Mobile Sensing: Health and Wellbeing

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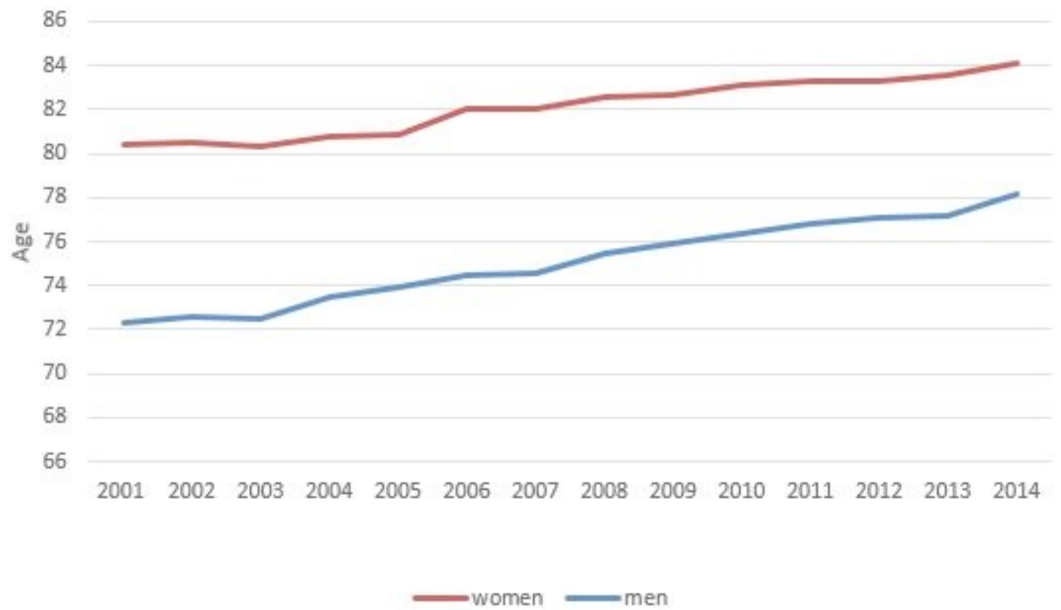
Health and Wellbeing

- Increasing importance of health and wellbeing
  - Higher life and longevity expectations
  - Accessibility (disability) awareness
  - Mental health awareness



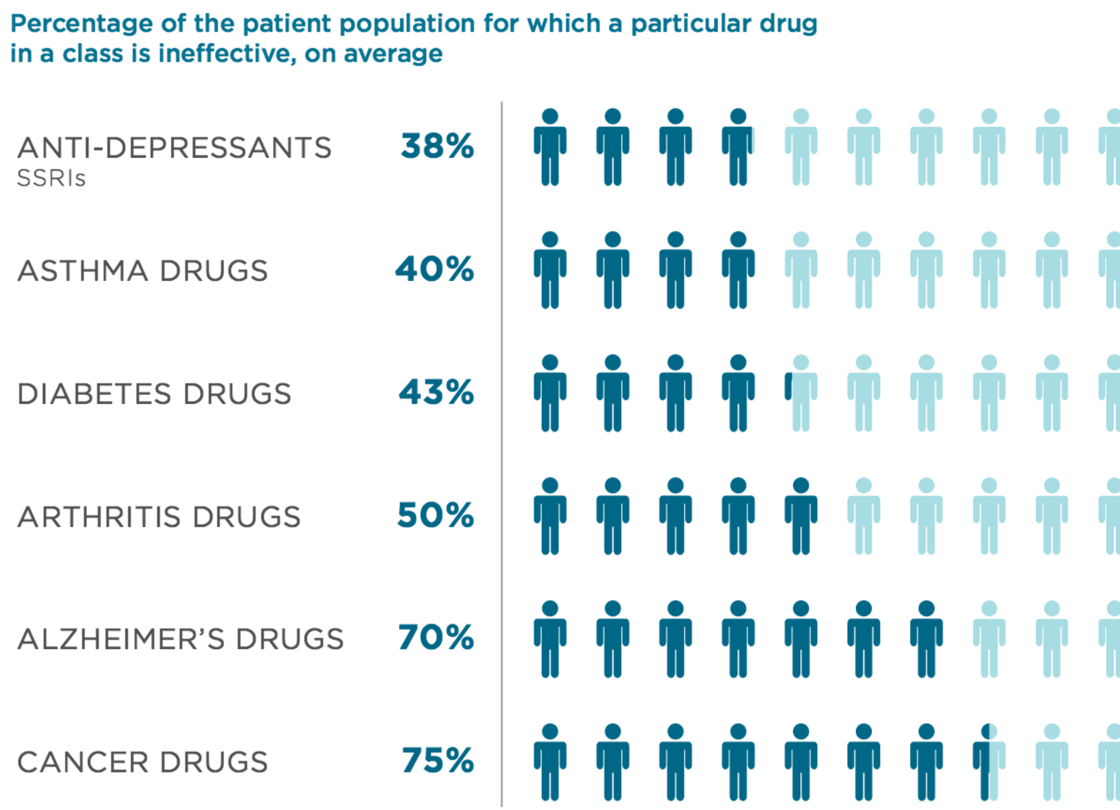
Life expectancy at birth (Slovenia), Eurostat, 2016

