Mobile and Ubiquitous Computing on Smartphones
Chapter 9b: Smartwatch, Health Tracking, Physiological Sensing & Voice Analytics

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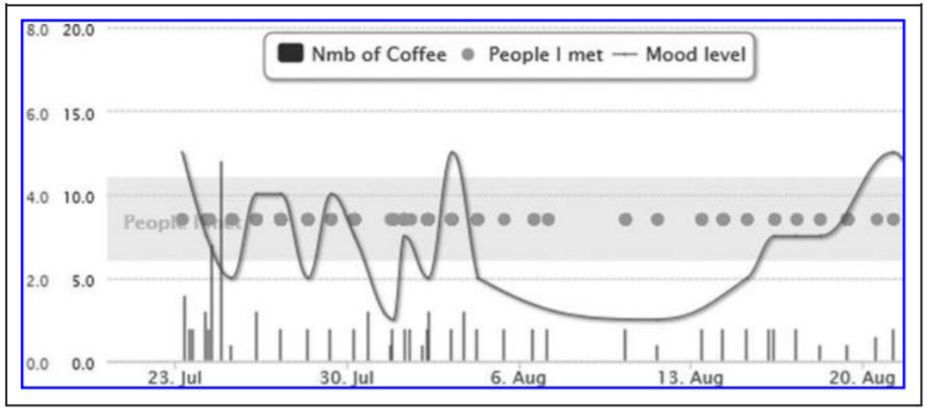
Tracking Health & Wellness

Tracking Health Data

- Increased interest in tracking personal health data
  - Sleep, daily step count, food consumed, air quality, mood, etc.
- Measurements done using wearables/technology, now cheaper
  - Activity trackers, steps, sleep tracker, calories burned, etc
- Why tracking?
  - Figure out causes of certain behaviors
    - E.g. Why do I feel tired on Friday afternoons?
  - Get data support choices/decisions
    - Did that cup of coffee make you more productive?
  - Discover new patterns that are fixable
    - When I go to my mother's house, I add 5 lbs. on Monday morning
    - Am I happier when I meet more people or when I drink more coffee?



Courtesy
Melanie Swan

Variety of Wellness Tracking Devices

Smart fork: eating/calories

Heart-rate monitor

Bluetooth scale

Body worn activity trackers (steps, activities, calories)

Smartwatches + Wearables

Main Types of Wearables

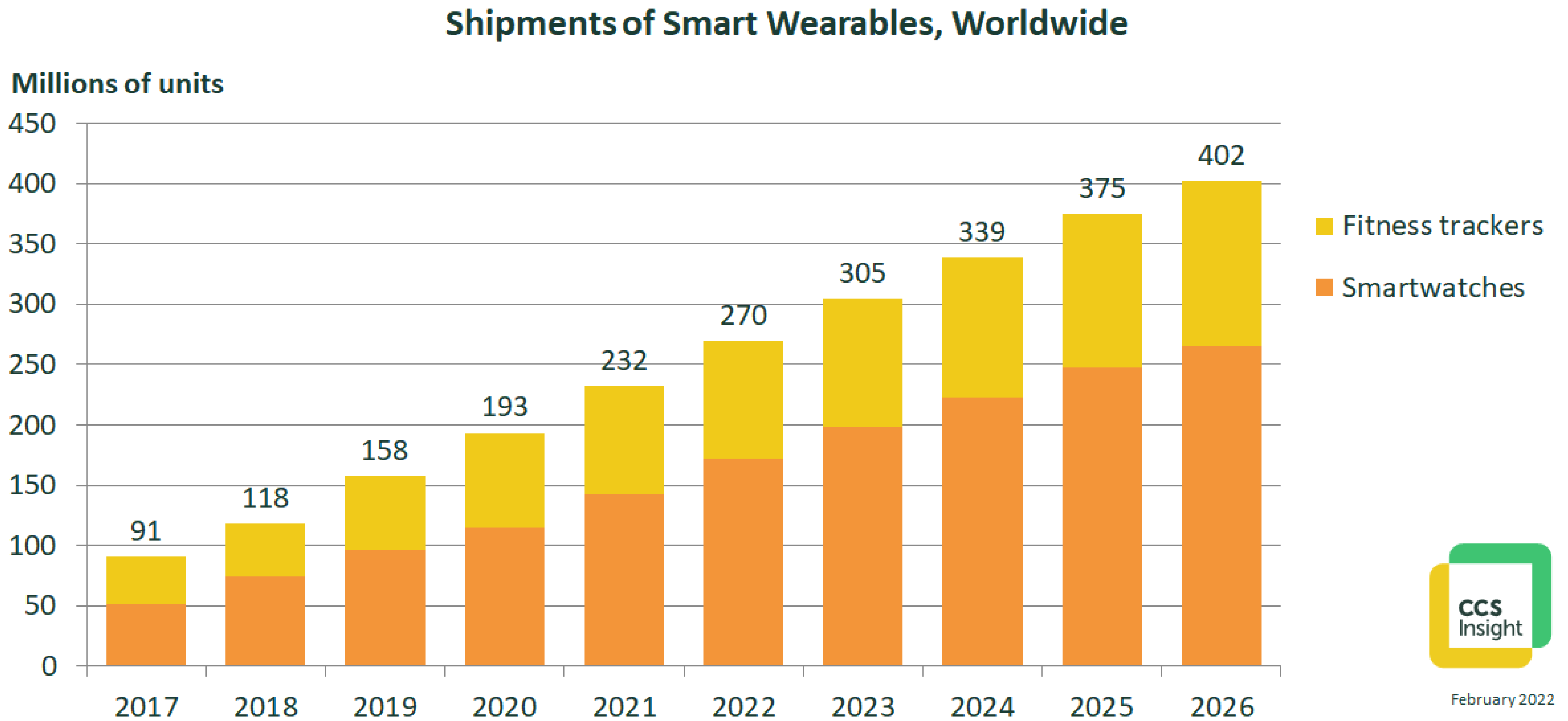
- **Activity/Fitness Trackers:**
  - physiological sensing (activity, step count, sleep duration and quality, heart rate, heart rate variability, blood pressure, etc)
  - E.g. Fitbit Charge 5
- **Smartwatches**
  - Activity/fitness tracking
  - Also programmable: notifications, receive calls, interact/control smartphone
  - E.g. Apple watch, Samsung Galaxy watch

Fitbit Charge 5

Apple Watch 9

Samsung Galaxy watch 6 SmartWatch

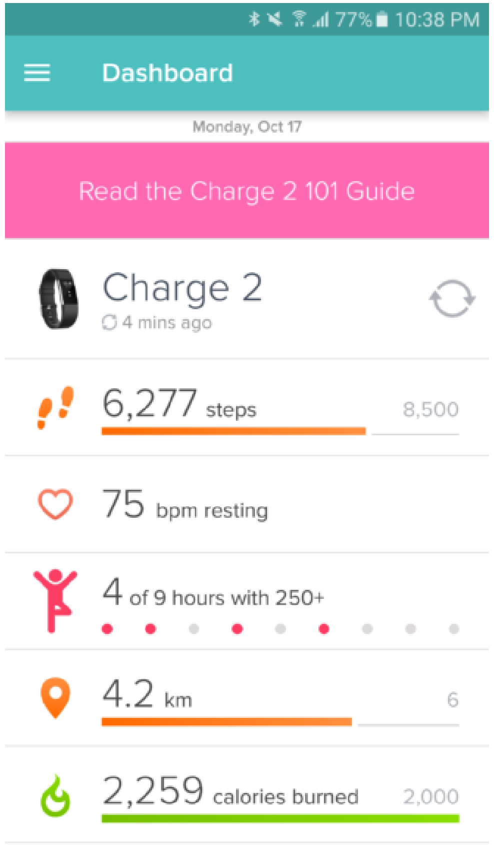
How Popular are Smartwatches/Wearables?



