

# Lecture 01

## Smart Phone Sensing

- Instructor

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- Lectures

- Monday: 08:30 – 10:30
- Wednesday: 15:30 – 17:30

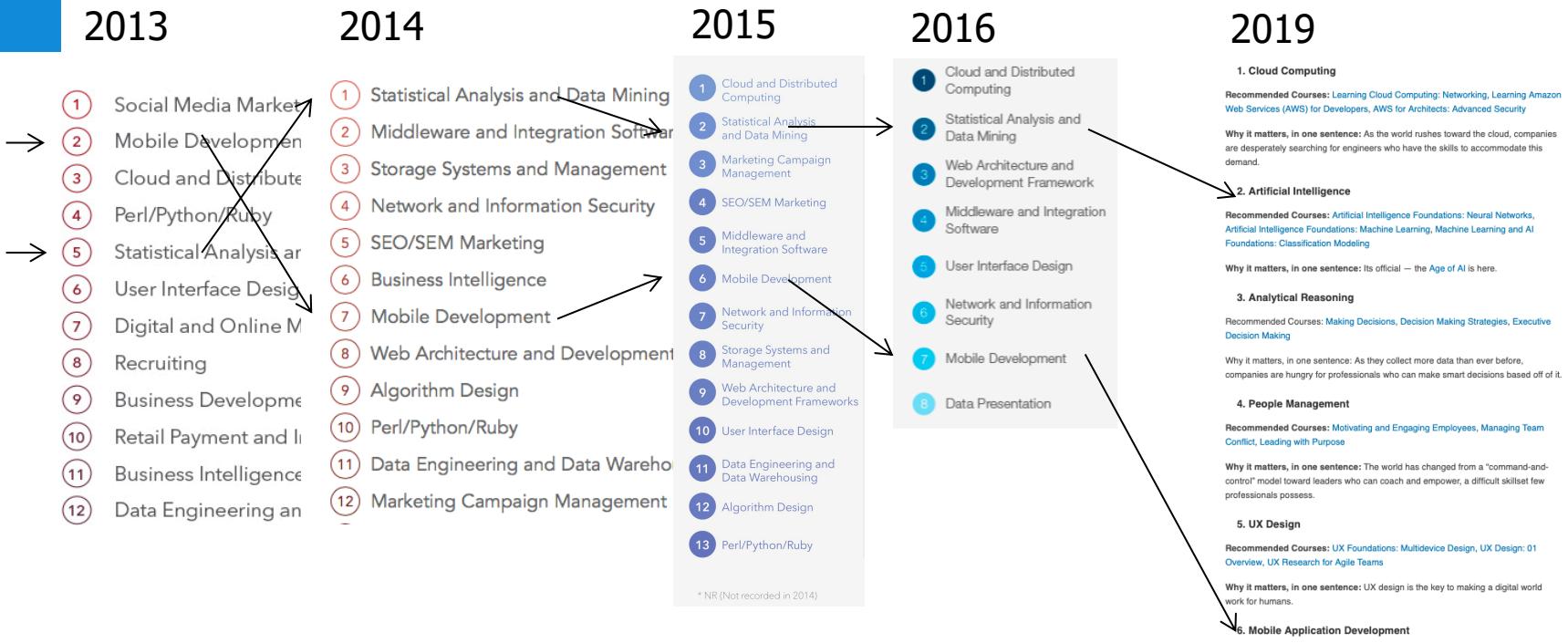
- Lab (not mandatory, mainly for advice and Q&A)

- Wednesday: 13:30 – 17:30 [Starting May 13<sup>th</sup>]