Health and Wellbeing

- Current health care systems difficult to sustain
  - Unfavourable demographic trends
    - More elderly people who need more care
  - Increased waiting times
  - Growing cost of healthcare
  - Lack of healthcare personnel, especially in certain developing countries
  - General treatments are often inefficient

Next Stop: Personalised Healthcare

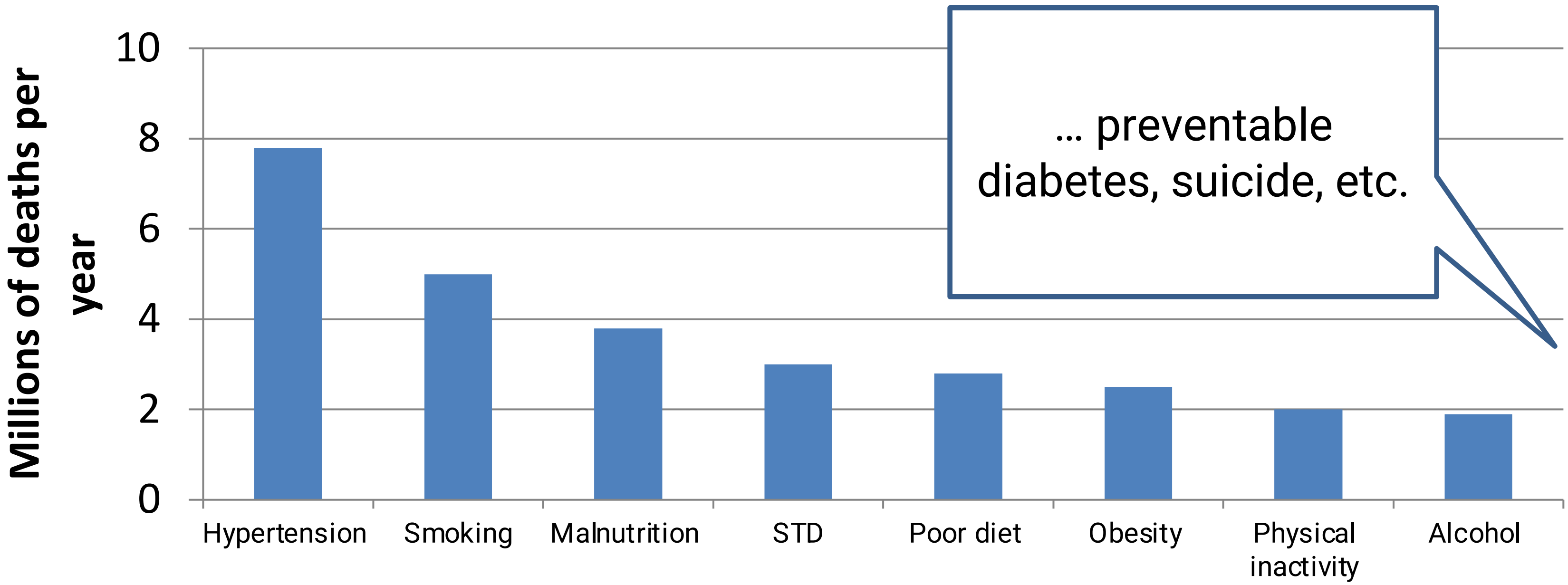
- One-size-fits-all treatments are ineffective – adapt the treatment to an individual!