Wearables Example: Fitbit Charge 5

Fitbit Charge 5

synchronize



Smartphone companion app
(displays all variables tracked)

Example: Samsung SmartWatch Uses

Image credits: Samsung

SmartPhone Vs Smartwatch

- Smartphone:
  - More processing power, memory, sensors
  - More programming APIs

- Smartphone Cons:
  - Sometimes not carried (Left on table, in pocket, bag, briefcase, gym locker)
    - Smartphone within arms reach, on person ~57% of the time (Anind Dey *et al*, Ubicomp 2011)
  - Why? Sometimes inconvenient, impossible (e.g when swimming)
  - Consequence: Missed activity (steps, activity, etc), incomplete activity picture

- Smartwatch:
  - Lower processing power, memory, sensors, but always carried/worn
  - Can sense physiological variables continuously, or require contact (e.g. skin temperature)

Android Wear Evolution

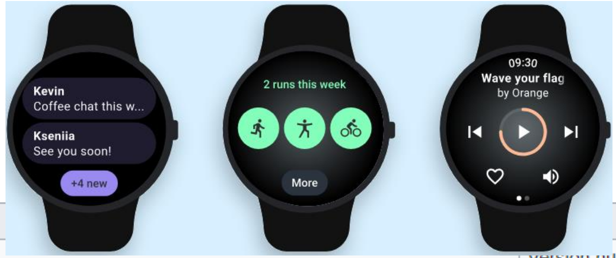
https://en.wikipedia.org/wiki/Android_Wear

Android Wear Version	Android Smartphone Version	Release Date	Major New Features
4.4W1	4.4	June 2014	**Initial release at Google I/O 2014**
4.4W2	4.4	Oct 2014	GPS support, music playback
1.0	5.0.1	Dec 2014	Watch face API (face design) Sunlight & theater modes, battery stats
1.1	5.1.1	May 2015	WiFi, Drawable Emojis, Pattern Lock, swipe left, wrist gestures
1.3	5.1.1	Aug 2015	Interactive Watch Face, Google Translate
1.4	6.0.1	Feb 2016	Speaker support, send voice messages
1.5	6.0.1	June 2016	Restart watch, Android security patch
2.0	7.1.1	Feb 2017	UI (material design, circular faces), watch keyboard, handwriting recognition, cell supp.

Evolved into Google Wear OS in June 2018!!

Wear OS Evolution

https://developer.android.com/design/ui/wear



Wear OS version	System versions	Release date	New features	Notes
1.0[51]	Android 8 Oreo	March 2018	• Rebranding to Wear OS[52] • Expand Google Pay Support in more countries	Version number reset to "1.0". Wear OS App version: 2.10[53]
1.4	Android 8 Oreo	July 2018	• Faster Google Pay startup • More glanceable design for events and appointments • Time zone sync bug fix[54]	Wear OS App version: 2.14[55]
2.0	Android 8 Oreo	September 2018	• Swipe actions for faster access to Google Assistant and Google Fit[56] • Google Assistant feed with proactive personalized information • New design for quick toggles and notifications stream • New music controls with physical button support • Bolder font in the app launcher	Wear OS App version: 2.18
2.2	Android 9 H MR1	November 2018	New features for System version H MR1: • Brings Android 9.0 Pie features to smartwatches • Enables Battery Saver mode to only display the time once the battery falls below 10% • Improves restoring the state of previously used apps • Watches now enter a deep sleep mode after 30 minutes of inactivity • Holding down the power button now provides options for shutting down or restarting the watch	Wear OS App version: 2.20
2.6	Android 9 H MR1	May 2019	• *Tiles* functionality when swiping left, providing access to next calendar events, weather forecast, heart rate, news headlines and timer functionality.[57]	Wear OS App version: 2.24
2.7	Android 9 H MR1	June 2019	• Bugfixes	Wear OS App version: 2.25
2.9	Android 9 H MR1	July 2019	• Notifications	Wear OS App version: 2.26
2.17	Android 9 H MR1	April 2020	• New 'Wash hands' timer regarding coronavirus. • New UI and Tiles for Google Fit	Wear OS App Version: 2.35
2.19	Android 9 H MR2	September 2020	Changes in System H MR2:[citation needed] • CPU core improvements: app launch and boot time up to 20% faster • SysUI improvements: more intuitive controls for managing different watch modes and workouts • Increased performance with the Qualcomm Snapdragon Wear 4100 and 4100+ platforms • Improved LTE support • Simplified pairing process • Better battery life • Support for an increased numbers of Tiles • New Weather Tile design • Upcoming changes to Music	Wear OS App version: 2.40
Upcoming	Android 11	2021	Brings Android 11 features to smartwatches • New features	Wear OS App version:

Evolved from Android Wear to Google Wear OS in June 2018!!

Physiological Sensing

Wearables for Physiological Sensing

- Some wearables measure more physiological signals
  - Cardiac rhythms (heartbeat), breathing, sweating, brain waves, gestures, muscular contractions, eye movements, etc
- **Whoop:** blood oxygen, skin temperature, heart rate, recovery, sleep
- **Amazfit band:** Blood Oxygen, Heart Rate, Sleep & Stress Monitoring
- **Nowatch:** steps, heart rate, respiratory rate, skin conductance and mental focus

Whoop

Amazfit

Nowatch

Empatica E4 WristBand

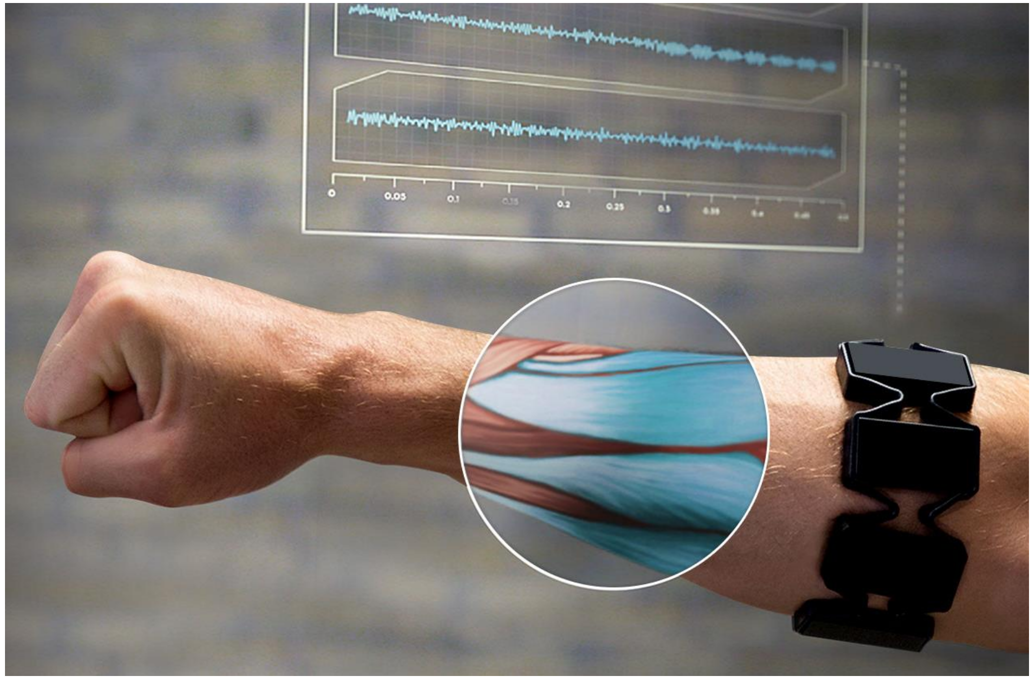
- Wristband measures physiological signals real time
- Measures: PPG, EDA, accelerometer, infra-red temperature reader