# WHY CARE?

# Why care?

## It is a good skill to have (LinkedIn)

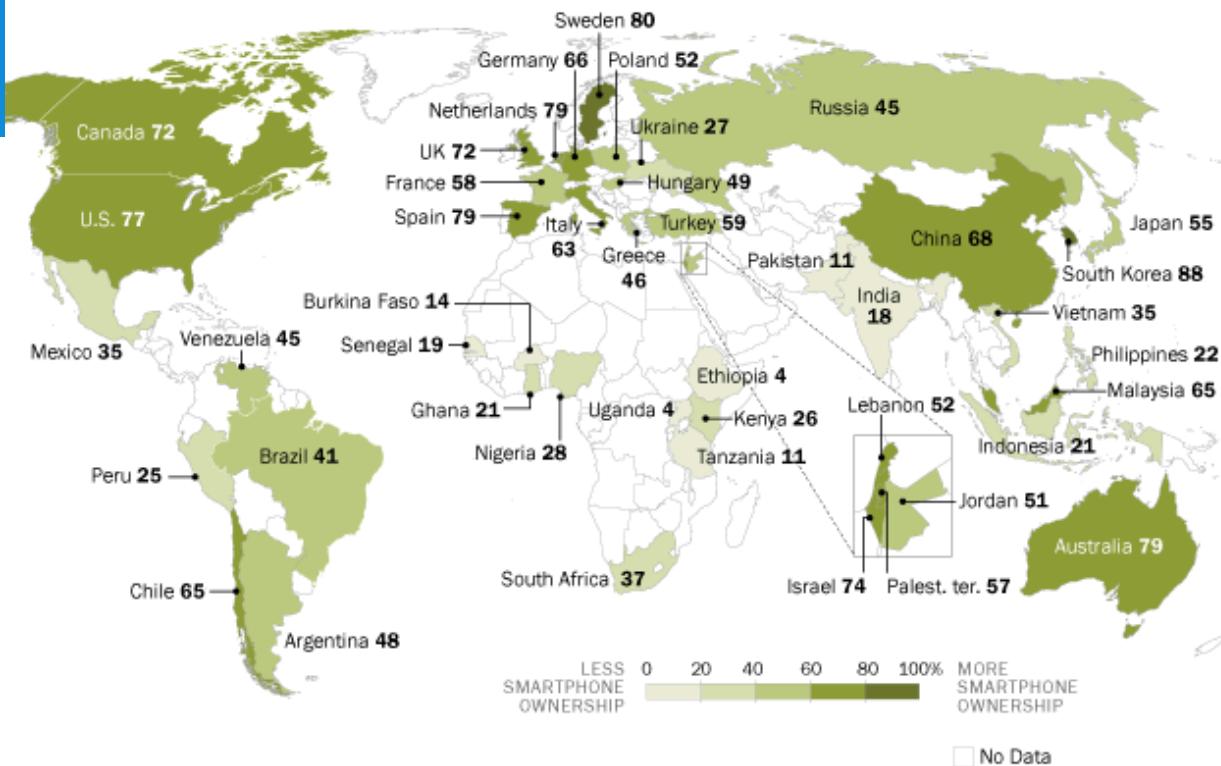


Source:LinkedIn

# Why is it a good skill? Planet of the phones

## Smartphones are more common in Europe, U.S., less so in developing countries

Percent of adults who report owning a smartphone



Note: Percentages based on total sample.

Source: Spring 2015 and 2016 Global Attitudes surveys.

PEW RESEARCH CENTER

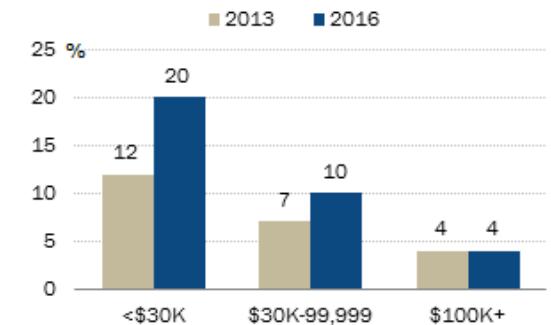
By 2019, US: 81, India: 24

45% of people in the world have a smartphone (by April 2020) [Source: statista.com]

Smartphones are far more popular than tablets and PCs

## Growing share of low-income Americans are smartphone-only internet users

% of U.S. adults who have a smartphone but no broadband at home, by annual household income



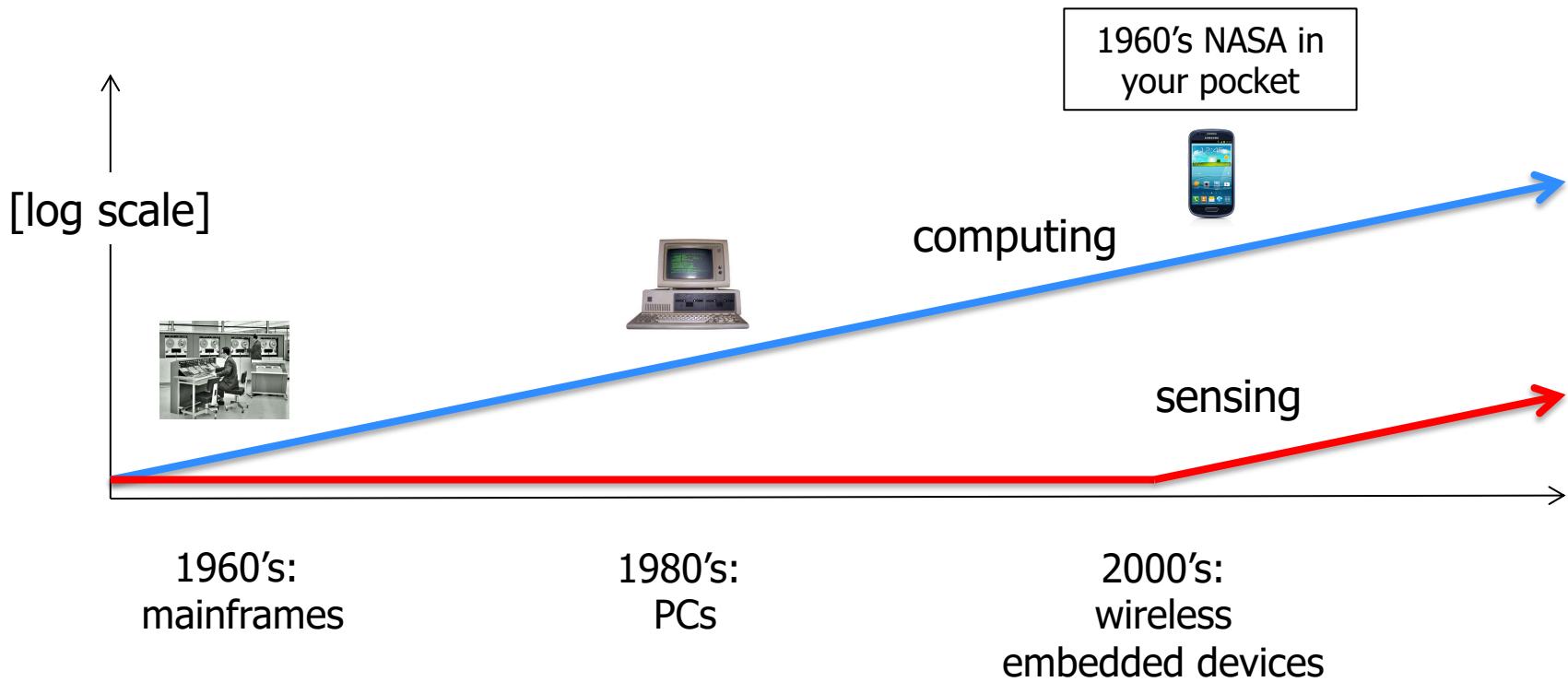
Source: Survey conducted Sept. 29-Nov. 6, 2016. Trend data from previous Pew Research Centers surveys.