[The Case for Personalized Medicine, Personalized Medicine Coalition, 2015]

Next Stop: Preventive Healthcare

- Preventable causes of death are taking tens of millions of lives every year



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Obstacles to Preventive Personalised Healthcare

- Health state prediction is difficult
- Health state monitoring does not scale to a larger population
- Personalisation requires fine-grain information we don't have time to collect
- Selecting the right treatment has to take into account numerous factors
- Remote therapies are difficult to deliver

Mobile Sensing for Personalised Preventive Healthcare

- Mobile computing technology:
  - Ubiquitous
    - >3 billion smartphones in the world
  - Used anytime/anywhere
  - Highly personal
  - Sensor-enabled

Prediction & Monitoring Use Case: Depression

“Trajectories of Depression: Unobtrusive Monitoring of Depressive States by means of Smartphone Mobility Traces Analysis”
Canzian and Musolesi, 2015.

Impact of Depression

- In developed countries up to 90% of people who die by suicide are affected by mental disorders
- Depression is the most common mental disorder associated with suicidal behaviour
- Depressive disorders have a strong negative economic impact

Depression Diagnosis and Monitoring

- Based on self-assessment questionnaires
  - PHQ-8

Over the **last 2 weeks**, how often have you been bothered by any of the following problems?
(circle ***one*** *number on each line)*

How often during the past 2 weeks were you bothered by...	**Not at all**	**Several days**	**More than half the days**	**Nearly every day**
1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself, or that you are a failure, or have let yourself or your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed. Or the opposite – being so fidgety or restless that you have been moving around a lot more than usual	0	1	2	3

Depression Diagnosis and Monitoring

- Based on self-assessment questionnaires
- Disadvantages:
  - Time consuming
  - Expensive
  - Self-reflections are prone to errors
- Idea: use mobile sensing for depression diagnosis and monitoring

Mobility Traces

- Previous interview-based studies have shown that depression leads to a change in mobility and activity levels
- Smartphones allow continuous location monitoring
- Potential of automated mobility trace collection for depression inference/prediction?

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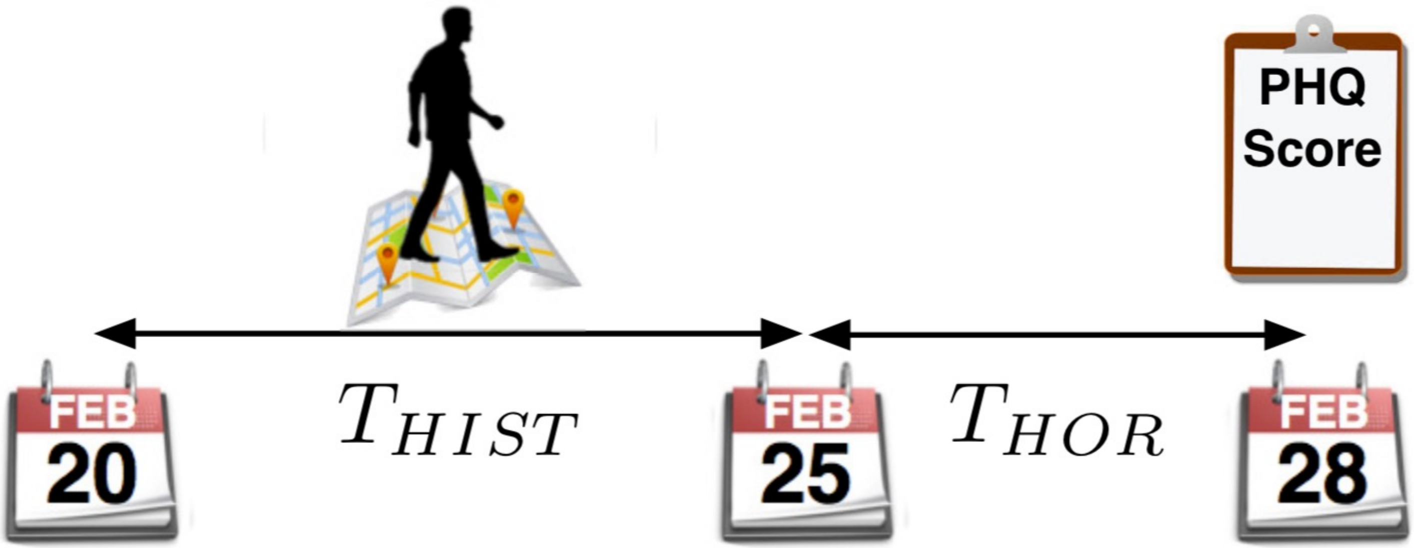
Mobility Traces and Depression Prediction

