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Discovery of Personal Processes from Labeled Sensor Data

An Application of Process Mining to Personalized Health Care

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Motivation – Health Care

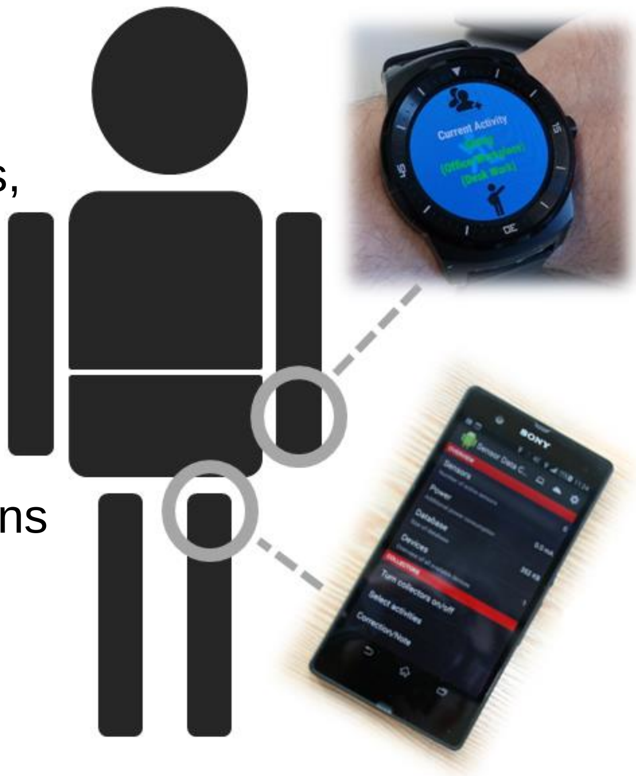
Noncommunicable diseases (NCDs) kill 38 million people each year. Such diseases include, for example, cardiovascular diseases, diabetes, osteoporosis, and certain types of cancer. (WHO, 2014)

- Activities of daily living are important for assessing changes in physical and behavioral profiles
- In context of medicine, a correct compliance is important.
- We want use modern techniques to support people and improve their healthiness.

Motivation – Self-Tracking

Customary smart-phone platforms are equipped with a rich set of sensors which enable self-tracking.

- Positioning technologies, sensor networks, and spatiotemporal data are available
- Personal behavior and processes can be derived to *learn* the daily routine and allows to detect specific patterns.
- Resulting predictions and recommendations could help to achieve a healthier life



Motivation - Scenario

In general, current self-tracking approaches are helpful in many scenarios

→ However, fine grain monitoring is not possible but necessary.

Normally, (elder) people get a brief instruction from the doctor how they have to take their pills, e.g., three pills every eight hours without eating one hour after the intake.

<u>Actual Daily Routine</u>

12:00 take pills
12:10 eating/drinking
20:12 take pills
21:00 eating/drinking
06:25 take pills
14:55 take pills

<u>Optimal Daily Routine</u>

12:00 take pills
13:00 eating/drinking
20:00 take pills
21:00 eating/drinking
04:00 take pills
12:00 take pills

→ Time-based monitoring makes sense.

Related Work

Smartphone and Healthcare

- Activity recognition from accelerometer data on a mobile phone, 2009
- Review of Healthcare Applications for Smartphones, 2012
- Smartphone Based Healthcare Platform and Challenges, 2015