E4 wristband

Companion app

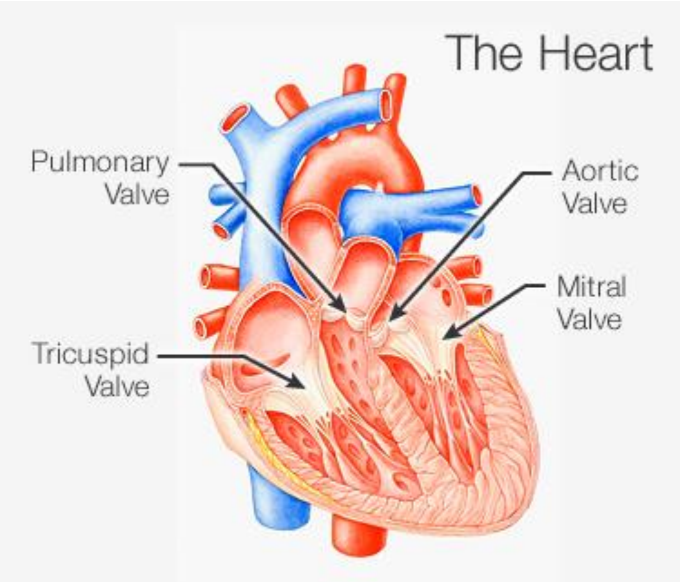
Myo Armband

- Measures muscle contraction (electromyography or EMG), detects gestures
- EMG measures electrical activity, used to assess health of muscles

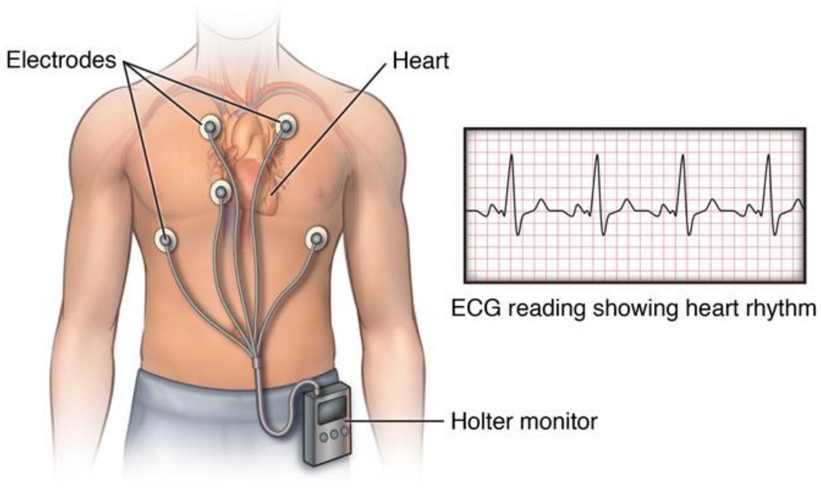


Electrocardiogram (ECG)

- Each heartbeat causes electrical signal from top to bottom of heart
- ECG (or EKG): recording of heart's electrical activity
- Electric Signal
  - is rhythmic, causes heart to contract and pump blood
  - Can be measured as electric activity between 2 electrodes placed on chest



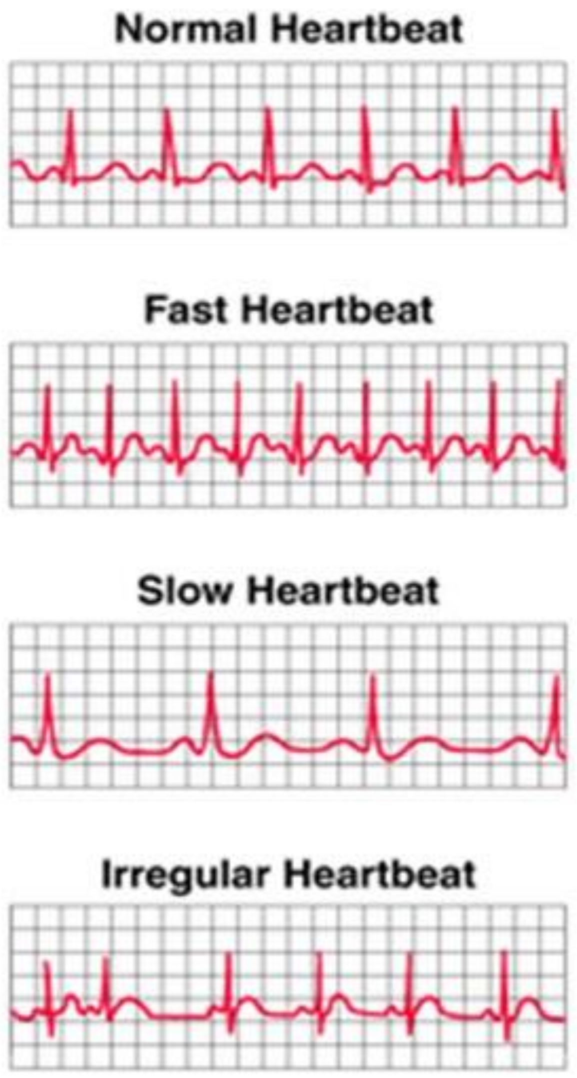
Holter monitor with ECG reading



Electrocardiogram (ECG)

