# Human behaviour monitoring and analysis

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# About me...

- Researcher at CREATE-NET, Trento, Italy
  - Data mining algorithms to understand sensed human behaviour
  - Application focus on healthcare
    - Depression, bipolar disorder, chronic stress, rehabilitation
- Lecturer at University of Trento
  - User interfaces course in Cognitive Sciences Faculty (Rovereto)
  - Doctoral course in Pervasive Computing
- PhD from WIT in Ireland
  - born in Prishtina, Kosovo

# Big picture

- Where did it come from?
- Where we are?
- What are we doing?

# Why?

- Why monitoring human behaviour?
- Applications?
- Quantified Self
  - http://quantifiedself.com
- Interests
  - Improve wellbeing and quality of life
  - Impact on health and healthcare

# Where did all come from?

- Ubiquitous Computing
- Pervasive Computing
- Context-aware computing

# Famous quote

- "The most profound technologies are those that ***disappear***. They weave themselves into the fabric of everyday life until they are ***indistinguishable*** from it" (Weiser, 1991)
- Mark Weiser (1952 – 1999)
  - Ubiquitous Computing

# Disappearing technology

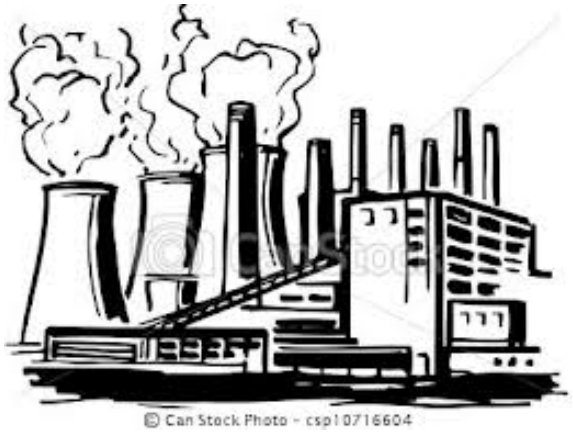
- Mobile phone vs pay-phone
- Fading into the background of user's attention


→

# Traditional PC vs Ubiquitous Computing

- *Ubiquitous* computing compares to a *traditional* PC, like *batteries* compare to a *power plant*:
  - not as powerful, but available everywhere, portable, in different shapes, for many different applications.

vs

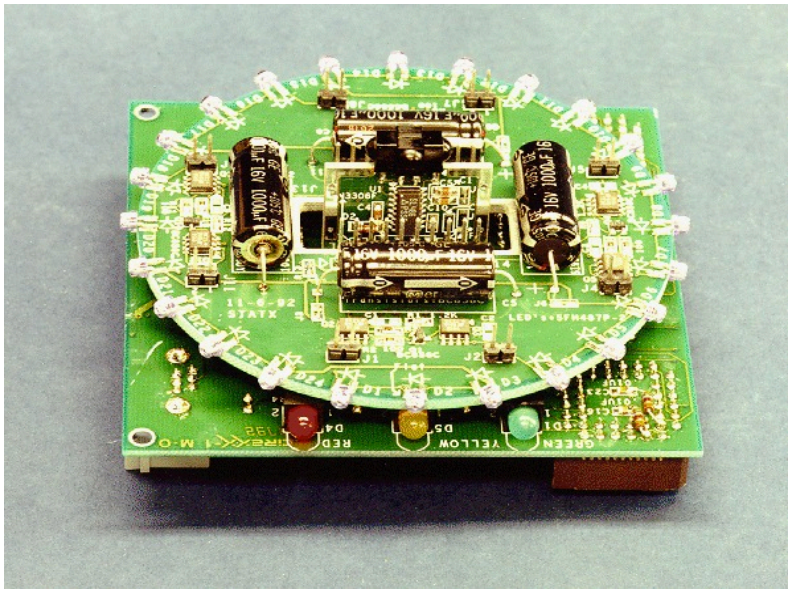


# Ubicomp (early 1990s)

- **ParcTab** – an **inch**-scale computer – pocket book or wallet
- **ParcPad** - a **foot**-scale device (serving the role of a pen-based notebook or e-book reader)
- **Liveboard** – a **yard**-scale device – functionality of a whiteboard

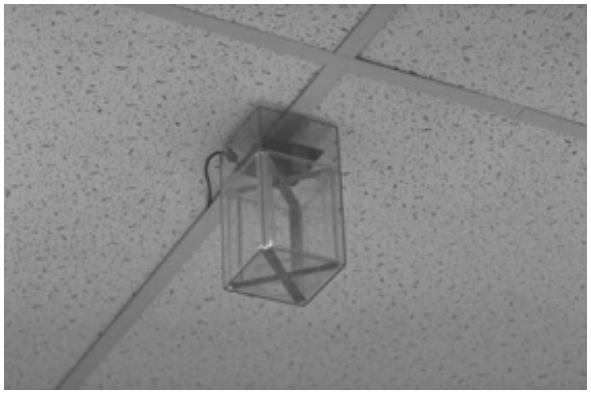
# ParcTab

- 105 x 78 x 24mm, 215g, 2 week battery, 128k RAM, resistive touch screen mono display, three buttons
- Wirelessly connected with a ceiling-mounted base-station using 10kbps IR signaling
- Room information, Locator