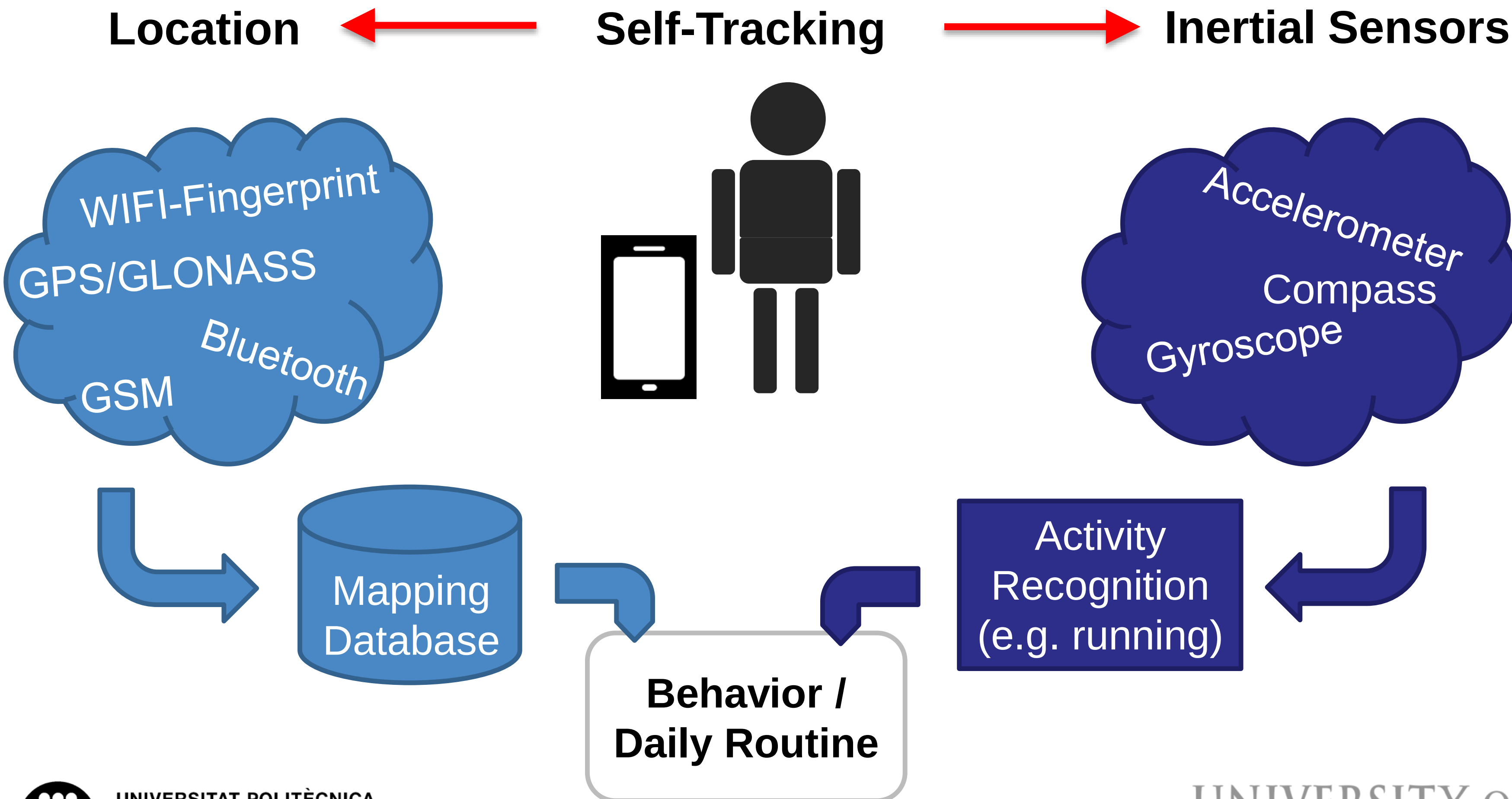
Processes

- Trajectory pattern mining, 2007
- Trace clustering in process mining, 2009
- Process mining: discovery, conformance and enhancement of business processes, 2011

Overview

1. Motivation
2. Related Work
3. **Personalized Health Care**
   - **Self-Tracking**
   - Use Cases and Experiments
4. Challenges
5. Summary

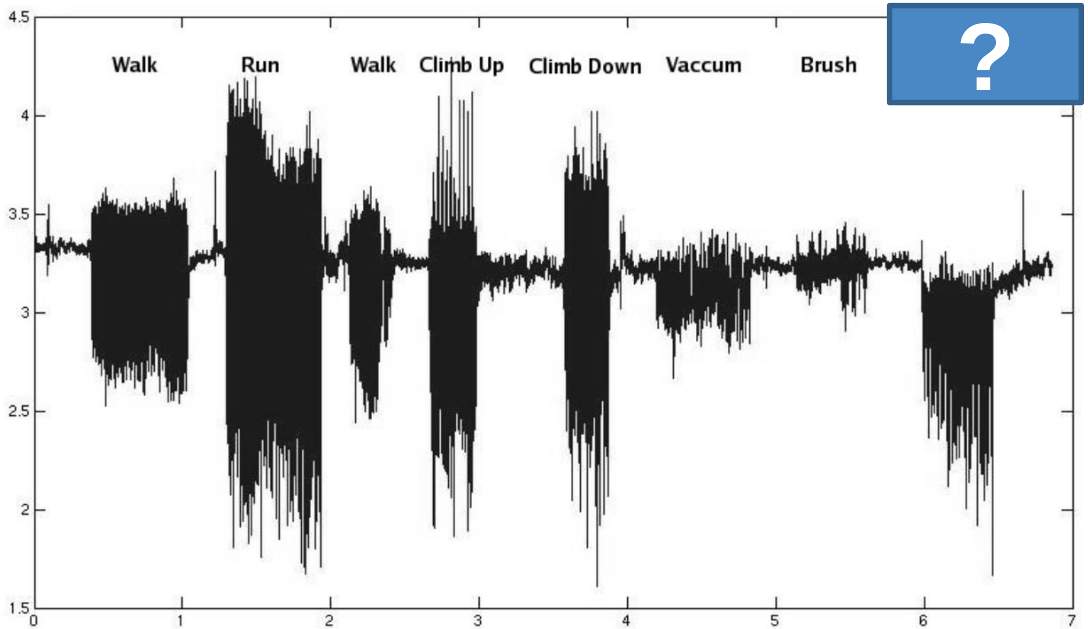
Personalized Health Care – Self-Montoring