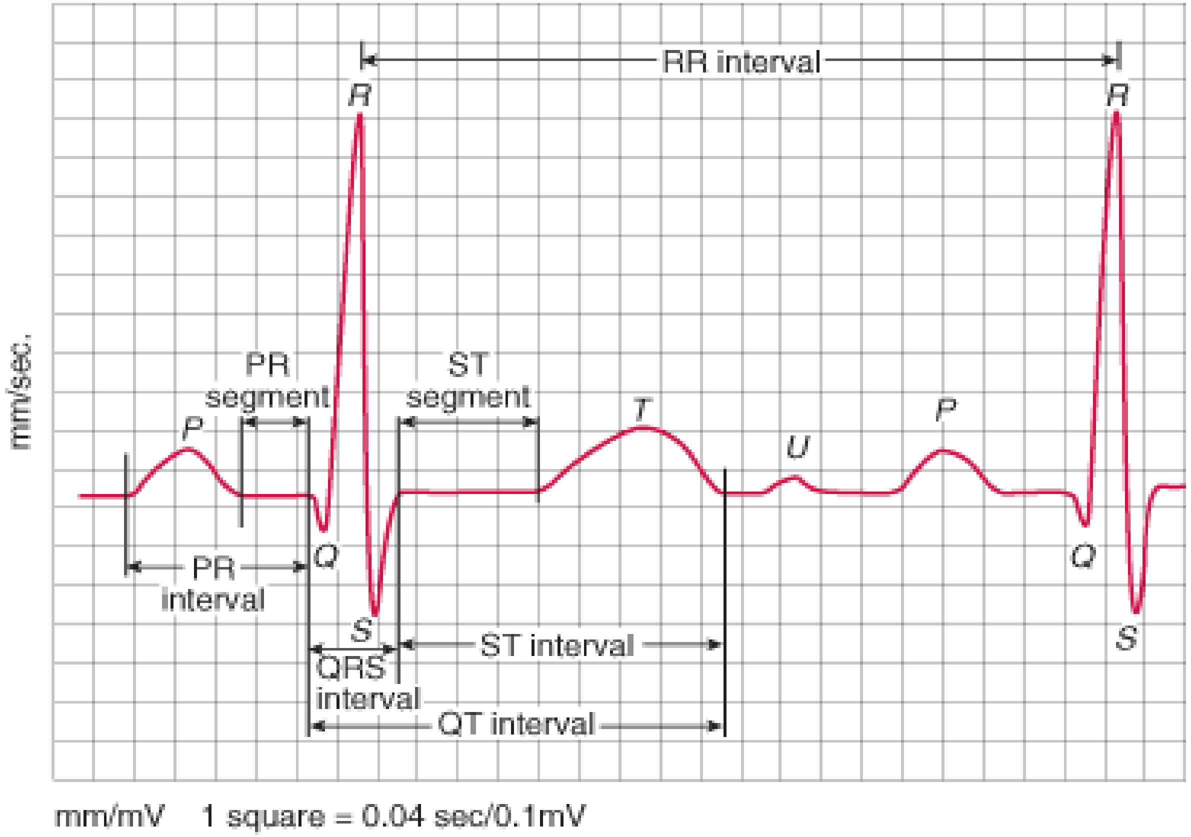
- ECG shows:
  - How fast the heart is beating
  - Rhythm of heartbeat (steady vs irregular)
  - Strength and timing of electrical signals

- **Arryhthmia:** fast or irregular heartbeat, can cause stroke or heart failure



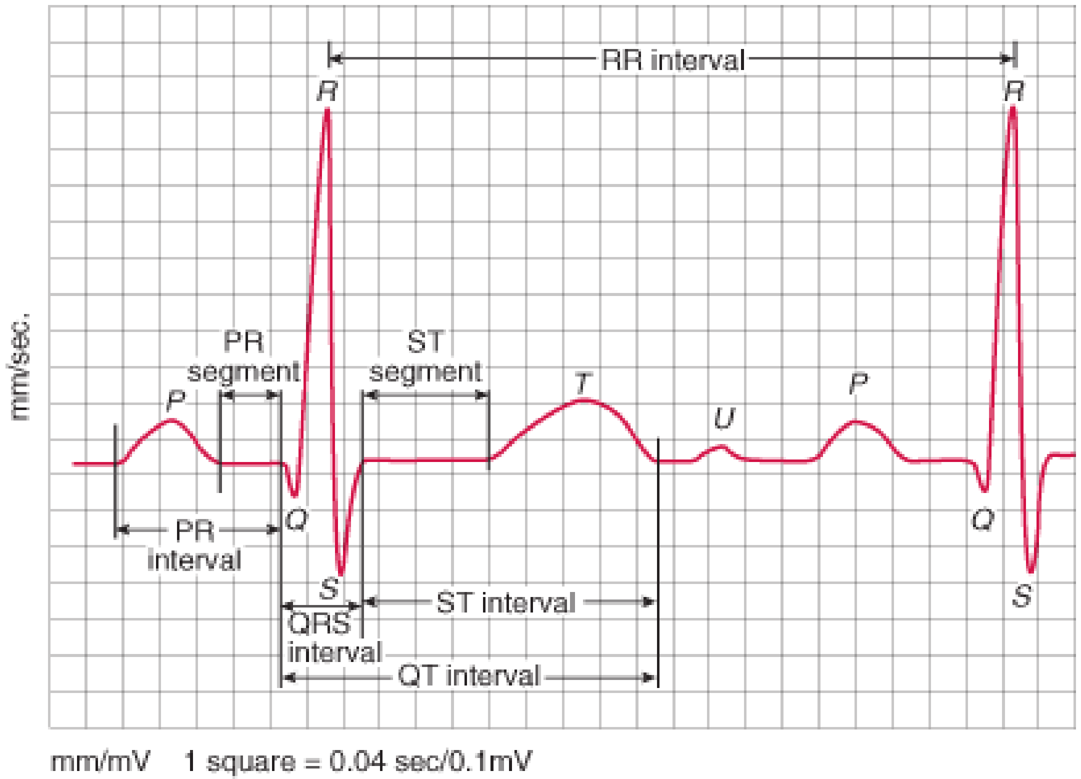
Electrocardiogram (ECG)

- ECG waveform comprises sequence of peaks and trough (P,Q,R,S,T), which repeats



ECG Features for Classification

- From a waveform can extract wave intervals as features for classification
  - RR interval
  - PR interval
  - QRS interval
  - QT interval, etc



- Heartrate is number of RR intervals/min = 60 / RR

- Note: RR in seconds

Trends: Mobile ECG

- E.g. AliveCor kardia ECG
  - Hold 2 fingers on metal plates (ECG recorder) for at least 30 seconds

Photoplethysmography (PPG)

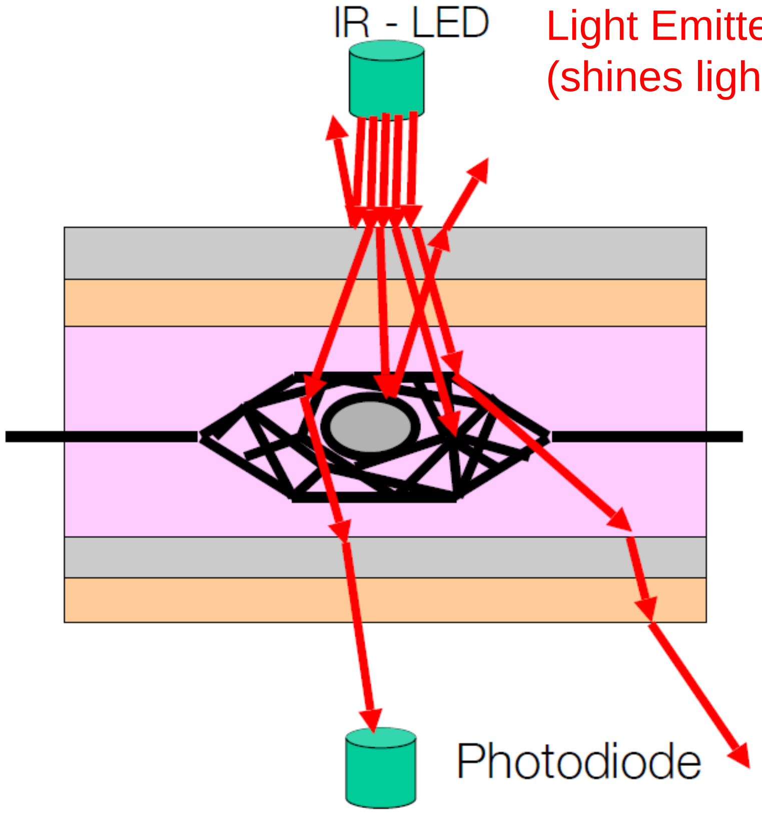
- **PPG:** Non-invasive technique for measuring blood volumes in blood vessels close to skin
- Now used as non-invasive method of extracting physiological measurements e.g. heart rate or oxygen saturation
- Traditional device for PPG is pulse oximeter
  - Measures concentration of oxygen in the blood
  - Low oxygen levels (< 80%) can compromise organs, lead to heart attack , etc