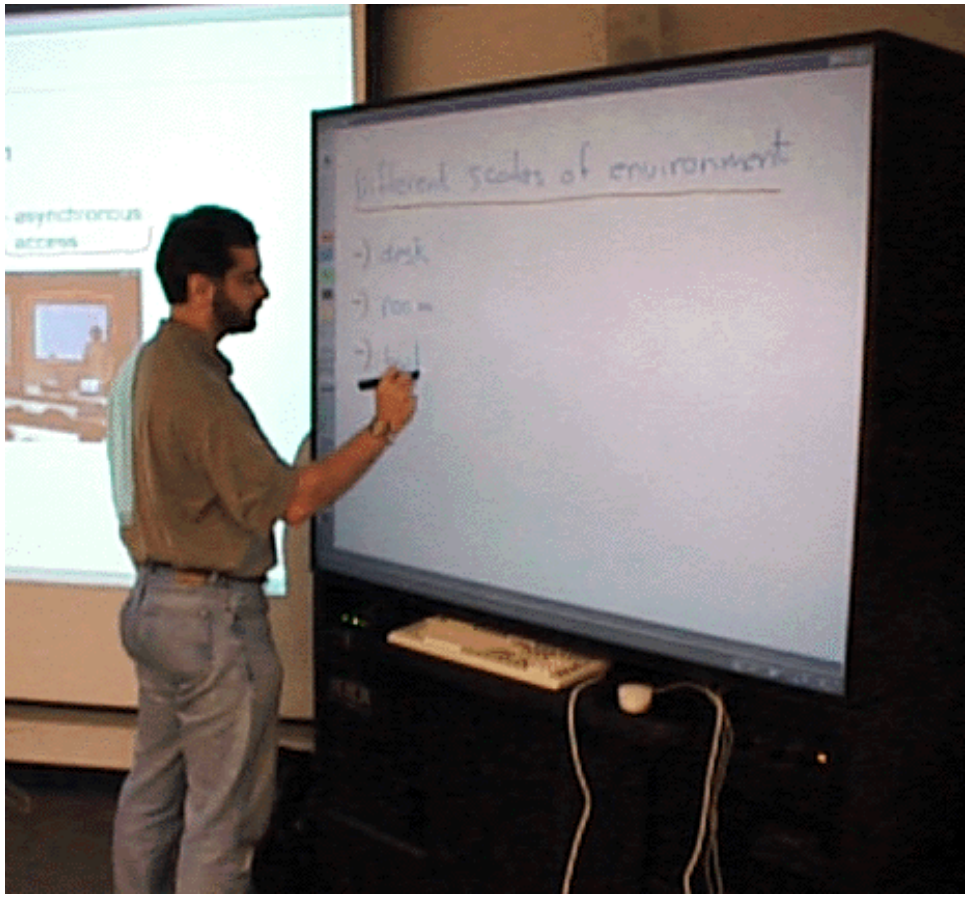
# ParcPad

- First Tablet computer (touch screen, wireless network)
- “Scrap Computer”
- Similar approach to PARC Tab, with  radio link, 25x more bandwidth at 250kbps, 3-4 m range
- Specs: 22 x 28 x 2.5 cm, 2,2kg, 540x480 4 level display

# Liveboard

- 67-inch LCD panel
- Infrared based
- Multi-site meetings, Lectures, Meeting capture



# However…

- Something was missing
- Insufficient to have *ubiquitous* devices only
- They should also respond to users and events (e.g. identity, time, location and activity)
- In other words
  - devices should be **aware** of their surroundings
- Hence, this led to
  - **context-aware** computing

# Context-awareness

- Humans are very good at adapting to changing situations
  - Behaviour based on current context
    - e.g. listening during a lesson; talking in turns
- Human to human interaction flows seamlessly
  - e.g. Greeting someone using their name or title, depending on formal/ informal setting
  - Based on making use of implicit information about the environment
- In contrast - computers need to be told things explicitly
  - Switching off the mobile phone, for example

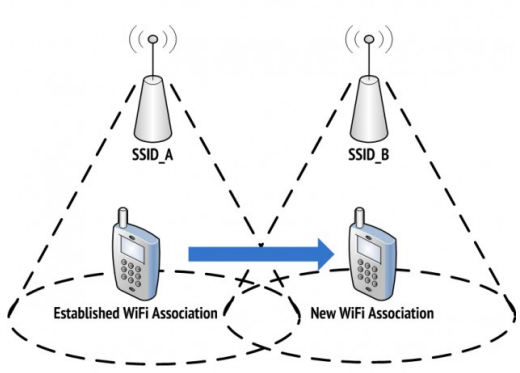
# Context-awareness

- Why can't computers do the same?
- *Traditional computers do not understand how the world works, cannot understand our current situation and lack the capability of sensing information about the environment.*
- But this is changing
  - Especially with increasing sensor modalities

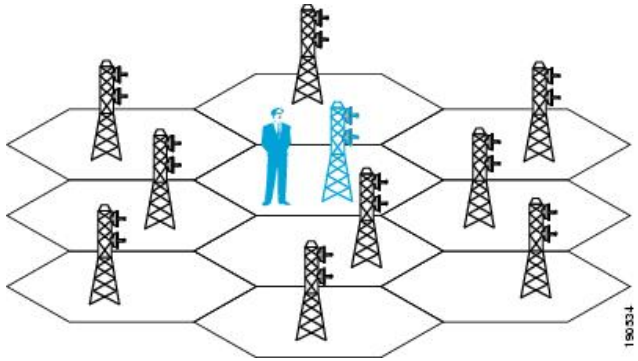
# Context-awareness

- Four main attributes (Dey et al.)
  - Time
    - Relatively easy
  - Identity
    - Not so easy – different technologies
  - Location
    - GPS for outdoors. But indoors?
  - Activity
    - Recognising human activities - difficult, diverse
- 4W - When, Who, Where, What
  - Work done within our lab…

# Location (indoor)



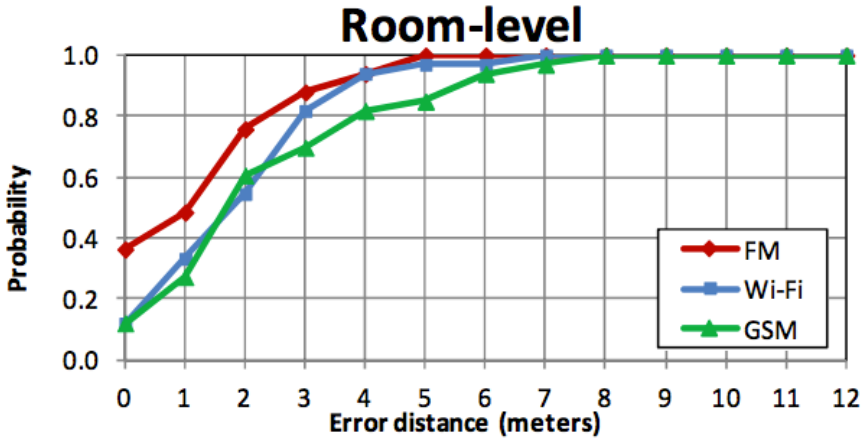

- Standard: WiFi localisation
  - Based on received signal strength indicator (RSSI) from multiple WiFi Access Points
  - Classification algorithms to compute approximate location
- Same principle for GSM signals
  - More difficult to localise
  - Why?