PEW RESEARCH CENTER

# **TECHNICALLY, WHY ARE SMARTPHONES CREATING SUCH A REVOLUTION?**

# Why is it a good skill?

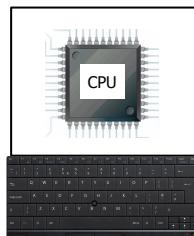
## Tackles a major technological change



For the first time in history we have plenty of **computing** and **sensing** capabilities

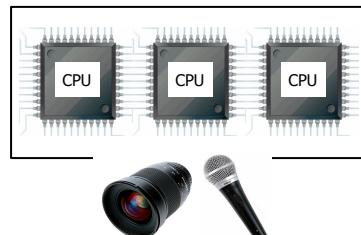
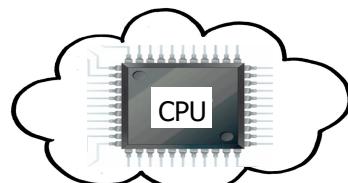
# Computation & Sensing

~until 2000



data

now



still missing



# tools creativity

# sensing computing

implies we can now gather tons of DATA  
implies we can process these tons of DATA



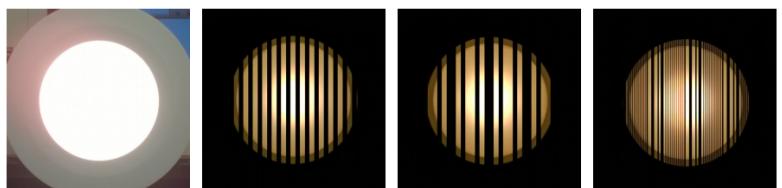
# Research example 1: Indoor localization

## Problem

- GPS does not work inside
- We spend almost 90% of our time indoors

## Solutions

- sensor: many, but let's look at a very recent one based on LEDs
- tool: Visible Light Communication
- output: information



Paper: "Luxapose: Indoor Positioning with Mobile Phones and Visible Light", ACM Mobicom 2014

# Research example 2: Sleep Apnea

## Problem

- treat sleep apnea at home

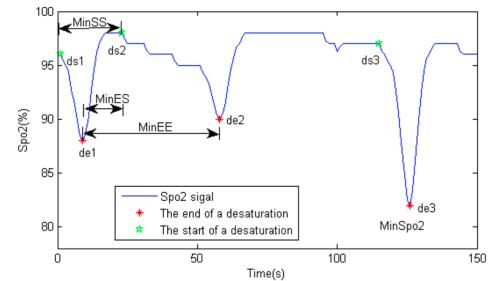


Paper:

"A real-time auto-adjustable smart pillow system for sleep apnea detection and treatment",  
IEEE/ACM IPSN 2013  
<http://dl.acm.org/citation.cfm?id=2461405>

## Solution

- sensor: pulsoximeter
- tools: machine learning
- actuation: adjustable pillow



# Reason to care

There are **lots of smartphones** out there ...  
... collecting **lots of data**  
... and enabling **lots of applications**

It is a good idea to know about them

# **WHAT APP WILL YOU DEVELOP?**

# Project (individual)

if there are too many students registered the project will be done in groups

## Option 1: Indoor Localization

- 1) Localization:  
RSS + KNN  
RSS + Filters  
IMU + Sensors
- 2) Innovation (beyond class):  
Light Sensors  
Your own ideas
- 3) GUI

## Option 2: Your own

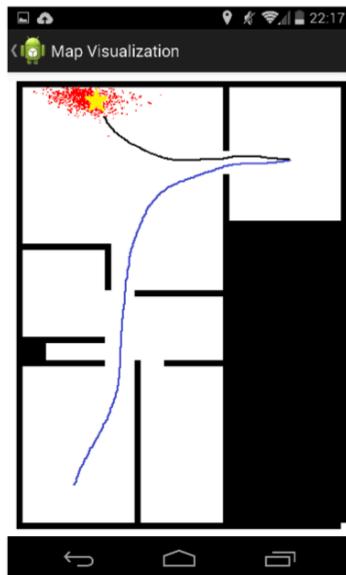
- Your own project  
Requires prior approval  
Evaluation criteria  
Technical depth & creativity

- Other Options:  
[COVID-19 tracker](#)

All code must be on the phone itself!