Pulse Oximeter

Pulse Oximeter PPG

- Amount of oxygen in the blood determines how much infared light absorbed, scattered, passes through (from LED to photodiode)

Image credit: Deepak Ganesan



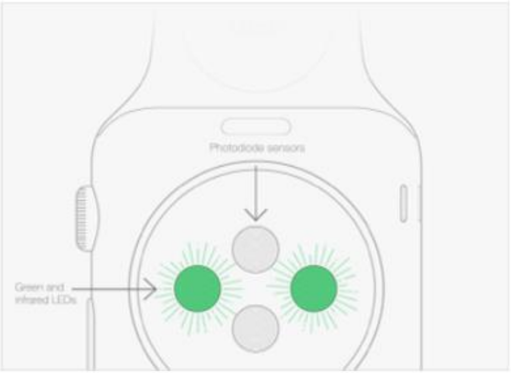
Light Emitter (shines light)

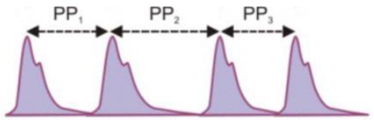
Light passes through finger

Light Detector detection

Smartphone/Smartwatch PPG: Estimating HR

- **Principle:**
  - Blood absorbs green light
  - LED shines green light unto skin (back of wrist)
  - Blood pumping changes blood flow and hence absorption, reflection rhythmically
  - Photodiode measures rhythmic changes in green light absorption, reflection => HR





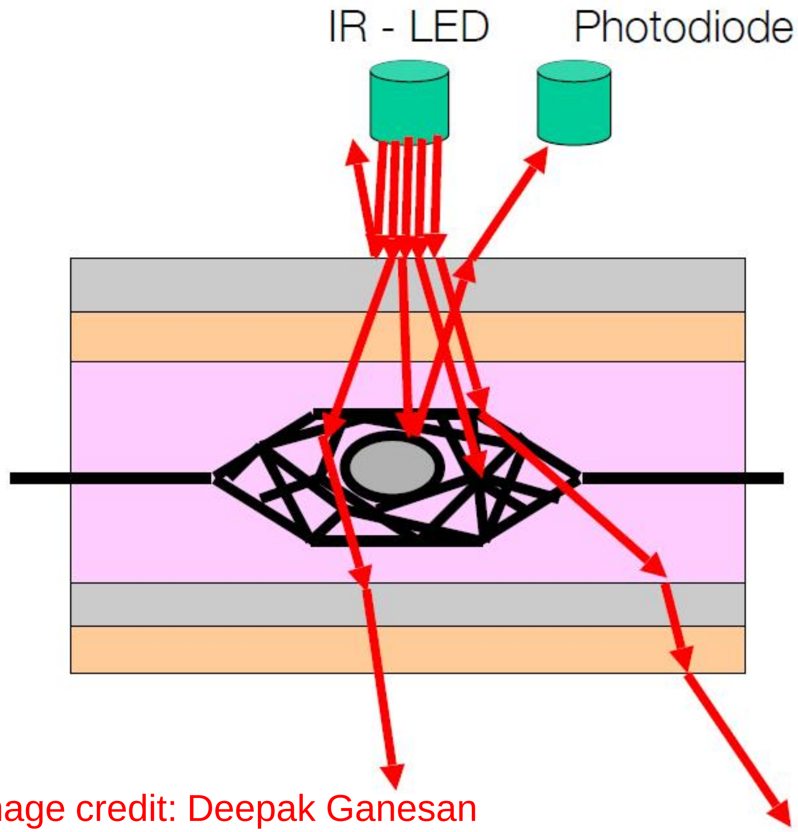


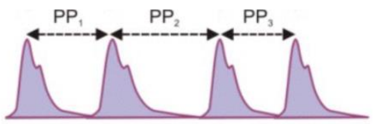
Image credit: Deepak Ganesan

Smartphone PPG: Heart Rate Detection

- Like smartwatch, use camera flash (emitter), camera as detector
- Place finger over smartphone's camera, shine light unto finger tip
- Heart pumps blood in/out of blood vessels on finger tip
  - Changes how much light is absorbed (especially green channel in RGB)
  - Causes rhythmic changes of reflected light (detected by camera)
- **Ref:** Scully CG, Lee J et al."Physiological parameter monitoring from optical recordings with a mobile phone", IEEE Trans Biomed Eng, 2012 Feb;59(2):303-6

Smartphone PPG: Heart Rate Detection

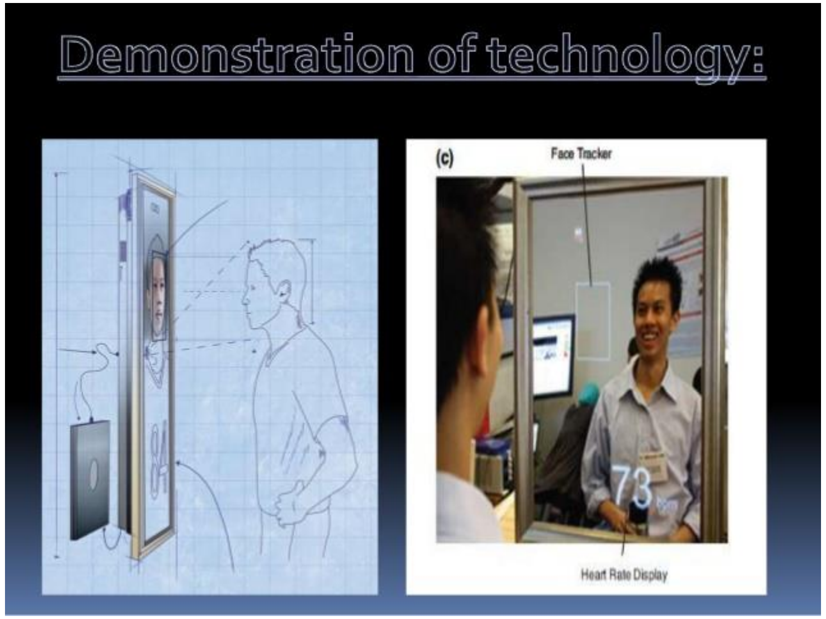
- **Idea:**
  - Color expressed as (R G B)
  - Track intensity of Green channel of Camera response
  - Use peak finding algorithm (similar to step counter)
  - Time between peak is 1 cycle
  - Heart rate = cycles per minute = 60 / time for 1 cycles
- Can also extract breathing rate, heart rate variability



PPG: Final Words

- PPG (or similar ideas) have been attempted:
  - on other body parts (ear lobes, face)
  - from video frames (detect, magnify small changes in facial color 100x)
  - Using other ubiquitous devices (e.g. Medical Mirror, Poh *et al*)

H.Y Wu, M. Rubinstein, E. Shih, J. Guttag, F. Durand, W.T. Freeman, Eulerian Video Magnification for Revealing Subtle Changes in the World. SIGGRAPH 2012



MZ **Poh**, D McDuff, R Picard A medical **mirror** for non-contact health monitoring, ACM SIGGRAPH 2011 Emerging technologies

Electrodermal Activity (EDA)