Personalized Health Care – Example

Activity Recognition

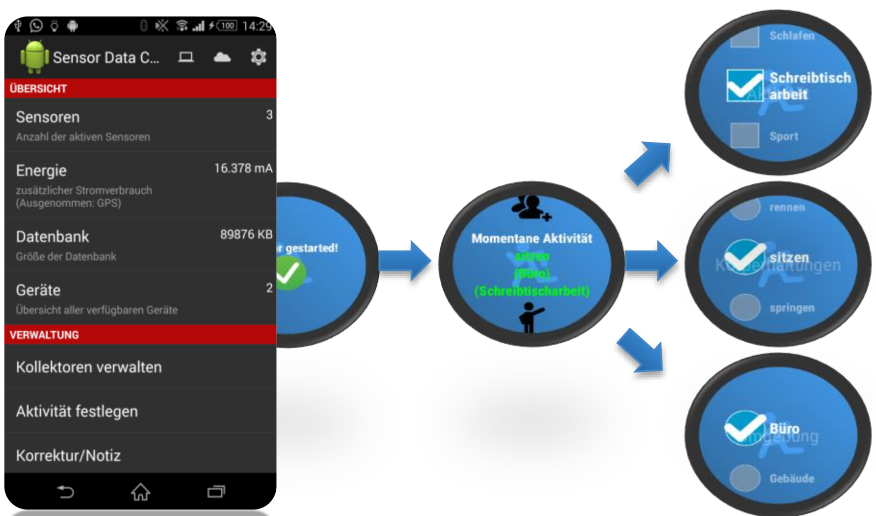
Activity Recognition is a learning problem but there are still many open issues …



Accelormeter, X-axis readings for different activities (Ravi et. al., 2005)

Personalized Health Care – Data Gathering

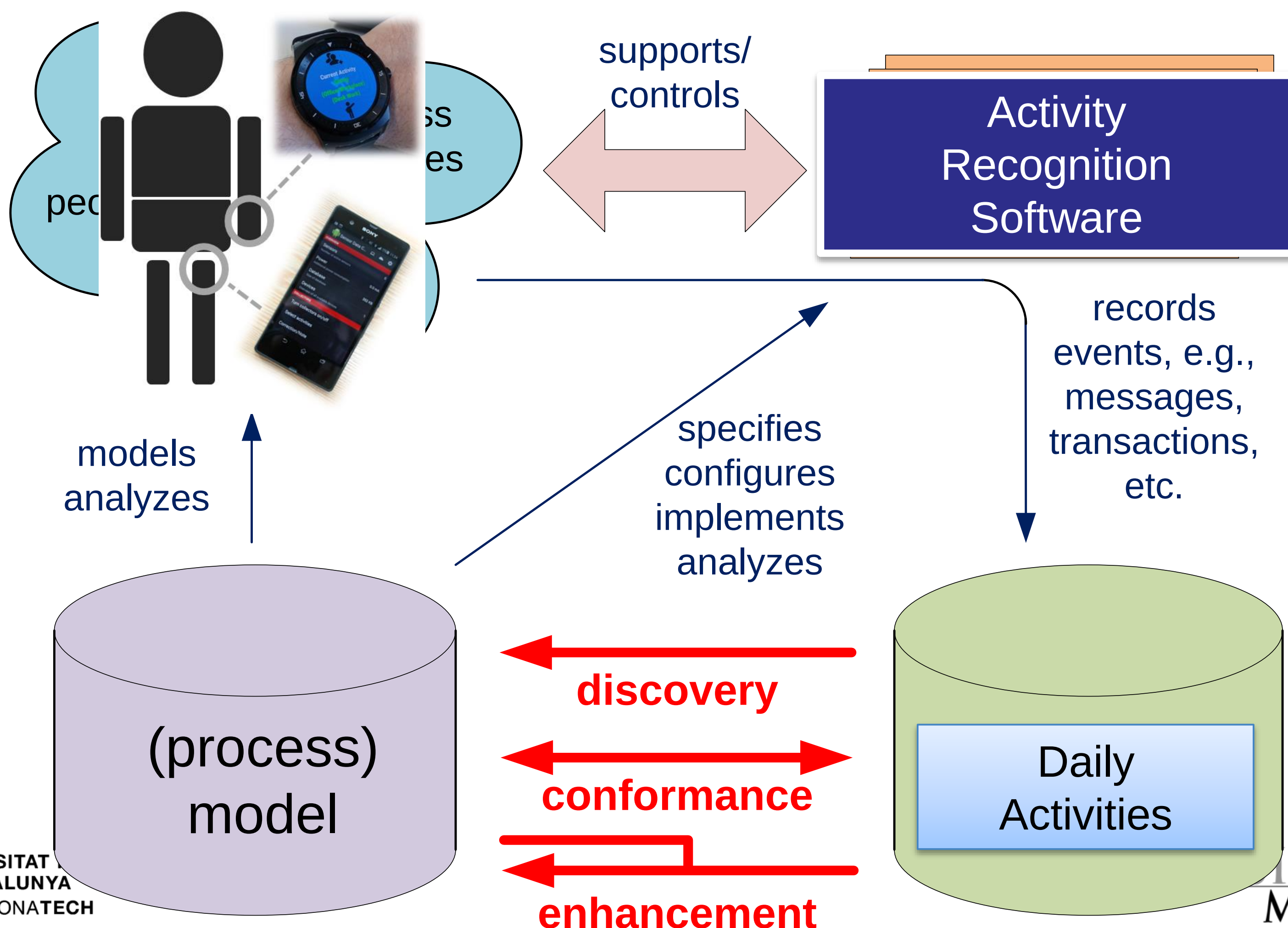
- ~12 hours/day, 2 weeks, 8 subjects
- recording **inertial sensors** and **location**
- subjects have to label their **activities** (e.g., “playing football”)
- it was possible to combine **activities** (e.g., “desk work” and “drinking coffee”)