If you want to go for option 2, please contact me asap.

# Last years



**TrackMe@Home:**  
a student tracking his  
location at his place

**TrackMe@Work:**  
a student tracking  
his location at EWI,  
9th floor



**Shazam:**  
a scaled-down version



# What this course is about: learning objectives

- Smartphone + data + math = Awesome Apps
  - You need to be familiar with
    - (1) the signals smartphones can gather,
    - (2) the math tools to process those signals
  - We use techniques from algorithms, signal processing and machine learning to develop some exciting apps!



$$p(X_k \mid \mathcal{Z}_{1:k-1}) = \int p(X_k \mid X_{k-1}) \, p(X_{k-1} \mid \mathcal{Z}_{1:k-1}) dX_{k-1}$$

# What this course is about: approach



# Theory

- (2) tools: math & algorithms

# Practice (pointers)

- (1) Sensors: data acquisition
  - (4) Cloud: communication

# Practice (pointers)

- ## ▪ (3) GUI & Actuation

# LOGISTICS

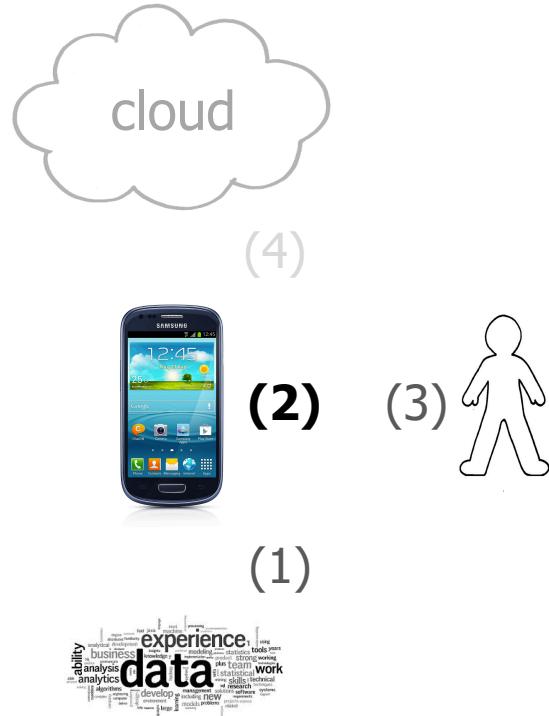
# Got a smartphone?

- If yes, please use your own
- If no, we have some smartphones available but we need to time-share them.
- If you need a smartphone, send an email to the TA.

# Grading

- Option 1
  - First Report (max 1 page text + figures) 10% week 3
  - Second Report (max 1 page text + figures) 10% week 6
  - Final online evaluation 80% week 9-10
    - Novel Twists 20%
- Option 2 (weekly mentoring)
  - First report (2 pages) 10% week 3
  - Second Report (5 pages), 10% week 6
  - App Evaluation 80% week 9-10
- There is NO resit

# **ACTIVITY MONITORING & LOCALIZATION**



## Option 1

### Indoor Localization

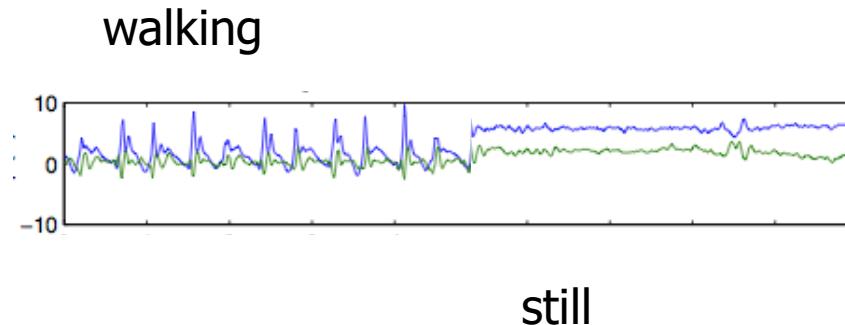
- 1) Localization
  - RSS + KNN
  - RSS + Filters
  - IMU + Filters

# Steps for classification: get raw signal

- (1) Raw signal (sensor information)
- (2) Feature extraction (art and science)
- (3) Classification method (art and science)

# Problem

- What am I doing?



