mail reminders](#) [Further detail](#) [Edit this list](#)  
[Subscribe using ical/vcal](#) ([Help](#))

Talks about applications of mobile and wearable systems to health


Tell a friend about this list:


If you have a question about this list, please contact: [Cecilia Mascolo](#); [tx229](#). If you have a question about a specific talk, click on that talk to find organiser.

11 upcoming talks and [17 talks in the archive](#).

### Dealing with uncertainty in physiological sensing in the wild

 Christian Holz, ETHZ.


 Computer Lab, FW26 and Online.


 Tuesday 23 January 2024, 16:00-17:00

### Title to be confirmed

20240123T160000


 Silvia Santini, Universita' della Svizzera Italiana.


 Computer Lab, FW26 and Online.

 Tuesday 30 January 2024, 16:00-17:00


### Title to be confirmed

 Alex Casson, University of Manchester.

 Computer Lab, FW26 and Online.

 Tuesday 06 February 2024, 16:00-17:00

### AI for Health with Wearables

 Chenyang Lu, Washington University in St Louis.

 Online.

 Tuesday 13 February 2024, 16:00-17:00



# Course Assessment

- **Two assignments** based on datasets :
- **First** assignment (worth 40% of the final mark): preprocessing and basic data analysis steps in a “colab” style report. (1000 words)
  - Deadline: **19<sup>th</sup> February 2024**
- **Second** assignment (worth 60% of the final mark) will be a fuller analysis where the students are asked to compare and contrast ML algorithms/solutions and discuss findings and interpretation in terms of health context.
  - **Part II:** This will be in the form of a colab and a reflection report of 1200 words.
  - **Part III/MPhil:** This will be in the form of a colab and a reflection report of 1800 words.
  - Deadline: **15<sup>th</sup> March 2024**

# Where to find information

- <https://www.cl.cam.ac.uk/teaching/2324/MH/>
- <https://www.cl.cam.ac.uk/teaching/2324/L349/>

# Student Support: Office Hours

## ✓ Assignment Support

### Office Hours for Assignment 1:

- 13/02/2024: 3:00 - 4:00 PM in room FW26 (after lecture)
- 15/02/2024: 3:00 - 4:00 PM in room FW26 (after lecture)

### Office Hours for Assignment 2:

- 05/03/2024: 3:00 - 4:00 PM in room FW26 (after lecture)
- 12/03/2024: 3:00 - 4:00 PM in room FW26 (no lecture, only office hour)

# Student Support: On Moodle

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## Assignment 1 Open Help Forum

Please feel free to post here any questions you may have with regards to Assignment 1.

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## Assignment 2 Open Help Forum

Please feel free to post here any questions you may have with regards to Assignment 2.



# Teaching Assistants



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Sotiris Vavaroutas



Yvonne Wu

Questions?