- Recorded: 74 cases, 1386 events
- Average duration of one day: 12.1 hours

Labels	Records (avg±sd)
Activities	20±7
Postures	80±62
Location	16±4
Dev. Position	8±6

Personalized Health Care as Process Mining



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Personalized Health Care – Use Cases Overview

I. Monitoring

Record and analyze the personal behavior

→ Visualize their personal processes to highlight unconscious behavior.

II. Deviations

Compare personal processes with reference processes to detect deviations.

→ Optimize the daily routine by adding missing activities or reorder them.

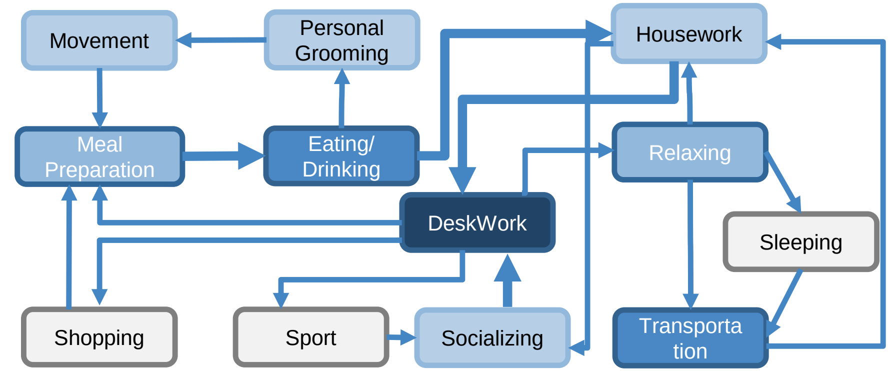
III. Operational Support

Combining spatio-temporal data and activity data to make predictions.

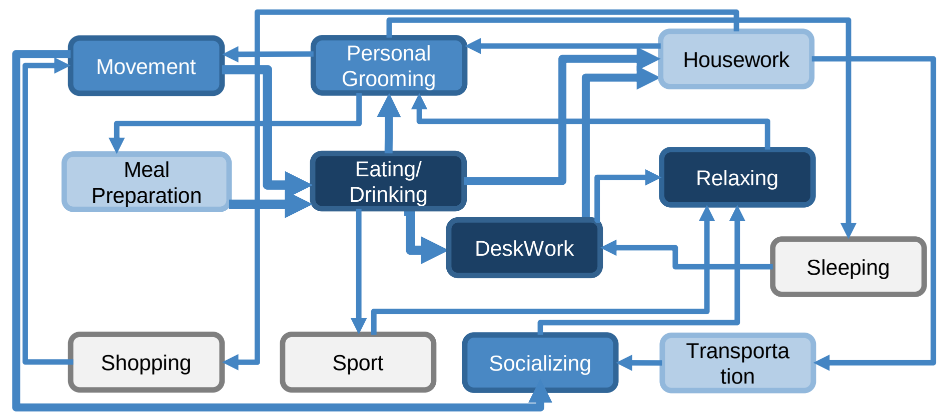
→ Make recommendations in order to accomplish certain goals.

Personalized Health Care – Use Case I

- **Variability**: for each individual, #process variants = #traces !!
- **Fuzzy Models** (using Disco) allowed to focus on the main activity
- Confirm tendencies:
    - Working vs. weekend days
    - Student vs. not Student