# Location

- Instead of WiFi we have investigated FM radio for indoor localisation

- Advantages over WiFi
  - Wide coverage – available worldwide
  - Lower frequency, less susceptible to obstacles
  - Performance comparable to WiFi




Andrei Popleteev, Venet Osmani, Oscar Mayora,"*Investigation of indoor localization with ambient FM radio stations*", Proceedings of PerCom 2012, 10th IEEE International Conference on Pervasive Computing and Communications, pp. 171 – 179, Lugano, Switzerland, 2012, http://dx.doi.org/10.1109/PerCom.2012.6199864

# Identity / Activity

- Understanding dressing process
- Smart dressing room
- Monitoring of dressing/undressing failures through computer vision and RFID for cognitively impaired patients


Aleksandar Matic, Priyal Mehta, James M. Rehg, Venet Osmani, Oscar Mayora, *"Monitoring Dressing Activity Failures through RFID and Video"* , Journal of Methods of Information in Medicine, Apr 29;50(4), 2011

# However…

- These experiments are done on the lab
- How do we do the experiments in the real world?
  - Outside the confines of a laboratory
  - Capture natural human behaviour
- We need an unobtrusive and familiar device that can sense the phenomena we are interested in

# What have we done?

- Experiments outside the lab:
  - Monitoring social interaction
  - Monitoring behaviour aspects of patients with bipolar disorder
  - Monitoring behaviour of workers to detect stress leading to burnout (upcoming)

# For each experiment

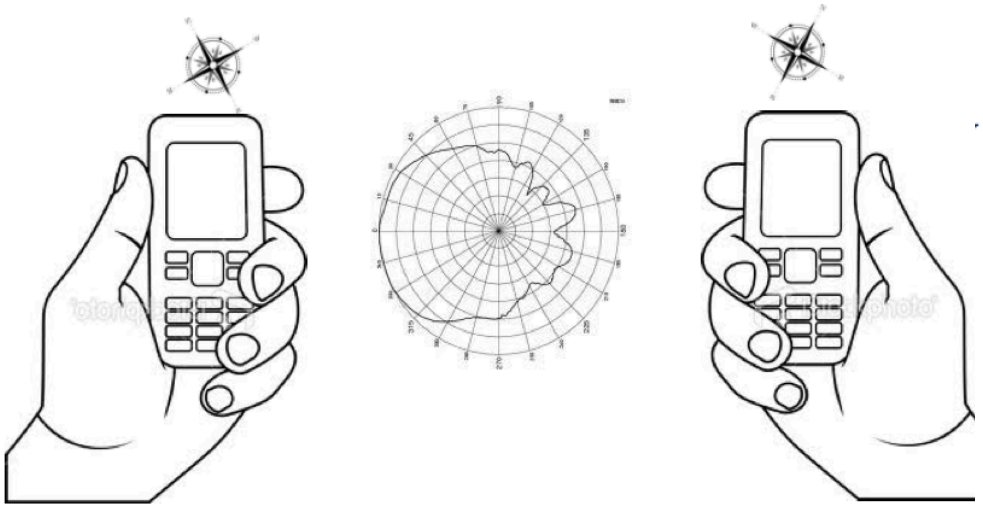
- We used an unobtrusive and familiar device
  - The mobile phone

- Why?
  - Sensor capability to sense a range of behaviour aspects
  - Being familiar, it minimally affects natural behaviour

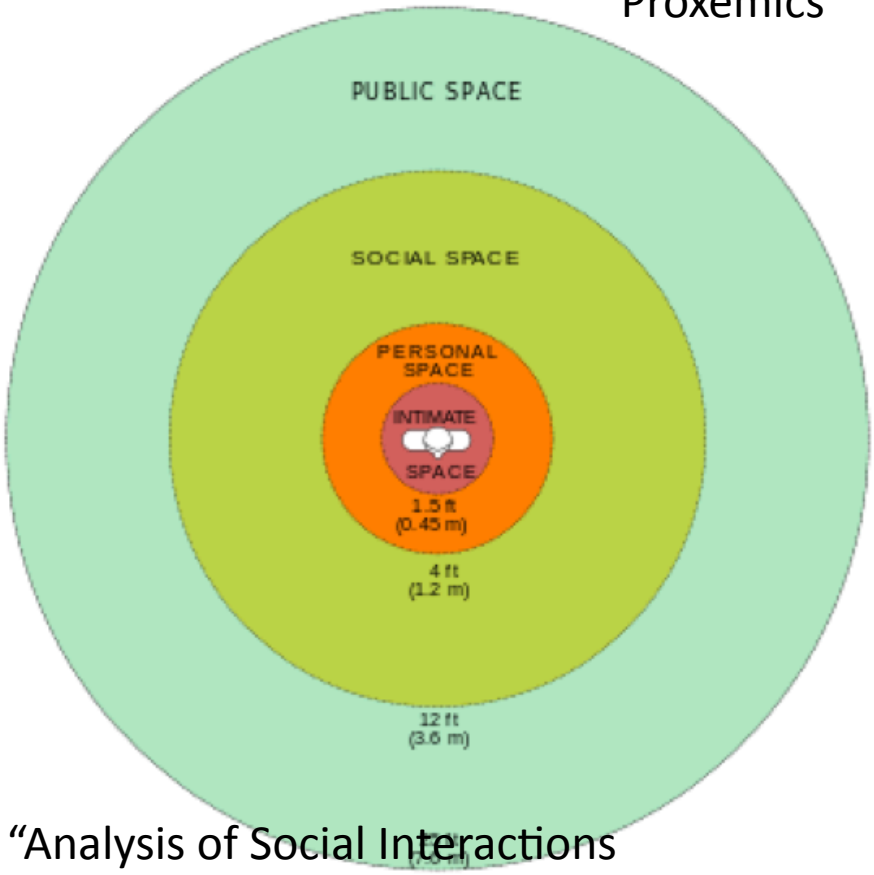
- But also **far more challenging** than using dedicated sensors – **data quality**