- Can the mobility trace from Feb 20th till Feb 25th predict the PHQ score on:
  - Feb 25th?
  - Feb 28th?



Mobility Traces – Features

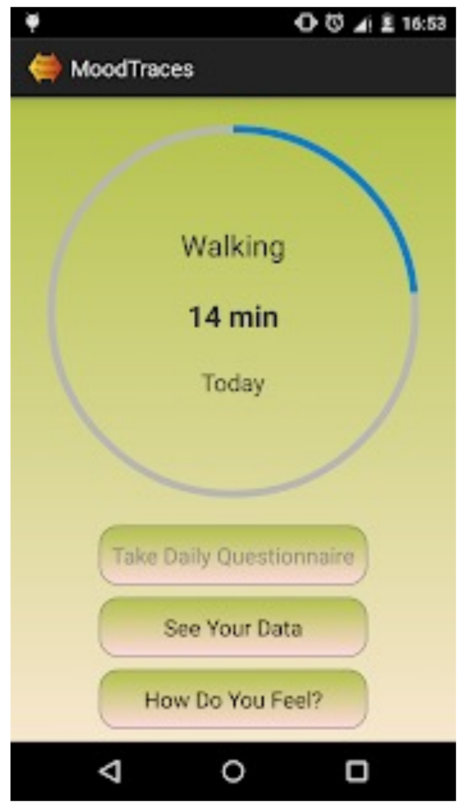
- Mobility trace is a sequence of stops and moves
- Extracted mobility metrics:
  - The total distance covered
  - The maximum distance between two locations
  - The radius of gyration
    - The deviation from the centroid of the places visited in an interval
  - The standard deviation of the displacements
  - The maximum distance from home
  - The number of different places visited
  - The number of different significant places visited

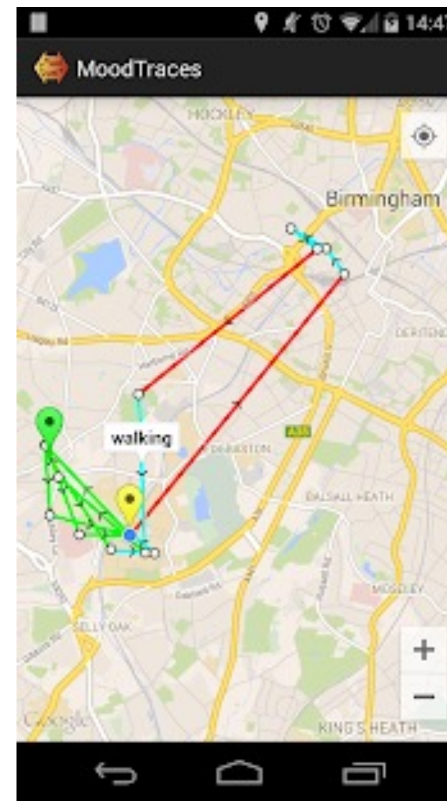
Mobility Traces – Features

- Mobility trace is a sequence of stops and moves
- Extracted mobility metrics:
  - The routine index
    - Quantifying how different the places visited by the user during the time interval $[t_1, t_2]$ are with respect to the places visited by the user during the same time interval in other days.