# Steps for classification: train your system

(1) Raw signal

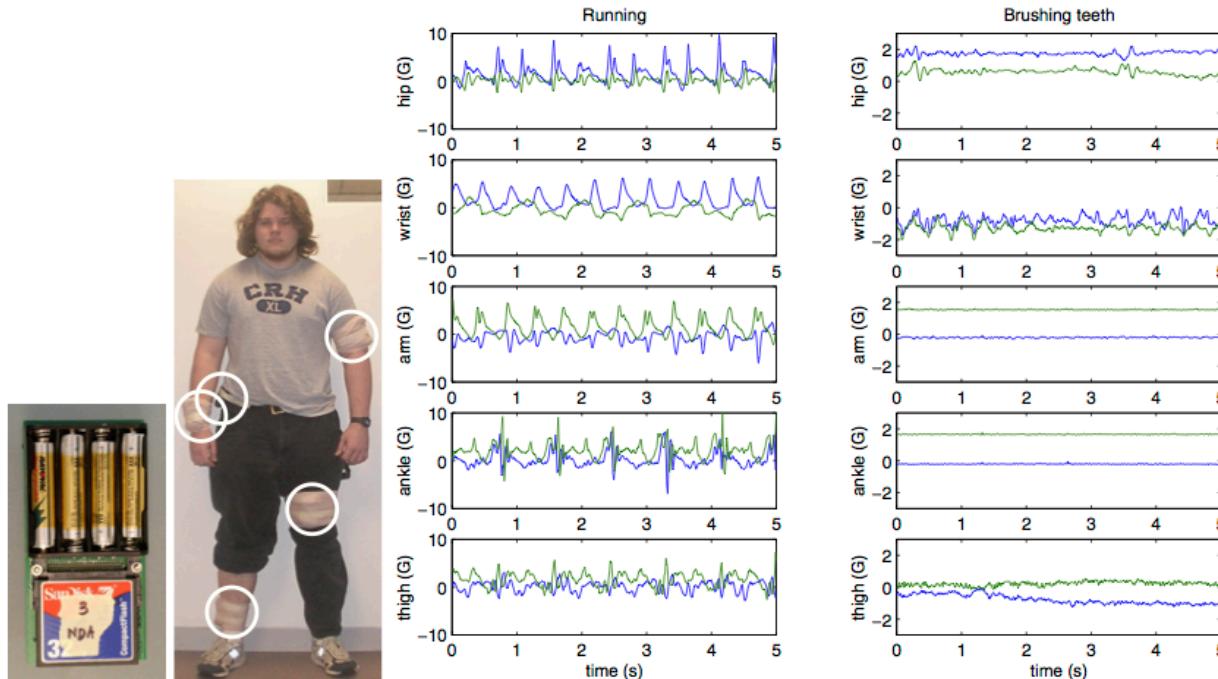
(2) Feature extraction (art and science)

Training

(3) Classification method (science)

# Activity recognition

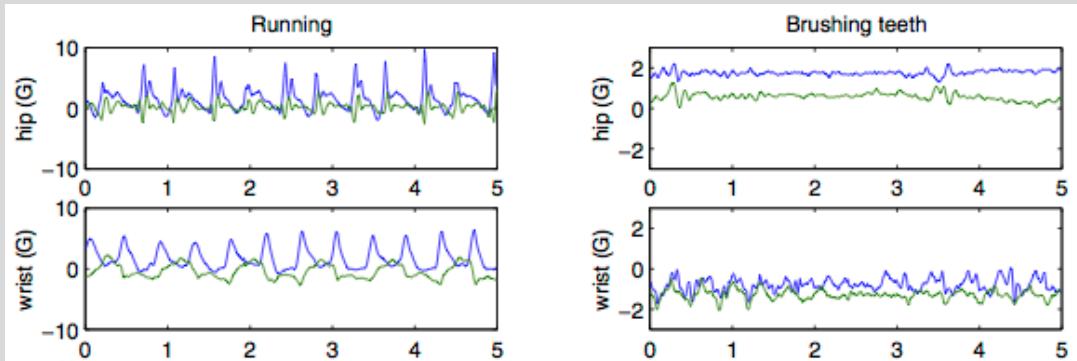
- Most smartphones have 3-axis accelerometers.
- Accelerometers can provide a lot of information.



Paper: "Activity Recognition from User-Annotated Acceleration Data", Pervasive 2004

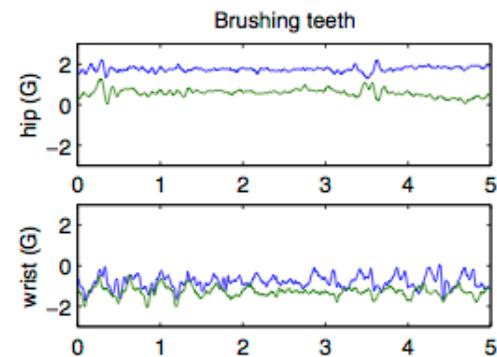
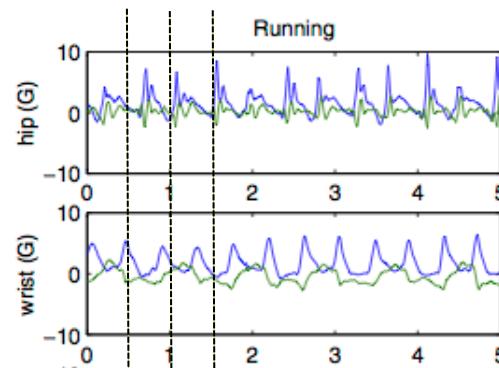
# Identifying Features

- How would you describe a signal statistically?