- When people experience emotional arousal (e.g. danger), stress, cognitive load or physical exertion => increased sweating
- Increased sweating changes electrical conductance of skin
- Sometimes called Galvanic Skin Response (GSR)
- This response cannot be controlled by person
  - Hence, widely used in emotion/lie detection

EDA Features

- Features useful for classifying measured human EDA response
  - **Latency:** time between stimulus and response
  - **Rise time:** time for skin conductance to peak
  - **Amplitude:** Height of conductance signal
  - **Half recovery time:** Time for conductance signal to lose half of its peak value

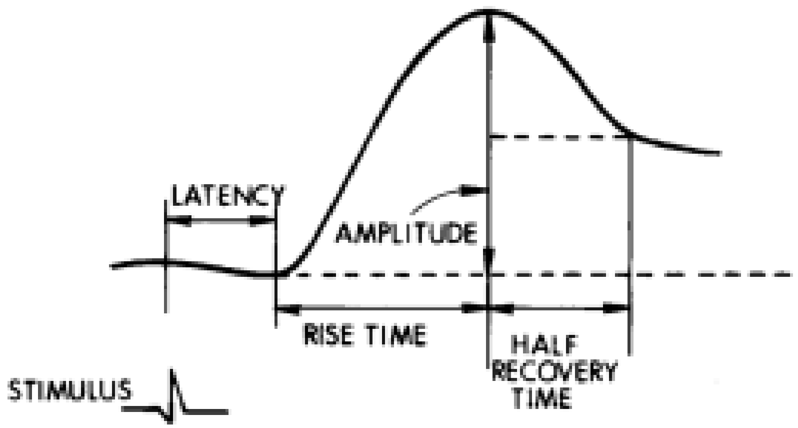
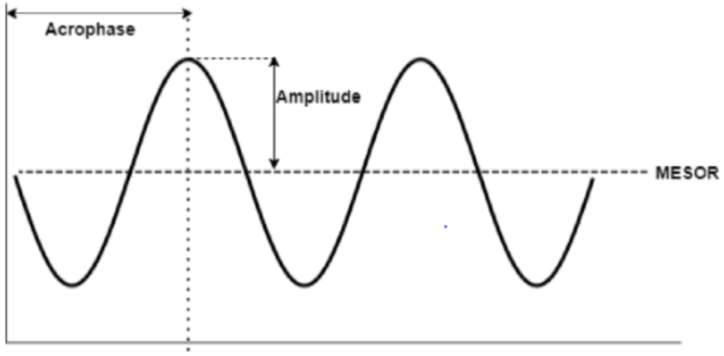


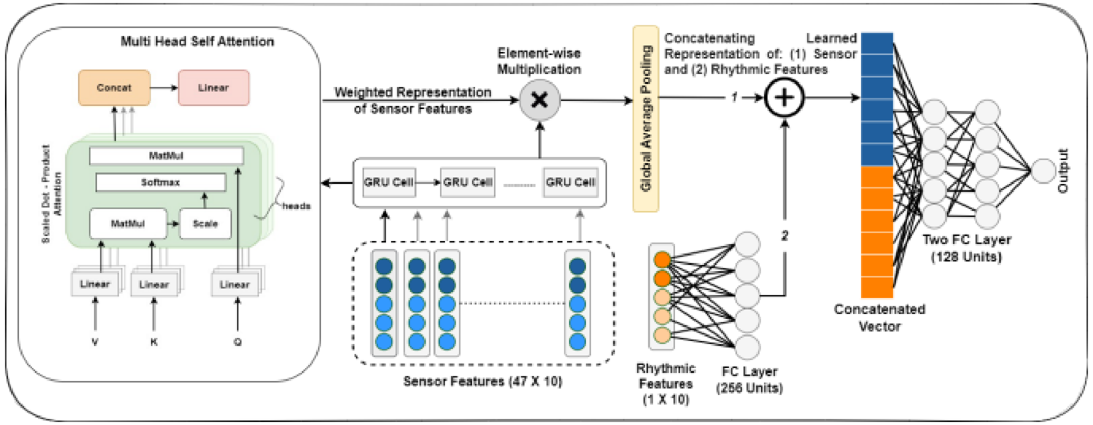
Figure 5. Graphical representation of principal EDA components.

Detecting Covid from Fitbit data

Sarwar, A., Agu, E.O. and Almadani, A., 2023. CovidRhythm: A Deep Learning Model for Passive Prediction of Covid-19 using Biobehavioral Rhythms Derived from Wearable Physiological Data. *IEEE Open Journal of Engineering in Medicine and Biology*.

- Circadian Rhythm: biological rhythms in human body.
  - E.g. Sleep-wake cycles
- Covid disrupts circadian rhythms
- Fitbit gathers step (wake), heart rate data
- Fit data to Cosinor function (sinusoid) sleep-wake cycle
- Extracted circadian rhythm features
- Classified using deep learning model
- 0.79 AUC-ROC





Speech Analytics

Voice Based Analytics

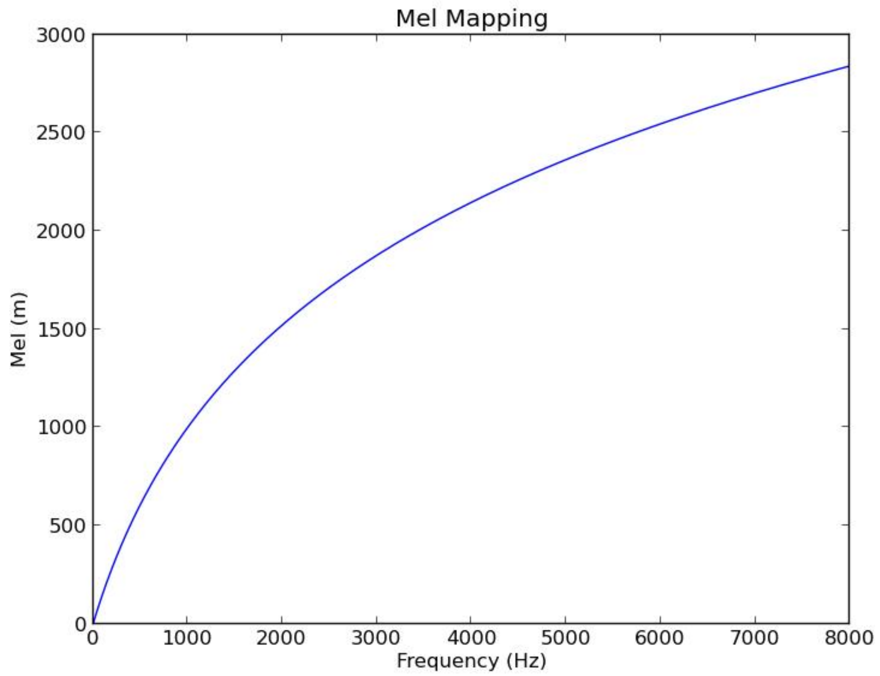
- Voice can be analyzed, lots of useful information extracted
  - **Speaker identification:** Who is talking?
  - How many social interactions a person has a day
  - Emotion of person while speaking
  - Anxiety, depression, intoxication, of person, etc.
- For speech recognition, voice analytics:
  - Discards useless information (background noise, etc)
  - Identify and extract linguistic content

Mel Frequency Cepstral Coefficients (MFCCs)