Data Collection App – Mood Traces

- Android app collecting:
  - Fine-grain location data in the background
  - PHQ-8 answers (for ground truth only)
- Location sensing is power hungry
  - State machine for energy-optimised location sensing





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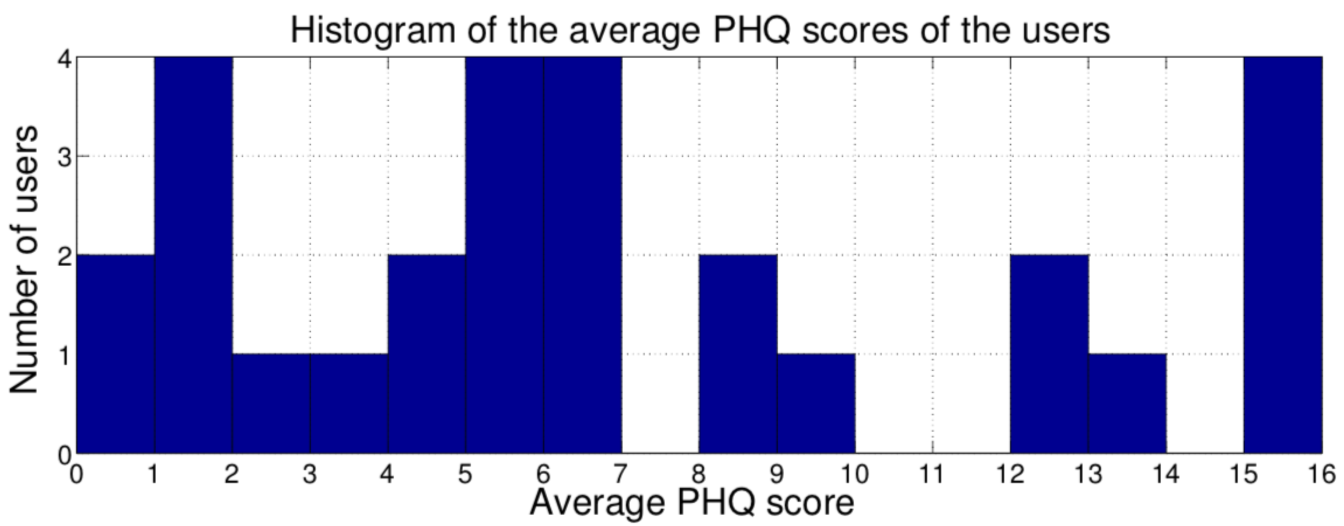
Data Sample

- Users:
  - 28 participants
    - 15 male, 13 female
    - On the average monitored for 71 day
  - Varying PHQ score



Data Preprocessing

- Mobility features:
  - Calculate stop points (centroids)
  - Calculate features for last N days
  - Subtract the average feature value for that interval of the day
- PHQ scores:
  - Get rid of “fake” answers: trap question, speed check
  - Calculate the deviation from the mean behaviour