# Social Interaction Detection

- Based on WiFi RSSI analysis for distance
- Compass for orientation



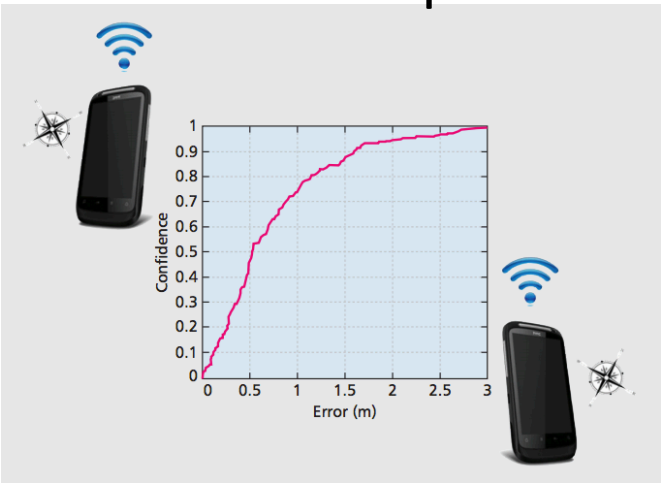
Proxemics

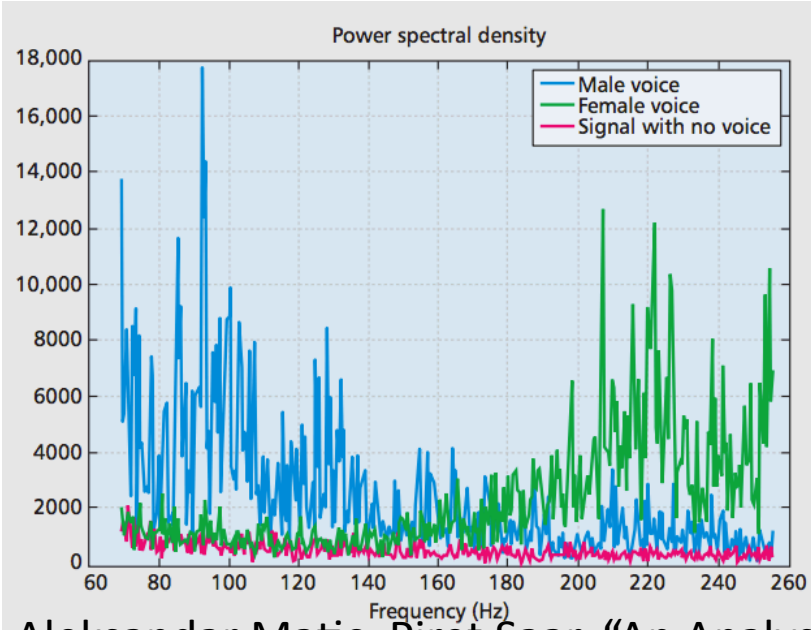


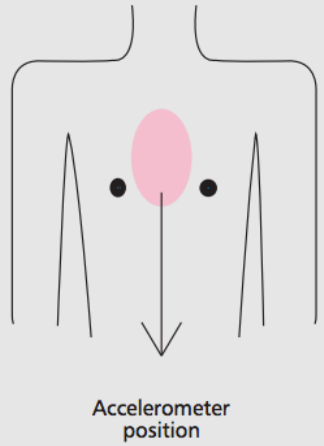

Aleksandar Matic, Venet Osmani,, Oscar Mayora, “Analysis of Social Interactions Through Mobile Phones". Journal of Mobile Networks and Applications (Springer), DOI: 10.1007/s11036-012-0400-4, August 2012

# Social Interaction Detection

- Three aspects:
  - Proximity, orientation and speech activity
    - For speech detection we did not use a mobile phone



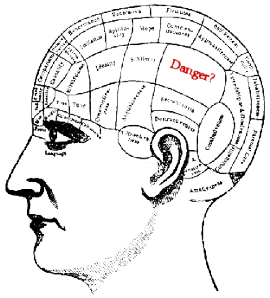




Venet Osmani, Iacopo Carreras, Aleksandar Matic, Piret Saar, “An Analysis of Distance Estimation to Detect Proximity in Social Interactions". Journal of Ambient Intelligence and Humanized Computing (Springer), DOI:10.1007/s12652-012-0171-6, January 2013

# Monitoring behaviour of bipolar patients

- Why mental diseases are particularly suitable for behaviour monitoring?

vs

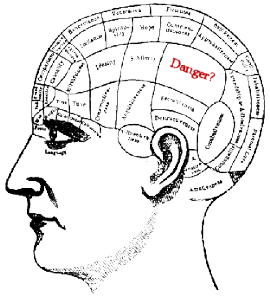



- In contrast with somatic diseases

# Somatic diseases vs Mental disorders

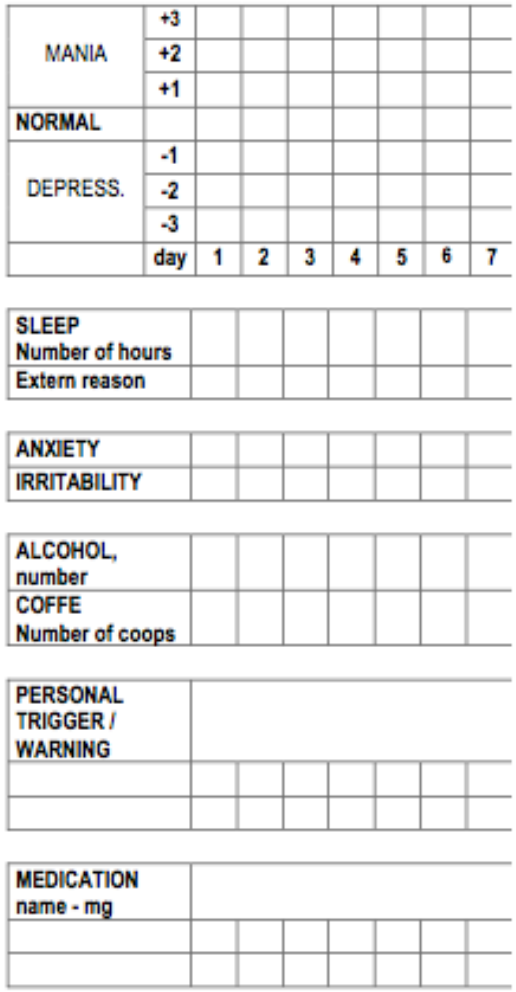
- Somatic diseases
  - Diagnosis based on objective (sensed) information
    - Biochemical markers (blood tests) or imaging (x-ray, CT)