# Features: Training Data

- Choose a window size
  - 20 samples
  - 500 ms
- Then select features
  - Mean
  - Max Min
  - Variance
  - Fourier Transforms
  - Autocorrelation



# Steps for classification: test your system

(1) Raw signal

(2) Feature extraction (art and science)

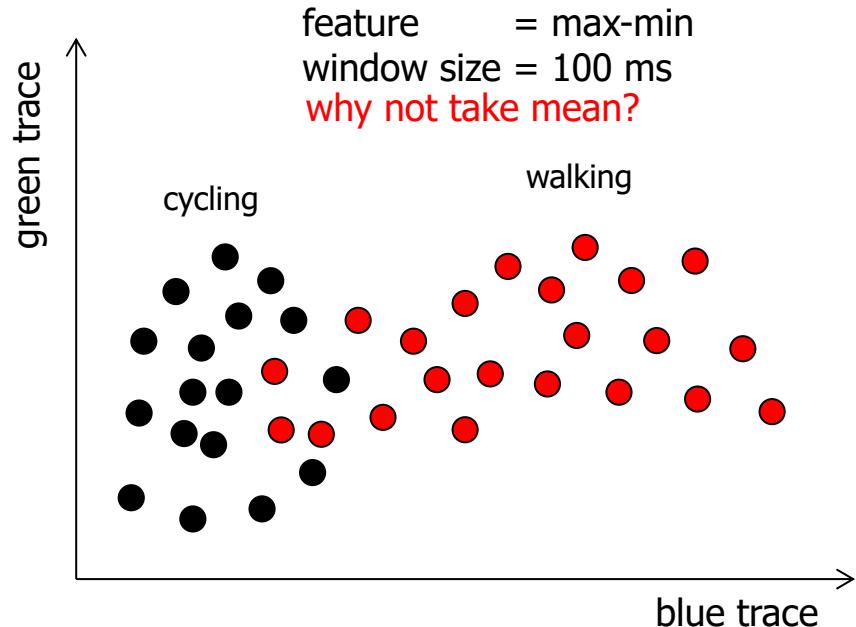
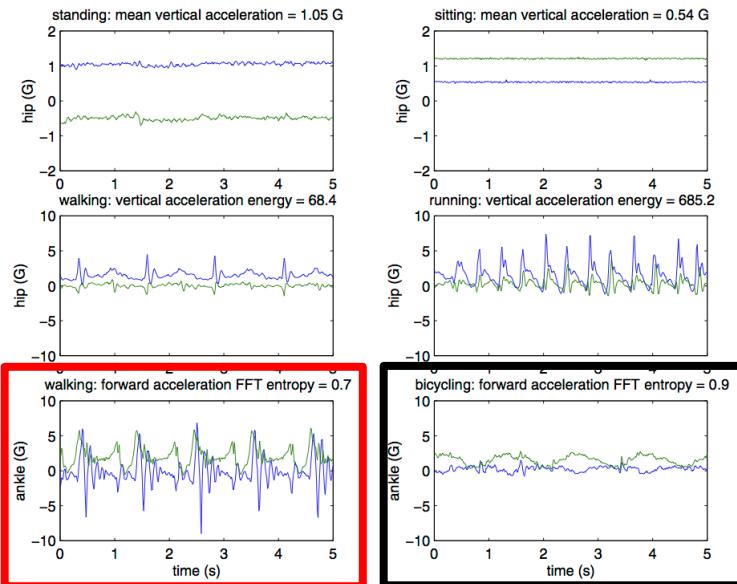
Training Phase

(3) Classification method (art and science)

Testing Phase

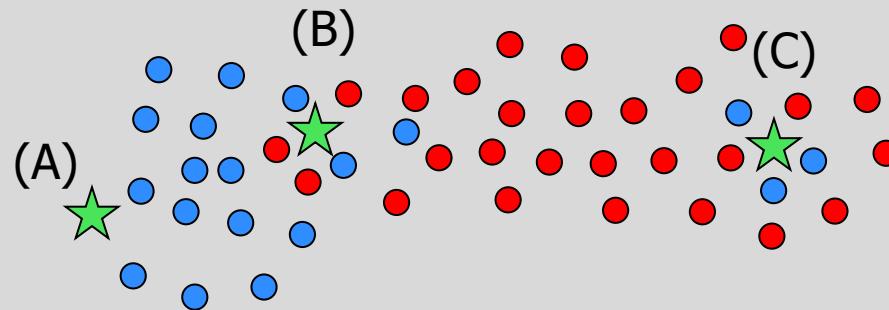
# Classification

- Let's get some features and plot them
- There is going to be an overlap depending on the window's size