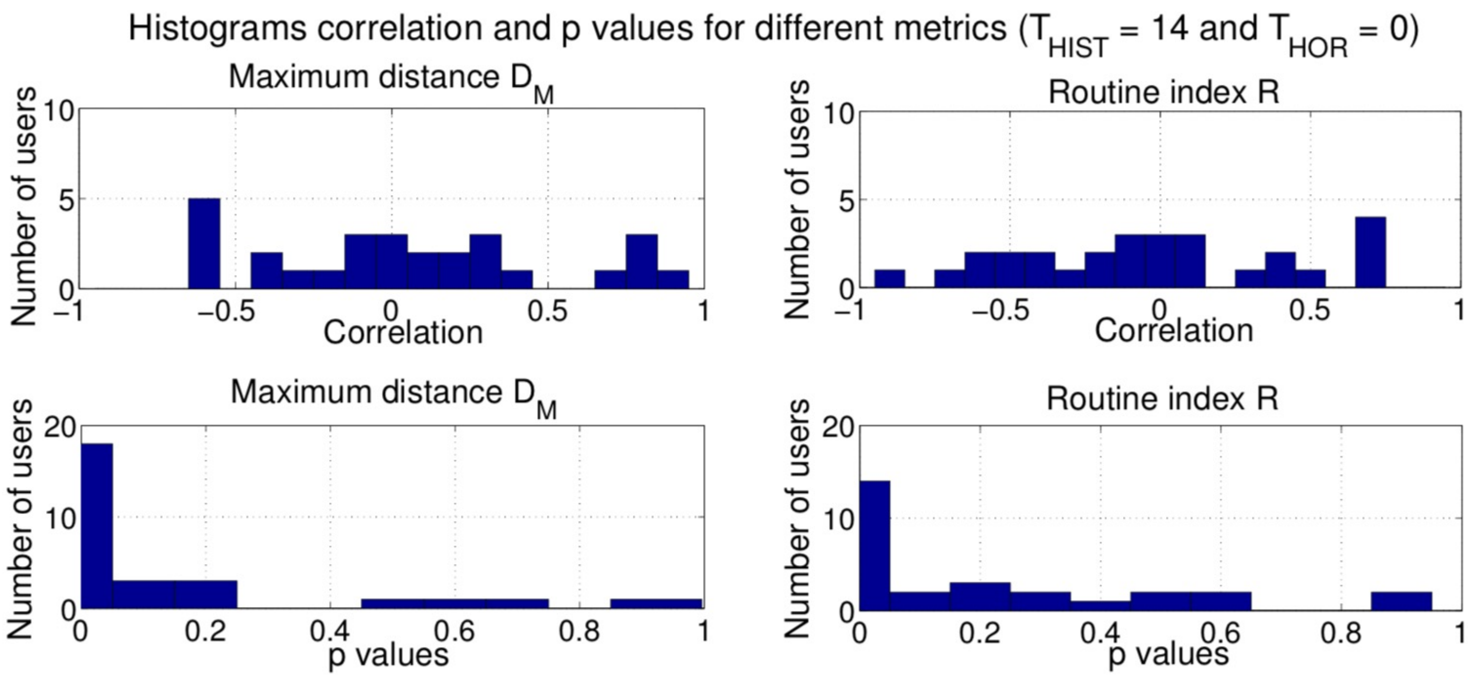
Mobility – PHQ Score Correlation Analysis

- Modest link between mobility metrics and the PHQ score, if aggregate data are analysed
- Stronger when a longer interval is considered

Mobility metric	Average abs. correlation		Average p-value	
	$T_{HIST} = 1$	$T_{HIST} = 14$	$T_{HIST} = 1$	$T_{HIST} = 14$
D_T	0.159	0.402	0.401	0.095
D_M	0.152	**0.432**	0.425	**0.069**
G	0.160	0.343	0.422	0.197
σ_{dis}	0.147	0.417	0.431	0.088
D_H	0.199	0.358	0.297	0.168
N_{dif}	0.191	0.360	0.335	0.157
N_{sig}	0.201	0.336	0.385	0.181
R	**0.227**	0.368	**0.262**	0.138

Mobility – PHQ Score Correlation Analysis

- For some individuals, the link is stronger
- Different individuals exhibit different changes of mobility metrics when PHQ score changes



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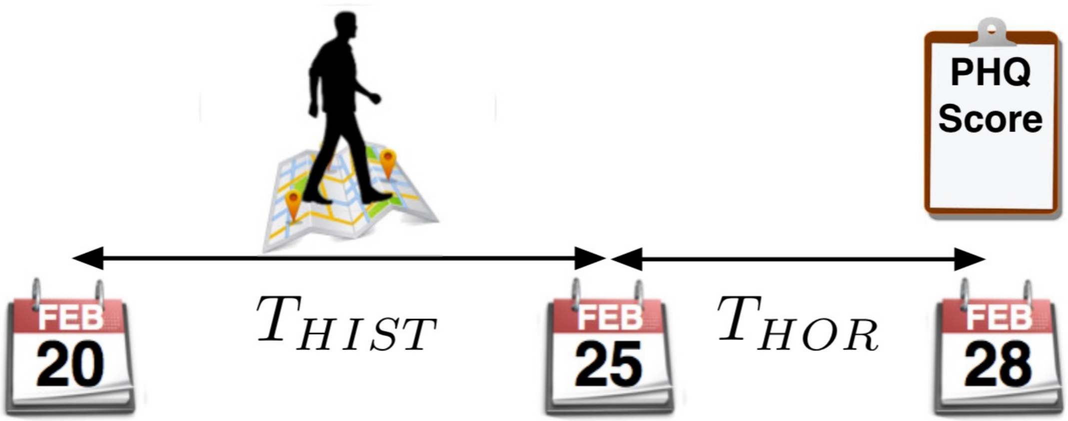
Mobility – PHQ Score Prediction Power