**VS**




- Mental disorders (e.g. bipolar disorder)
  - No biochemical markers and neither imaging (as reliable as those of somatic diseases)
  - However, a strong **behaviour component**
    - **Q: How is behaviour currently captured?**

# Tools to capture patient's behaviour



| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| MANIA | +3 | | | | | | | |
| | +2 | | | | | | | |
| | +1 | | | | | | | |
| NORMAL | | | | | | | | |
| DEPRESS. | -1 | | | | | | | |
| | -2 | | | | | | | |
| | -3 | | | | | | | |
| | day | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| SLEEP Number of hours | | | | | | | | |
| Extern reason | | | | | | | | |
| ANXIETY | | | | | | | | |
| IRRITABILITY | | | | | | | | |
| ALCOHOL, number | | | | | | | | |
| COFFE Number of coops | | | | | | | | |
| PERSONAL TRIGGER / WARNING | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| MEDICATION name - mg | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |

**State of the Art (Subjective Monitoring)**

**HAM-D** – Hamilton Rating Scale for Depression (29 item)

**BDI** - Beck Depression Inventory

**YMRS** – Young Mania Rating Scale (17 Item)

# State of the Art Assessment


objective

vs

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| MANIA | +3 | | | | | | | |
| | +2 | | | | | | | |
| | +1 | | | | | | | |
| NORMAL | | | | | | | | |
| DEPRESS. | -1 | | | | | | | |
| | -2 | | | | | | | |
| | -3 | | | | | | | |
| | day | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| SLEEP Number of hours | | | | | | | | |
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| | | | | | | | | |
| | | | | | | | | |
| MEDICATION name - mg | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |

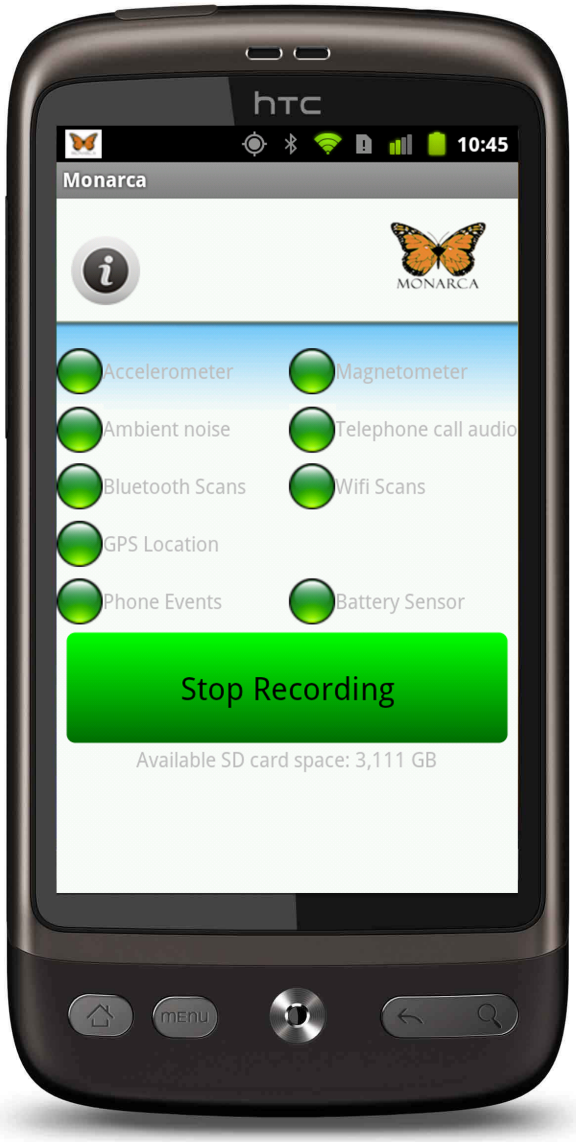
subjective

# Issues with subjective data

- Memory dependence
  - Difficulty recalling events in the past (e.g. sleep quality, diet)
- Recall bias
  - Difficulty in recalling completely and accurately events in the past
- Unsuitable for long-term monitoring (prevention)
  - Contrast this with A1C test (blood sugar levels for the past 2-3 months)