- MFCC features widely used in speech and speaker recognition for representing envelope of **power spectrum of voice**
- **Power spectrum?** Amount of power at various frequencies
- Power in male vs. female voices
  - Male voice: low frequency (bass)
  - Female voice: high frequency (treble)
- Popular approach in Speech recognition
  - MFCC features + Hidden Markov Model (HMM) classifiers (or other Machine learning classifiers)

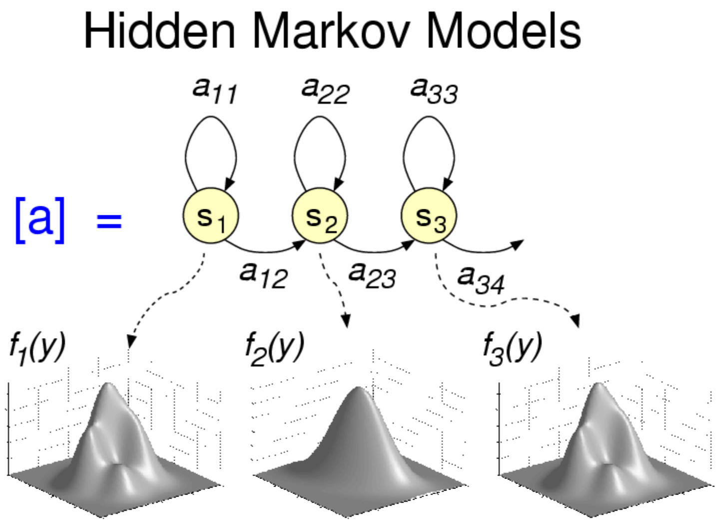
MFCC uses Mel Scale

- Transforms speech attributes (frequency, tone, pitch) on non-linear scale based on human perception of voice
  - Result: non-linear amplification, MFCC features that mirror human perception
  - E.g. humans good at perceiving small change at low frequency than at high frequency



Speech Classification

- Human speech can be broken into phonemes
- Example of phoneme is /k/ in the words (**c**at, s**ch**ool, s**k**ill)
- Classic Speech recognition tries to recognize sequence of phonemes in a word
- Typically uses Hidden Markov Model (HMM)
  - Recognizes letters, then words, then sentences
  - Like a state machine that strings together (transition) sequence of sounds recognized



Speech/Language Analytics/NLP

Audio Project Ideas

- OpenAudio project, http://www.openaudio.eu/
- Many tools, dataset available
  - OpenSMILE: Tool for extracting > 1000 audio features
    - Windowing
    - MFCC
    - Pitch
    - Statistical features, etc
    - Supports popular file formats (e.g. Weka)
  - OpenEAR: Toolkit for automatic speech emotion recognition
  - iHeaRu-EAT Database: 30 subjects recorded speaking while eating

Affect Detection

Physiological Measurement of Emotion

- Emotions cause physical response in humans

Emotion	Physiological Response
Anger	Increased heart rate, blood vessels bulge, constriction
Fear	Pale, sweaty, clammy palms
Sad	Tears, crying
Disgust	Salivate, drool
Happiness	Tightness in chest, goosebumps

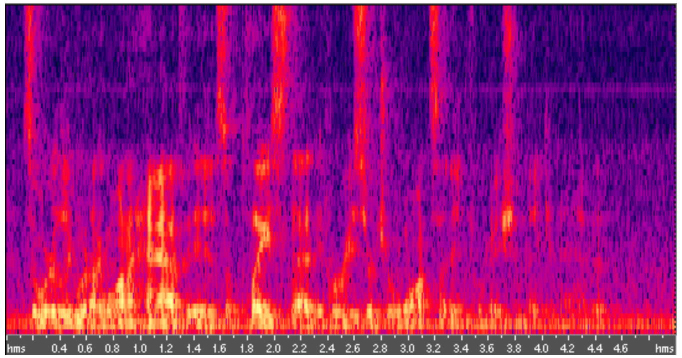
Audio Features for Emotion Detection

- MFCC good for analysis of speech content, Automatic Speaker Recognition (ASR)
  - Who is speaking? Bob vs. Susan
- Other audio features better to capture sound characteristics/dynamics (prosody)
  - E.g. detecting emotion in speech
- **Pitch:** the frequency of a sound wave. E.g.
  - Sudden increase in pitch => Anger
  - Low variance of pitch => Sadness

Audio Features for Emotion Detection

- **Intensity:** Energy of speech, intensity. E.g.
  - Angry speech: sharp rise in energy
  - Sad speech: low intensity

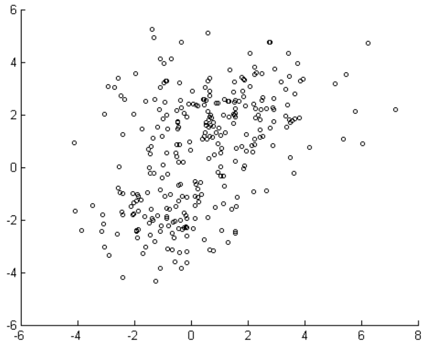
- **Temporal features:**
  - Speech rate, voice activity (e.g. pauses)
  - E.g. Sad speech: slower, more pauses

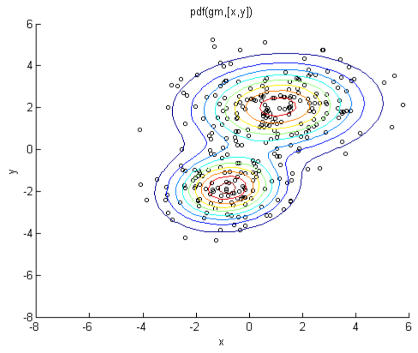


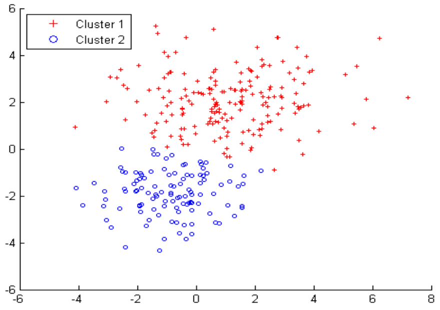
- **Other emotion features:** Voice quality, spectrogram, statistical measures

Gaussian Mixture Model (GMM)

- GMM used to classify audio features (e.g. depressed vs not depressed)
- **General idea:**
  1. Plot subjects audio features in a multi-dimensional feature space
  2. Cluster points (e.g. depressed vs not depressed)
  3. Fit to gaussian (normal) distribution (assumed)
  4. Parameters of GMM are features for classification of health condition







Uses of Affect Detection
E.g. Using Voice on Smartphone

- Audio processing (automatically detect affect, mental health) can revolutionize healthcare
  - Detection of mental health issues automatically from patients voice
  - Population-level (e.g campus wide) mental health screening
  - Continuous, passive stress monitoring
    - Suggest interventions: breathing exercises, play relaxing music
  - Monitor social interactions, recognize conversations (number and duration per day/week, etc)

Voice Analytics Example: Mental Illness Diagnosis

- What if depressed patient lies to psychiatrist, says “I’m doing great”
- Mental health (e.g. depression) detectable from voice, can be used to detect lying patient
- Doctors pay attention to speech aspects when examining patients

Category	**Patterns**
Rate of speech	slow, rapid
Flow of speech	hesitant, long pauses, stuttering
Intensity of speech	loud, soft
Clarity	clear, slurred
Liveliness	pressured, monotonous, explosive
Quality	verbose, scant

- E.g. depressed people have slower responses, more pauses, monotonic responses and poor articulation

Voice Analytics Example: SpeakerSense (Lu et al)

Lu, H., Brush, A.B., Priyantha, B., Karlson, A.K. and Liu, J., 2011, June. Speakersense: Energy efficient unobtrusive speaker identification on mobile phones. In *International conference on pervasive computing* (pp. 188-205). Springer, Berlin, Heidelberg.