Paper: "Activity Recognition from User-Annotated Acceleration Data", Pervasive 2004

# Classify points: Testing Data



# k-NN in one slide

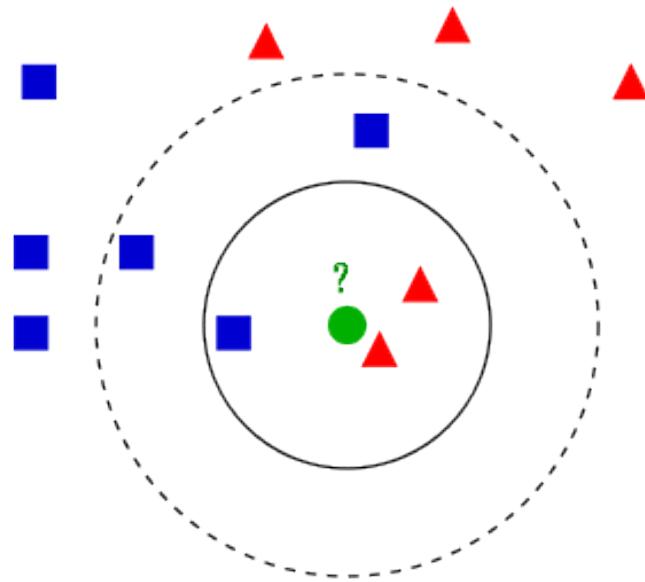


image from wikipedia: [http://en.wikipedia.org/wiki/K-nearest\\_neighbor\\_algorithm](http://en.wikipedia.org/wiki/K-nearest_neighbor_algorithm)

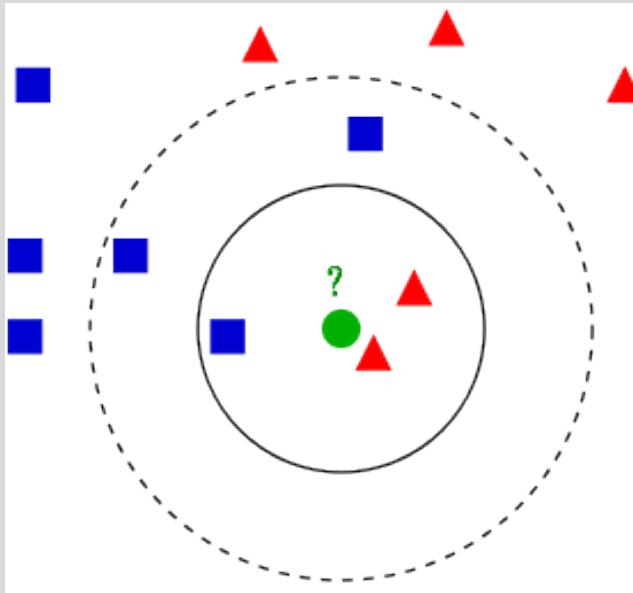
# What is the best value for k?

What happens if  $k=1$ ?

What happens if  $k = n$ ?

$n$  is the total number of training points

What is the best value of  $k$ ?



# What K? What distance?

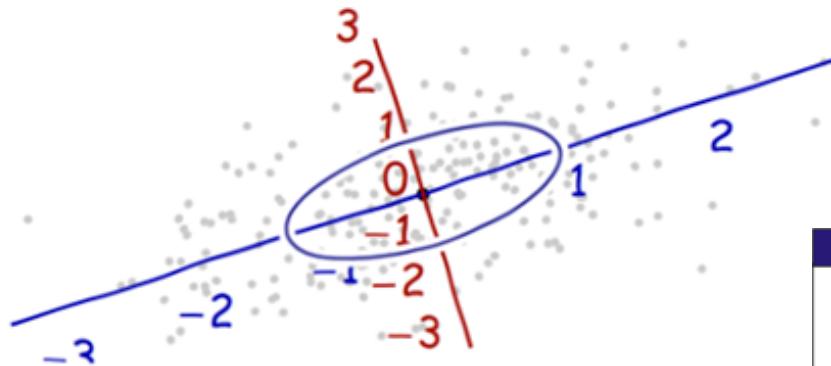
- Value of K:
  - Odd number
  - $\sqrt{n}$
- Distance:
  - Euclidean:  $D(\mathbf{w}_i, \mathbf{v}_i) = \sqrt{\sum (\mathbf{w}_i - \mathbf{v}_i)^2}$
  - Manhattan:  $D(\mathbf{w}_i, \mathbf{v}_i) = \sum |\mathbf{w}_i - \mathbf{v}_i|$
  - Hamming:  $D(\mathbf{w}_i, \mathbf{v}_i) = \sum I(\mathbf{w}_i, \mathbf{v}_i)$
  - Mahalanobis:  $D(\mathbf{w}_i, \mathbf{v}_i) = \sqrt{(\mathbf{w} - \mathbf{v})^T S^{-1} (\mathbf{w} - \mathbf{v})}$