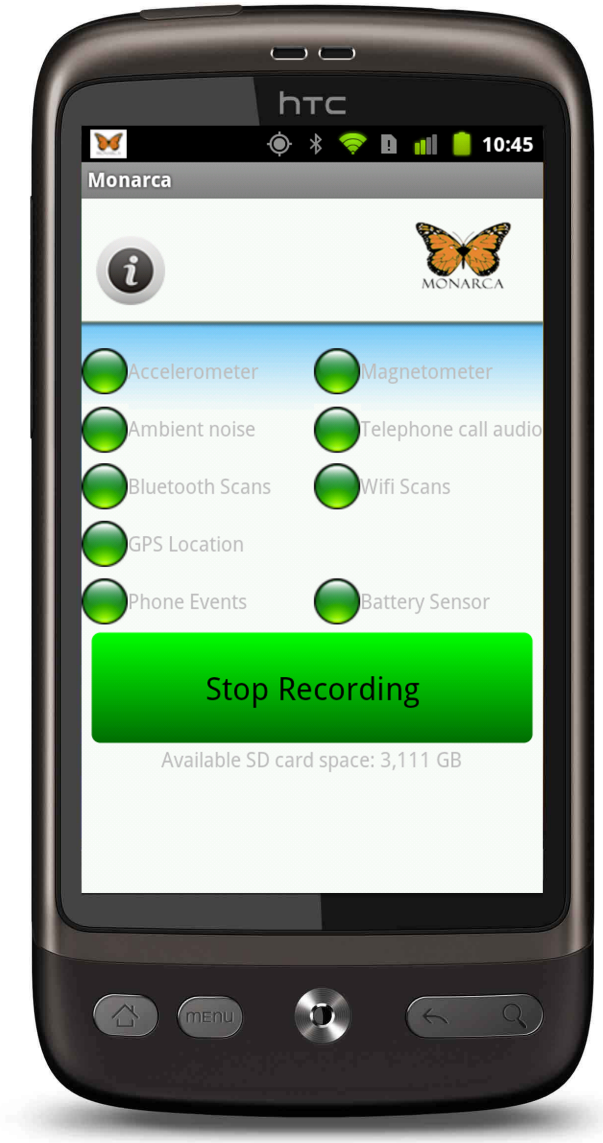
# Mobile phone to the rescue!

- The question is:
  - What can we learn about the patients' behaviour by relying on sensors on the mobile phone only
  - Can we detect an episode (Manic/Depressive) based solely on phone sensor data?



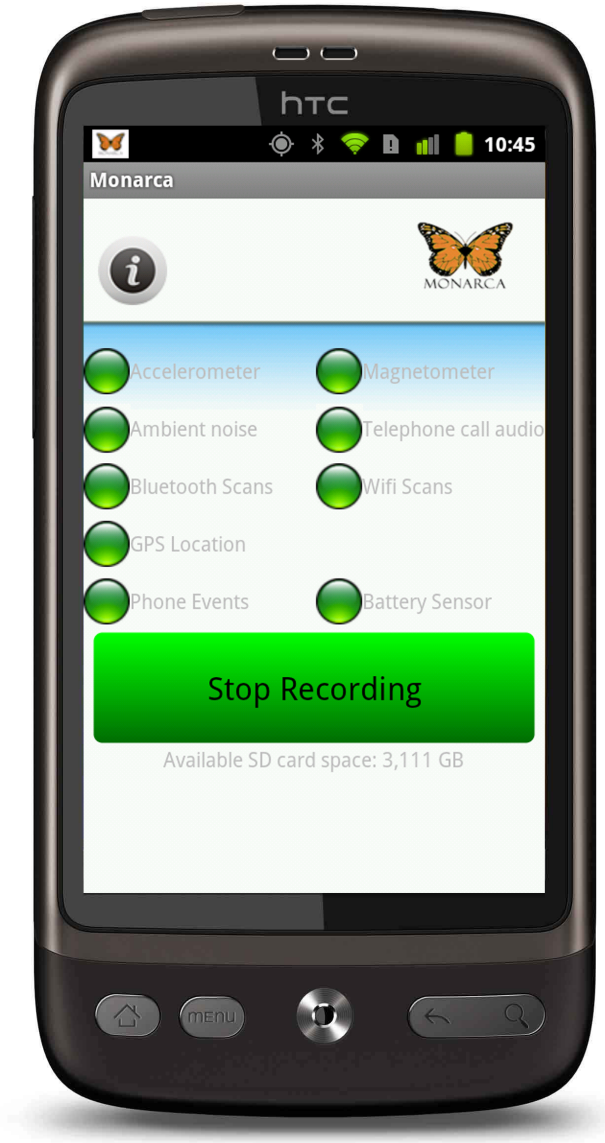
# Monarca App

- Set-up :
  - Automatic recording – start on device-boot and run in background
  - Data encrypted on SD-card
  - Questionnaire appears at 8 pm
  - Data stored on SD-card until transmitted
  - Data transmitted at doctors visit



# Collected Data

- (Almost) everything that can be recorded
  - WiFi, Bluetooth, GPS
  - Calls, SMS
  - Accelerometer, Compass
  - Scrambled voice during phone calls
  - Ambient noise
  - Mobile phone usage
  - Battery levels



# Two clinical trials

- *Innsbruck, Austria* and Copenhagen, Denmark
- Criteria
  - Male or female 18-60
  - Diagnosed with bipolar disorder
  - Rapid cycling
  - Ability to use smartphone
- Trial
  - 12 Patients (11 female, 1 male)
  - Age: 30-55
  - 10 patients final stages of the trial
  - Around 30 GB of data per patient

# Clinical trial (Innsbruck)

- Duration 12+ weeks
- Psychiatric evaluation every 3 weeks
- Each day patients fills in the questionnaire
  - 10 Questions on daily activities
- Provides permission for the data to be transmitted for the day

# Psychiatric evaluation

- Normalised psychiatric scores (-3 very severe Depression to +3 very severe Mania)

| | P0302 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1. Testung | Teleinterview | 2. Testung | Teleinterview | 3. Testung | Teleinterview | 4. Testung | Teleinterview | 5. Testung | abges. |
| Gr.- Truth | 11/12/2012 | 27/12/2012 | 08/01/2013 | 22/01/2013 | 29/01/2013 | 12/02/2013 | 19/02/2013 | 05/03/2013 | 12/03/2013 | |
| +3 | | | | | | | | | | |
| +2 | | | | | | | | | | |
| +1 | | | | | | | | | | |
| 0 | | | | | 0 | 0 | 0 | 0 | 0 | |
| -1 | | | | -1 | | | | | | |
| -2 | | | -2 | | | | | | | |
| -3 | -3 | -3 | | | | | | | | |

| | P0402 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1. Testung | Teleinterview | 2. Testung | Teleinterview | 3. Testung | Teleinterview | 4. Testung | Teleinterview | 5. Testung | abges. |
| Gr.- Truth | 18/12/2012 | 08/01/2013 | 15/01/2013 | 29/01/2013 | 05/02/2013 | 19/02/2013 | 26/02/2013 | 12/03/2013 | 19/03/2013 | |
| +3 | | | | | | | | | | |
| +2 | | | | | | | | | | |
| +1 | | | | | | | | | | |
| 0 | | | | | | | | | | |
| -1 | | | | | | | | | | |
| -2 | | | | | | | | | | |
| -3 | -3 | | -3 | | -3 | | -3 | | -3 | |

# Issues and challenges

- Uncontrolled trial --> Patient compliance
  - Not carrying the phone
  - Turning off the phone
- Patient state evolution
  - No change in psychiatric scores
    - No correlation possible
- Large amount of data
  - Over 1000 days of monitored data
  - Close to half TB of data

# Initial analysis

- Objective:
  - Is there a correlation between measured physical activity and psychiatric evaluation scores?