- Identifies speaker, who conversation is with
- Used GMM to classify pitch + MFCC features

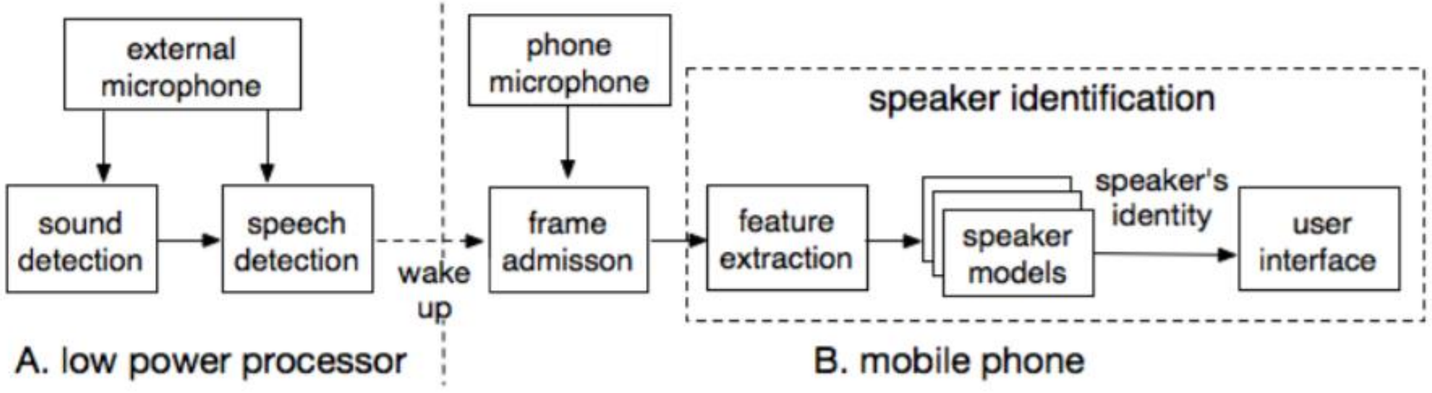


Fig. 1. The SpeakerSense architecture.

Voice Analytics Example: StressSense (Lu et al)

Lu, H., Frauendorfer, D., Rabbi, M., Mast, M.S., Chittaranjan, G.T., Campbell, A.T., Gatica-Perez, D. and Choudhury, T., 2012, September. Stresssense: Detecting stress in unconstrained acoustic environments using smartphones. In *Proceedings of the 2012 ACM conference on ubiquitous computing* (pp. 351-360).

- Detected stress in speaker's voice
- Best features: MFCC, pitch, speaking rate
- Classification using GMM
- Accuracy: indoors (81%), outdoors (76%)

Deep Learning

- Most speech analytics tasks now use deep learning
- Outside the scope of this class

Detection of COVID from Respiratory sounds

Brown, C., Chauhan, J., Grammenos, A., Han, J., Hasthanasombat, A., Spathis, D., Xia, T., Cicuta, P. and Mascolo, C., 2020. Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data. *arXiv preprint arXiv:2006.05919*.

- large-scale crowdsourced dataset of respiratory sounds collected to aid diagnosis of COVID-19.
- Are coughs and breathing of COVID-19 subjects distinguishable from those with asthma or healthy controls?
- Simple binary machine learning classifier distinguished healthy vs. COVID-19 sounds.
- Were able to distinguish
  - User who had COVID-19 + cough vs healthy user with a cough
  - Users who had COVID-19 + cough vs. Users with asthma and a cough.
- Models achieved an Area Under the Curve (AUC) of above 80% across all tasks.

Detection of COVID from Respiratory sounds

Brown, C., Chauhan, J., Grammenos, A., Han, J., Hasthanasombat, A., Spathis, D., Xia, T., Cicuta, P. and Mascolo, C., 2020. Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data. *arXiv preprint arXiv:2006.05919*.

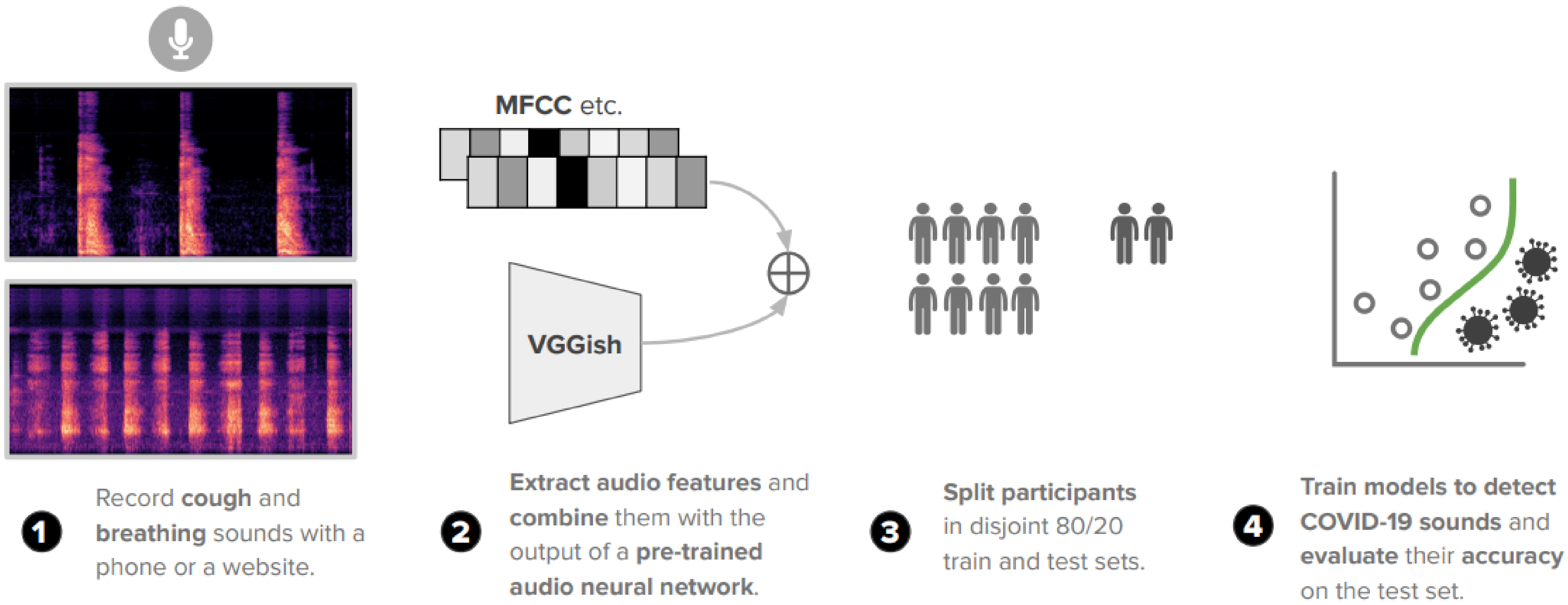


Figure 4: Description of our machine learning pipeline, describing sounds input (coughs and breathing), the extracted feature vector, and our training and testing split of the users that are used to train classification models.