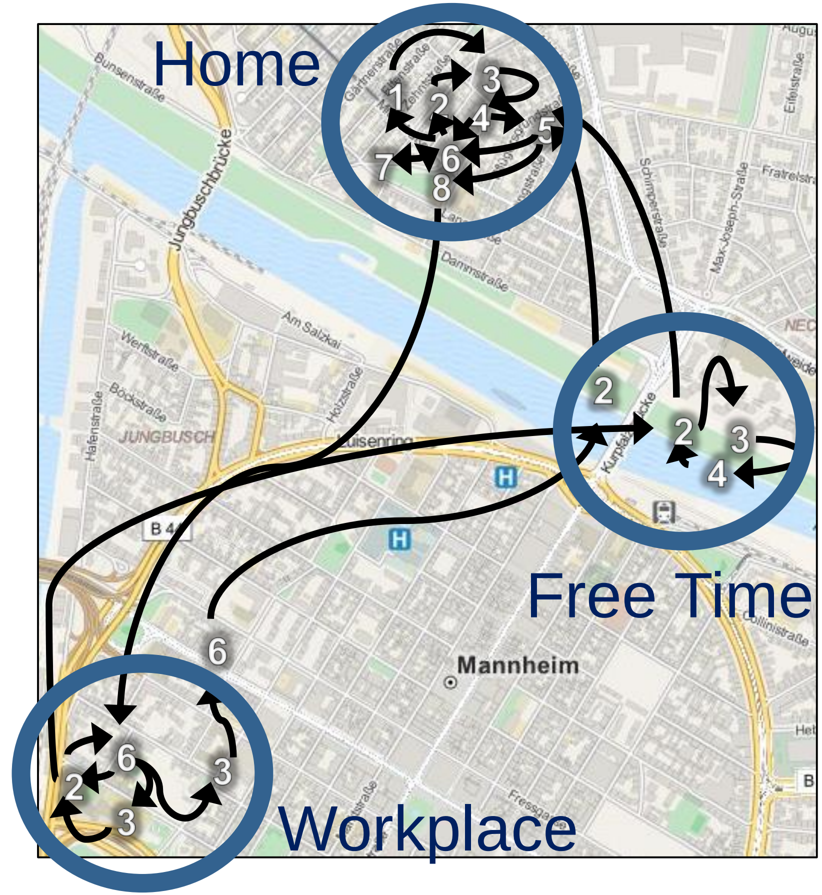
Personal activity during working week days



Personal activity during weekend days

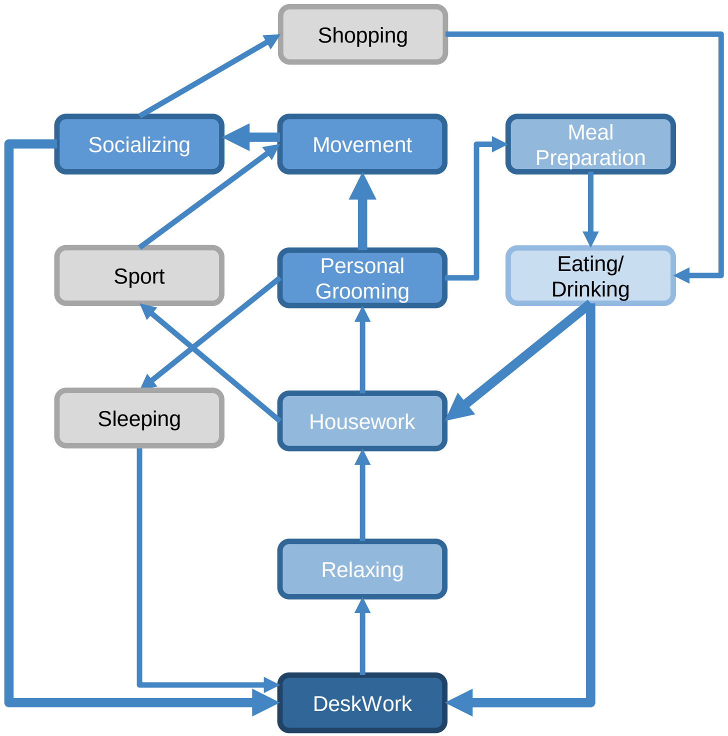
Model Enhancement Using Personal Data

- personal activity-position map
- space, time, and activity (trajectory pattern)
- New possibilities:
  - Geographical Label Splitting
  - Geographical Abstraction and Clustering



Reference Models

- They can be obtained by
  - An expert (e.g., a doctor)
  - Using *elite* data
  - Elicitating them from textual information using NLP+Process Extraction (Friedrich *et al.*)
- Starting point to
  - Check deviations
  - Forensics
  - ...