- Physical Activity data
  - Magnitude from raw acc. readings (*x,y,z*)
    - Use mag. variance over 128 samples for activity score
  - Exclude readings when phone was inactive
  - Exclude readings on days when psychiatric evaluation was carried out (visit to the clinic)

# Initial results

- Taking into account ***daily*** physical activity levels
- Pearson's correlation coefficient between physical activity levels and psychiatric scores

**Table 2 Correlation between patient state and overall physical activity levels ($p < 0.05$, N = 5)**

| Patient ID | *r* |
|---|---|
| P0101 | **0.672** |
| P0102 | **0.377** |
| P0201 | **0.332** |
| P0302 | **-0.148** |
| P0702 | **0.290** |

- But, can we do better?

# Daily interval analysis

- Objective: *Is there a specific daily interval where correlation is strongest?*

- Divided the day into 4 intervals
  - Morning (06 AM to 12 PM), Afternoon (12 PM to 06 PM), Evening (06 PM to 12AM) and Night (12 AM to 06 AM)
- Calculated average physical activity over each hour and activity score for the intervals

# Daily interval correlation results

**Table 5 Correlation between patients' state and physical activity level during day intervals ($p < 0.05$, N = 5, $N^{\ddagger} = 3$)**

**(*n/s not statistically significant result ($p > 0.05$) - *n/d not enough data recorded, due to phone being off)**

| | *r* | | | |
|---|---|---|---|---|
| Patient ID | Morning | Afternoon | Evening | Night |
| P0101 | n/s* | 0.315 | -0.045 | n/d* |
| P0102 | 0.581 | -0.542 | **0.619** | n/d* |
| P0201 | 0.261 | **0.586** | 0.243 | n/d* |
| P0302 | **0.858** | -0.842 | -0.627 | 0.604 |
| P0702 ‡ | **-0.746** | 0.213 | 0.452 | 0.007 |

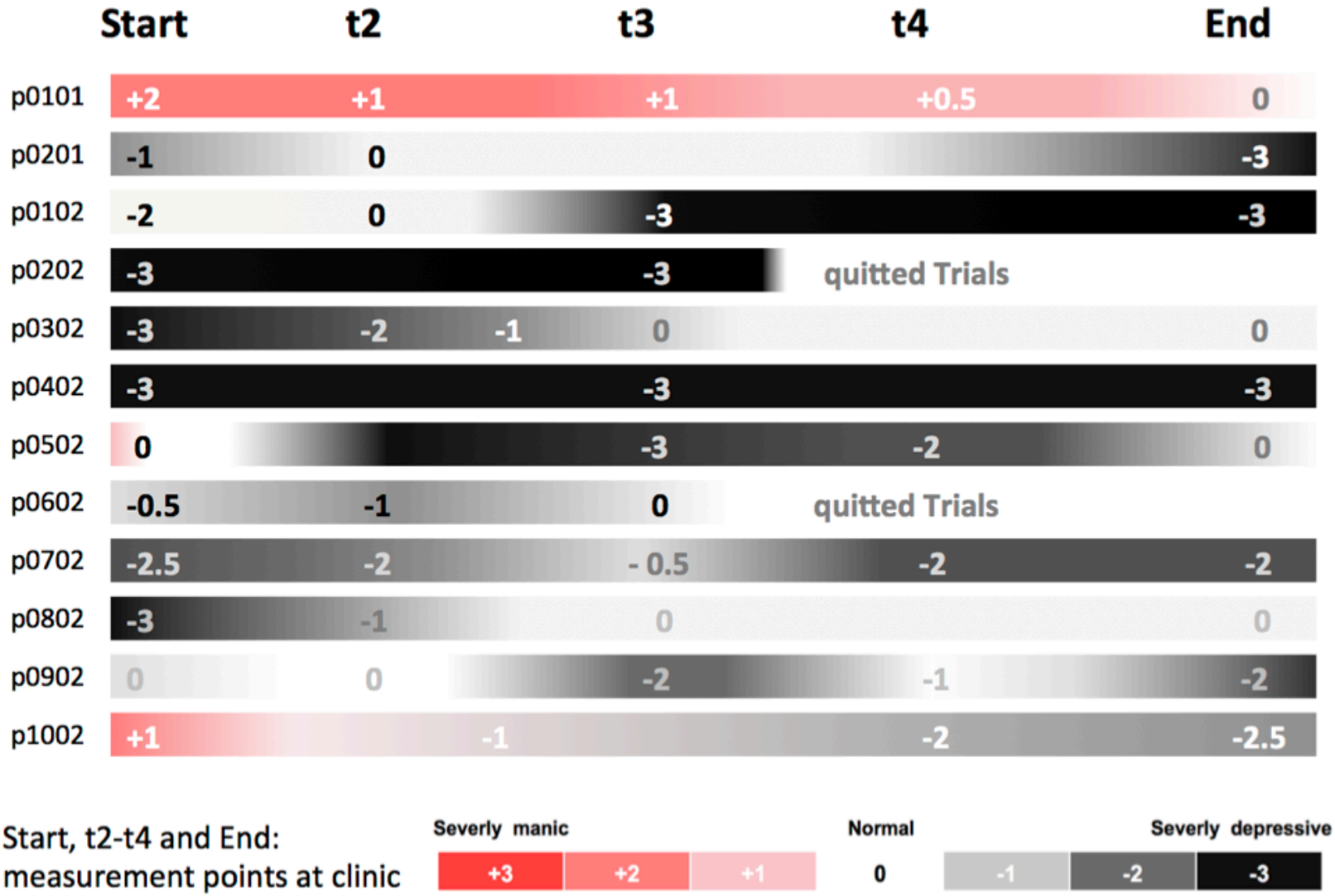
Venet Osmani, Alban Maxhuni, Agnes Grünerbl, Paul Lukowicz, Christian Haring, Oscar Mayora, *"Monitoring activity of patients with bipolar disorder using smart phones",* ACM Proceedings of Conference on Mobile Computing and Multimedia (MoMM2013), Vienna, Austria, December 2013