- Predict whether the PHQ score will jump to above one standard deviation from that person's mean PHQ
- Train on T_{HIST} data, predict at T_{HOR} in future



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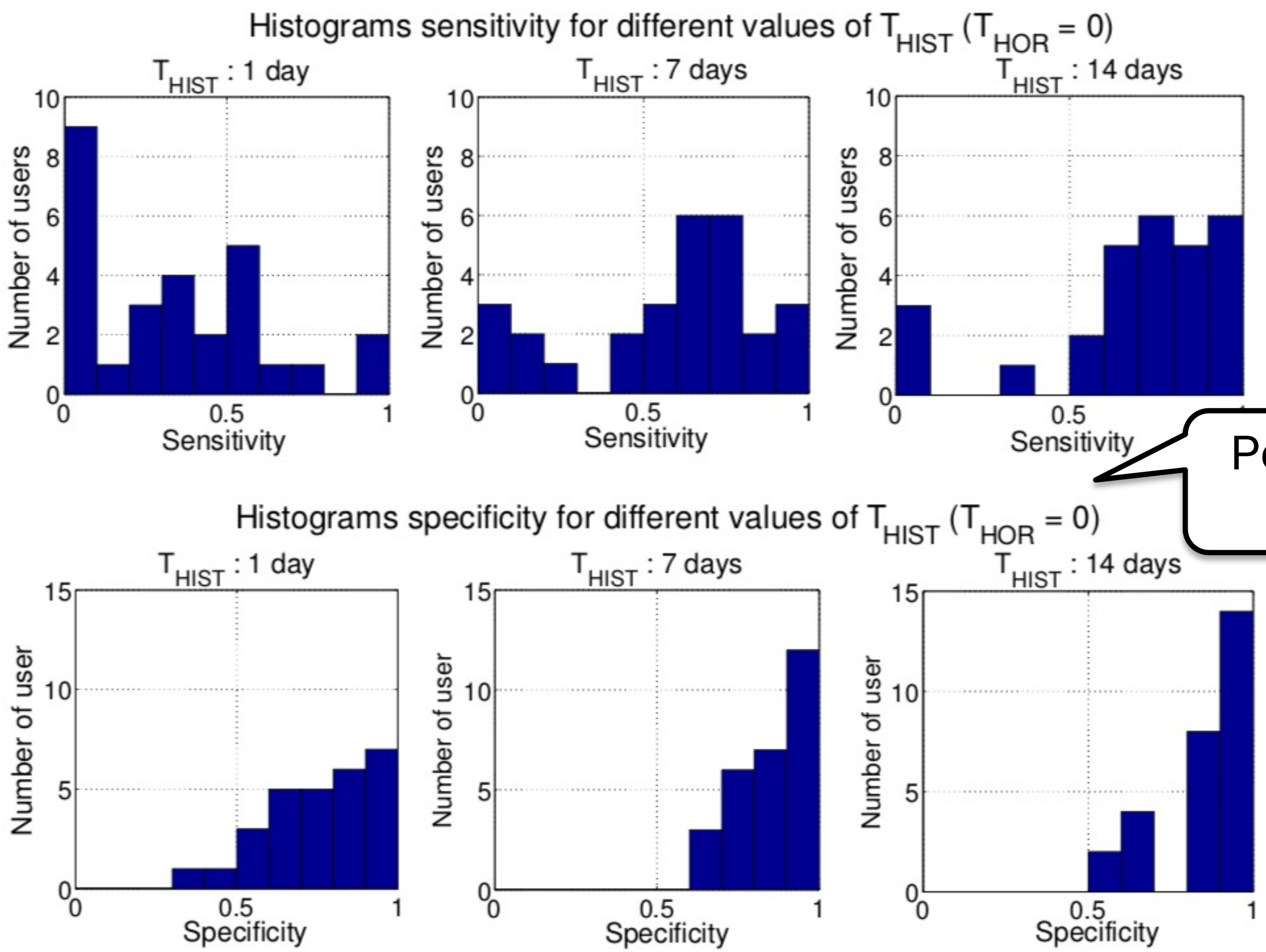
Mobility – PHQ Score Prediction Power

- Classifier:
  - SVM with a Gaussian radial basis function kernel
  - Personal classifier for each user
  - General classifier for all users
- Performance metrics:
  - Sensitivity (true positive)
  - Specificity (true negative)

Why is this impractical?