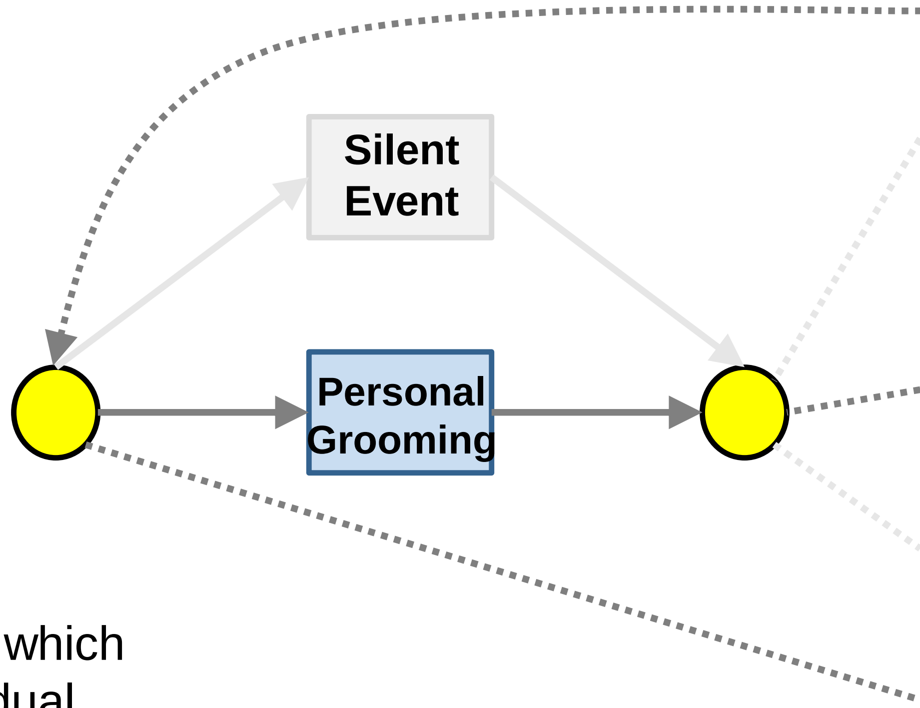
Main Personal Activity

Reference Models

- specific *order*, explicit *choices*, *concurrency* actions
- (flexible) conformance checking
- deviations, costs, and quantities

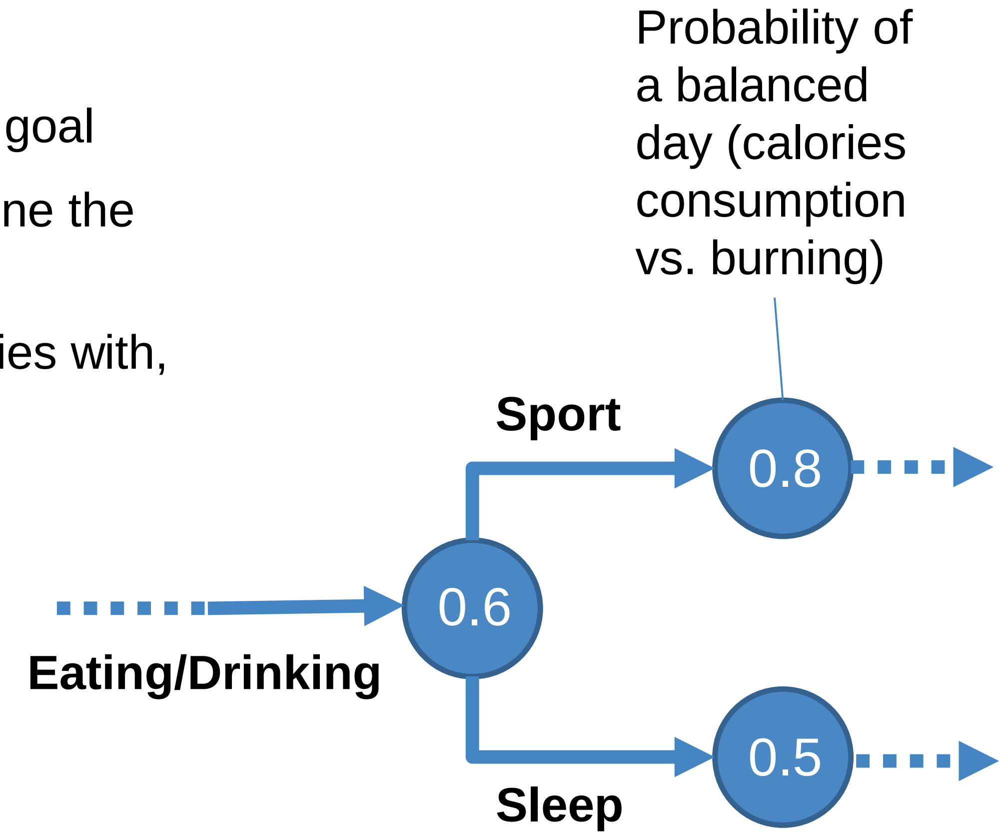
➡ could be expensive!

<u>Simplification</u>: rules or patterns which should be satisfied by an individual.



State-based prediction

- probability to reach a particular goal
- process models help to determine the influence of the next step
- aggregate historical data/activities with, e.g., amount of calories.
- amount of calories vs. labels



Personalized Health Care – Use Case III

State-based prediction

- Important question: Does concurrency plays an important role ?
  - Yes: then event-based models may be used for operational support
  - No: state-based models like the one before are sufficient
- Potential concurrency pairs in our context:
  - Movement/Transportation
  - Transportation/Socializing
  - Deskwork/Socializing
  - ... but in practice they were not so common !