# Current analysis

- Objective 1: Can we detect patients' bipolar episodes by relying solely on smart phone sensed data? (*State Recognition*)

- Objective 2: Can we detect transitions between bipolar episodes? (*Change Detection*)
  - This would be very useful in preventing an episode (detection of EWS (early warning signs))

# Patients' status (psych. assessment)



# Sensor data used in the analysis

- Accelerometer Activity (ACC)
- Accelerometer data processing:
  - Magnitude (invariant to phone orientation (unkn))
  - Removed “phone not on body” periods
    - Discarded data where acc variance is below a threshold
  - Using 10 second sliding window, calculate:
    - RMS
    - Frequency features - Freq. Centroid and Freq. Fluctuation (using FFT)

# Sensor data used in the analysis

- GPS Location (LOC)
- Anonymised data
  - Coordinates translated into an artificial coordinate system
- Feature extraction (daily window size)
  - Number of distinct locations
    - DBSCAN Clustering of GPS points
  - Number of hours outdoors
  - % of time spent outdoors
  - Mean/variance ‘time of the day’ spent outdoors
  - Number of stays outdoors and distance travelled

# Sensor data classification

- Classification algorithms used
  - Naïve bayes
  - knn
  - J48
  - Conjunctive rule learner
  - Very similar results for each classifier, so Naïve Bayes was the main algorithm
- Using MATLAB with WEKA libraries
- Next results pertain to individual (ACC or LOC) and fused modalities (ACC + LOC)

# Patient State Recognition

| | Percentage correct (total number of instances) | | |
|---|---|---|---|
| **Patients** | **Fusion** | **LOC** | **ACC** |
| p0101 | 70% (70) | 77% (26) | 75% (70) |
| p0102 | 84% (46) | 82% (34) | 76% (46) |
| p0201 | 68% (38) | 77% (36) | 68% (38) |
| p0302 | 82% (60) | 92% (47) | 66% (60) |
| p0502 | 71% (58) | 85% (28) | 72% (58) |
| p0602 | 77% (31) | 71% (31) | 66% (21) |
| p0702 | 74% (42) | 77% (31) | 73% (42) |
| p0802 | 79% (62) | 89% (37) | 77% (62) |
| p0902 | 83% (35) | 85% (35) | 70% (35) |
| p1002 | 68% (43) | 79% (22) | 71% (43) |
| **Average** | **76%** | **81%** | **72%** |

## Overall results

| | Recall | Precision |
|---|---|---|
| **LOC** | **81,7%** | **80,8%** |
| **ACC** | **62,9%** | **64,8%** |
| **Fusion** | **70,3%** | **74,0%** |

# Patient State Change Detection

- Setup a baseline model to describe normal state (fit a Multivariate Gaussian Distribution)
- Use Mahalanobis distance to measure how far a sample is from the baseline (normalised)
- Test the model performance
- Repeat above 1k times
  - Evaluate different distance thresholds (0 to 5 in steps of 0.1)

# Patient State Change Detection

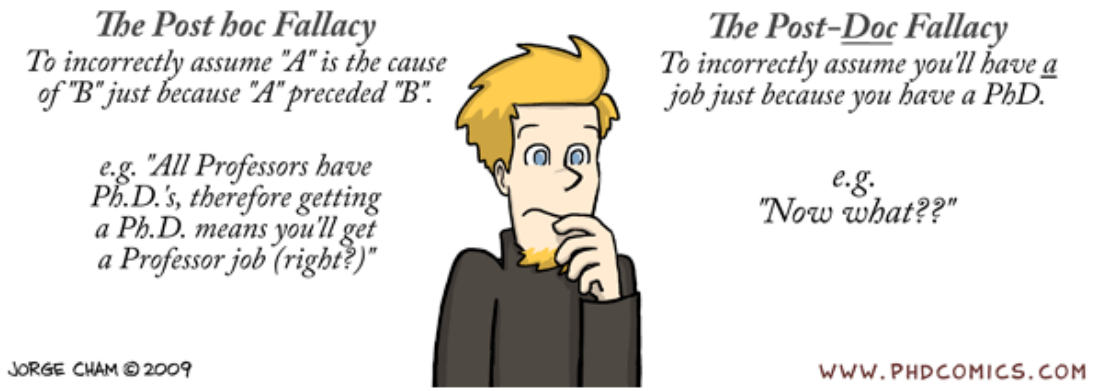
- Change of mental state of Patient (e.g. from normal to depressive) can be detected with 94.2% precision
- Out of all state changes, 94.2% can be detected as actual state changes

| | Fused WEIGHTED | |
|---|---|---|
| **Patient** | **Recall** | **Precision** |
| p0101 | 91.1% | 93.4% |
| p0102 | 86.2% | 96.8% |
| p0201 | 97.3% | 92.9% |
| p0302 | 100.0% | 93.8% |
| p0502 | 97.8% | 97.6% |
| p0602 | 100.0% | 87.4% |
| p0702 | 96.8% | 97.1% |
| p0802 | 95.6% | 95.2% |
| p0902 | 100.0% | 97.1% |
| p1002 | 100.0% | 91.2% |
| **Average** | **96.5%** | **94.2%** |

# Conclusion

- Analysis of human behaviour
  - huge potential in transforming health care
  - especially in mental health
- Very exiting times ahead!
  - Not only in detecting patient state
  - But the potential to discover new medical knowledge from mining large scale data

# Do you know a Post-Doc?




- I'm looking for a post-doc in data mining and pervasive healthcare
- Description of the position:
- http://venetosmani.com

Thank you!