Mobility – PHQ Score Prediction Power



Personalised models

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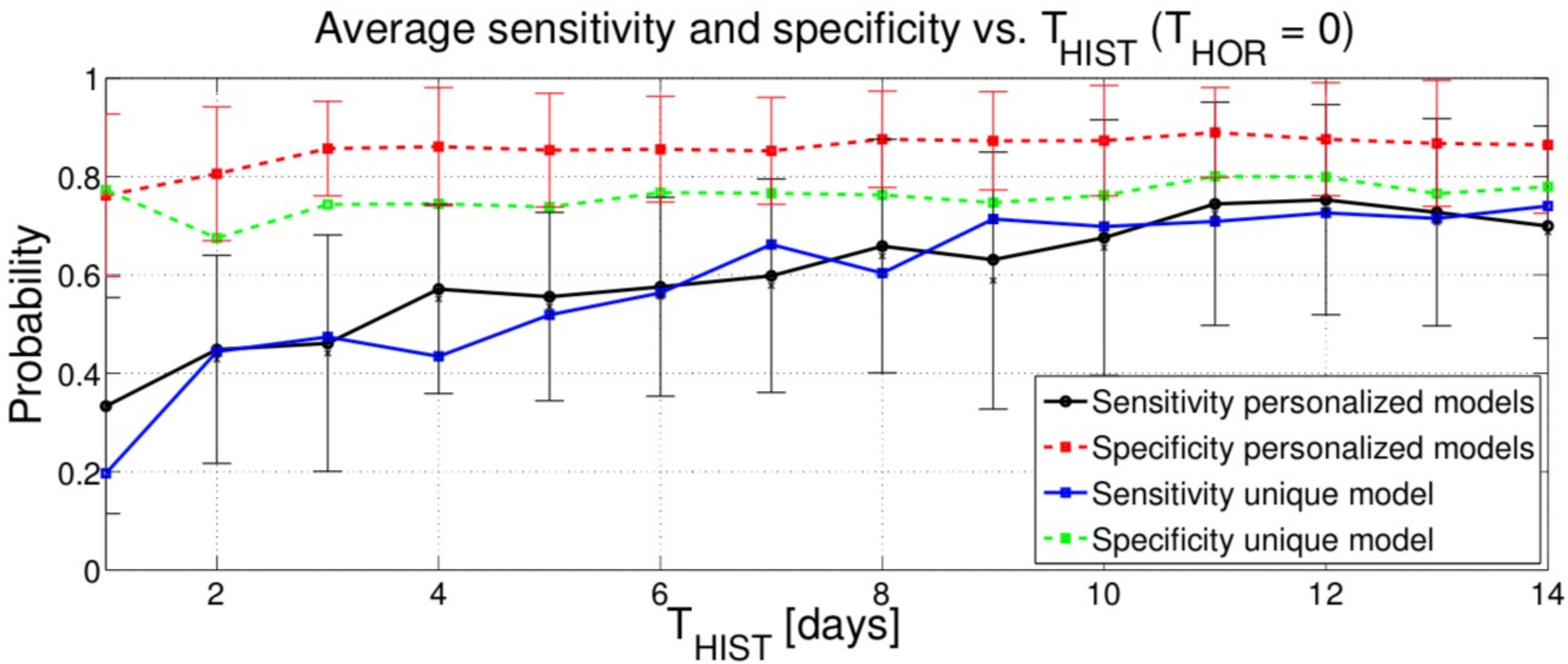
Mobility – PHQ Score Prediction Power

- General (unique) depression prediction model



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Mobile Sensing for Depression Prediction

- Potential means for automated early depression warning
- Relatively low sensitivity
  - Certain depression onsets will not be recognised
- Feature engineering
  - Mobility behaviour connected with depression can be complex and difficult to formalise
  - Do we know that the features are good?
  - Can we construct more informative features?