Overview

Challenges

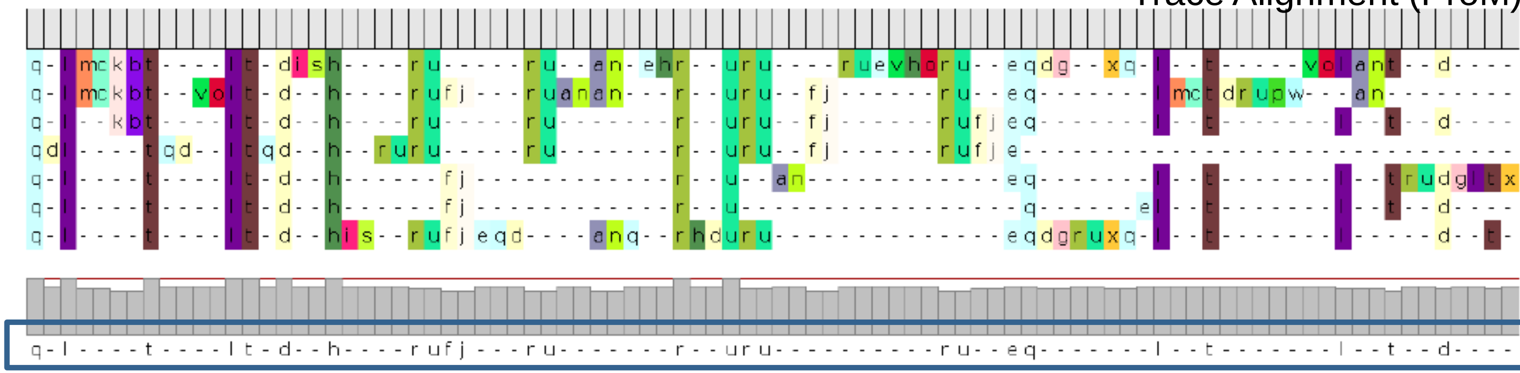
1. **Trace Alignment**
   - The behavior of a person is very individual any may depend on the day (working day vs weekend) and other factors.

2. **Uncertainty**
   - The daily routine of a person is flexible and does not follow a fix order of activities.

3. **Analytics**
   - Several different dimensions such as space, time, and activity has to be considered in context of the daily routine.

Challenges (1) - Trace Alignment & Clustering [5]

Trace Alignment (ProM)



Cluster Trace

- Aims to extract common and frequent behavior but also highlight exceptional behavior.
- Cluster Log: (multi)set of cluster traces that may be the starting point for analysis (discovery, conformance, ...)
- How many clusters ?

Challenges (2) - Uncertainty

Trace: < Stand Up , Washing , Breakfast , Working >

Probabilistic Trace: < Stand Up , {Jogging 0.6 / Washing 0.2 / Shaving 0.2} , {Phone 0.2 / Breakfast 0.8} , {Working 0.7 / Social 0.1 / Hiking 0.2} >

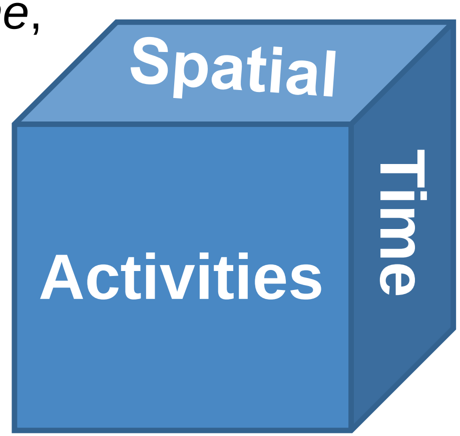
A new theory for probabilistic process mining is needed

Models ? Algorithms ? Metrics ?

Challenges (3) - Analytics

Process Cubes

- Process Cubes as a solution to handle, i.e., *Spatial*, *Time*, *Activity*, and *Transportation Modes*.
- Find tailored behaviors (e.g., reference models) according to particular goals
- May open the door to gamification (e.g., try to match a very particular behavior)



Summary

Personal Healthcare is important and we want to support people automatically and we believe this is a very promising field for process mining.

We outlined our **ideas** and **challenges** to support the following use cases:

- *Monitoring*
- *Deviations*
- *Operational Support*

However, we just started …

… and these are the things we are working on. We hope for ideas for future work.