# Mahalanobis distance

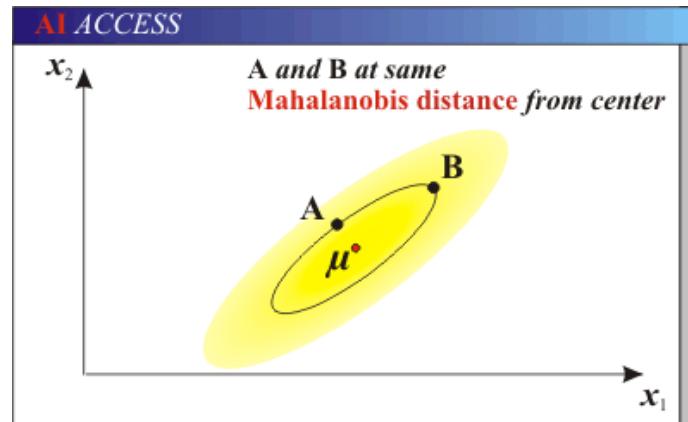
:  $D(\mathbf{w}_i, \mathbf{v}_j) = \sqrt{(\mathbf{w} - \mathbf{v})^T S^{-1} (\mathbf{w} - \mathbf{v})}$

S: covariance metric.  $S_{\mathbf{w}\mathbf{v}} = E[(\mathbf{w} - \mathbf{u}_{\mathbf{w}})(\mathbf{v} - \mathbf{u}_{\mathbf{v}})]$

Intuition =  $(\mathbf{x} - \mathbf{u}) / \sigma$



- unit-less measure
- If S=identity matrix, then mahalanobis = euclidean



Images taken from:

<http://stats.stackexchange.com/questions/62092/bottom-to-top-explanation-of-the-mahalanobis-distance>

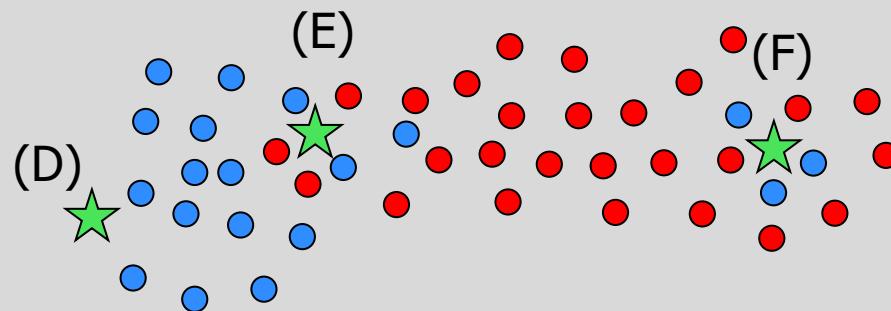
<http://blog.csdn.net/lovelyloulou/article/details/6339976>

Localization paper using mahalanobis distance:

“Paper Lightweight Map Matching for Indoor Localisation Using Conditional Random Fields”, IEEE/ACM IPSN 2014.

# Classify the points below

Assume k=5 and Euclidean distance



# K-NN is a top-10 machine learning tool

- A formal definition:
  - A supervised method: training & testing.
  - $x$  features,  $Y$  label:  $(x_i, x_j, \dots, Y)$
- KNN is non parametric
  - does not make any assumption on underlying data distribution.  
This is very useful!
- Simple training, costly testing (in time and memory)
- Data (features) are in a metric space.
- Very good for being that simple:

for  $K=1$ :  $P^* \leq P \leq P^* (2 - c/(c-1)) P^*$

where “ $P$ ” is the 1-NN error, “ $P^*$ ” is the Bayes error and  $c$  is the number of classes

More theory of KNN: <https://www.cs.rit.edu/~rlaz/PatternRecognition/slides/kNearestNeighbor.pdf>

# POINTERS

# Pointers: theory (1)

- K-NN:
  - [http://en.wikipedia.org/wiki/K-nearest neighbor algorithm](http://en.wikipedia.org/wiki/K-nearest_neighbor_algorithm)
  - [http://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-034-artificial-intelligence-fall-2010/tutorials/MIT6\\_034F10\\_tutor03.pdf](http://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-034-artificial-intelligence-fall-2010/tutorials/MIT6_034F10_tutor03.pdf)
  - <http://saravananthirumuruganathan.wordpress.com/2010/05/17/a-detailed-introduction-to-k-nearest-neighbor-knn-algorithm/>
- Mahalanobis distance:
  - [http://en.wikipedia.org/wiki/Mahalanobis\\_distance](http://en.wikipedia.org/wiki/Mahalanobis_distance)
  - <http://stats.stackexchange.com/questions/62092/bottom-to-top-explanation-of-the-mahalanobis-distance>

# Pointers theory (2)

- What's going on in other schools
  - UIUC: <http://www.ece.illinois.edu/mediacenter/article.asp?id=1274>
  - Dartmouth: <http://www.cs.dartmouth.edu/~campbell/smartphonesensing.html>