Thank you

Thank you for your attention

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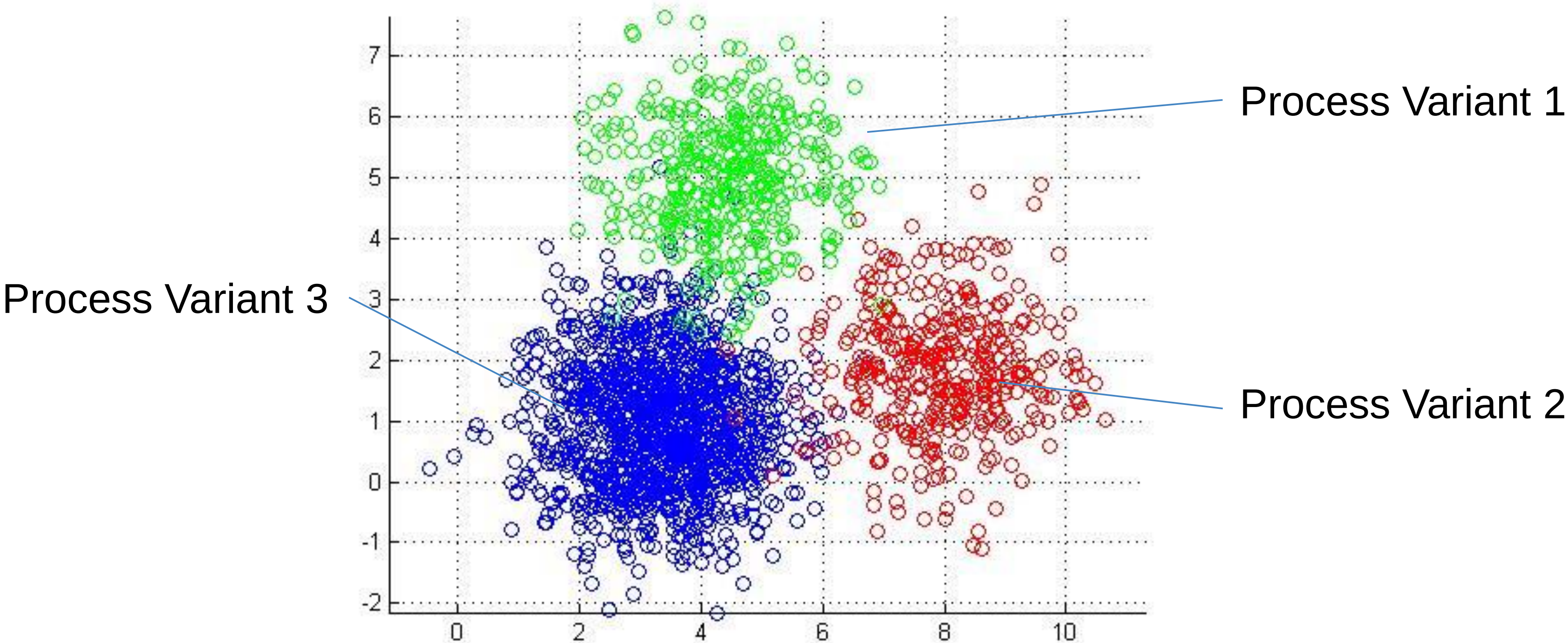
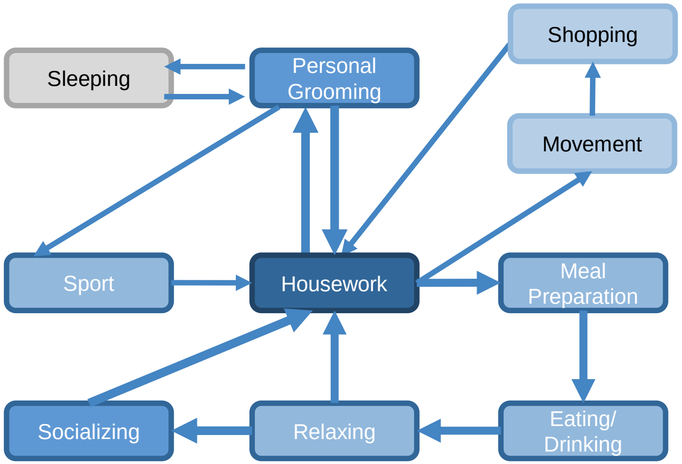
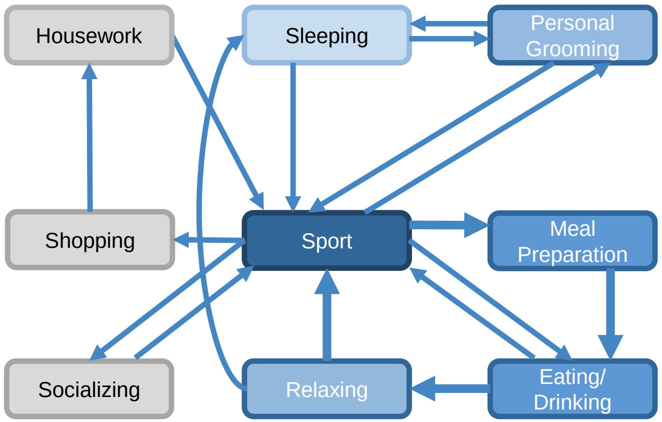
Backup - Challenges (1) - Variability



Backup - Challenges (3) – Analytics - Example



Daily activity in the period 2013-2014 for females between 20-30 years old, non-smokers



Daily activity in the period 1980-1981 for athletes between 20-30 years old, non-smokers