FOM Hochschule

RapidMiner Wisdom 2015,
August 31 – September 1, 2015 | Ljubljana Castle – Ljubljana, Slovenia

Recognizing Drinking ADLs in Real Time using Smartwatches and Data Mining

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Introduction

1. Motivation and problem
2. Research questions
3. Smart watches
4. ADL Recognition
    1. ADL Recognition
    2. Data collection
    3. ADL modelling
    4. ADL real time detection
    5. Demonstration
5. Summary

Motivation and problems

Drawbacks of current technologies for the elderly

- Support of elderly during daily life limited
  - Mostly near home
  - Requires hardware installation in home
  - expensive
- Activity analysis– ADL (activities of daily living)
  - Only indirect recognition with fixed devices – slow reaction time
  - ADL-recognition of activities like drinking not supported etc.
  - Changes over time not detectable
- Stigmatization effect associated with most devices
- No apps for the target group

Research questions

Key question: Is it possible to detect drinking ADLs with a smartwatch?

- Drinking is a key health factor
- Insufficient fluid in-take of elderly people
- Dehydration evokes
  - subtle lethargy
  - Weakness
  - Irritability
  - Phantasmagorias
  - lack of concentration
    - enhancing domestic accidents, tumbles

Source: Rainer Lutze, lustcon, http://www.lustcon.de

- **More general: Can other ADLs be detected too?**
- **Which parameters are sufficient to characterize an ADL?**

Smart watches

The Alternative: SmartWatch

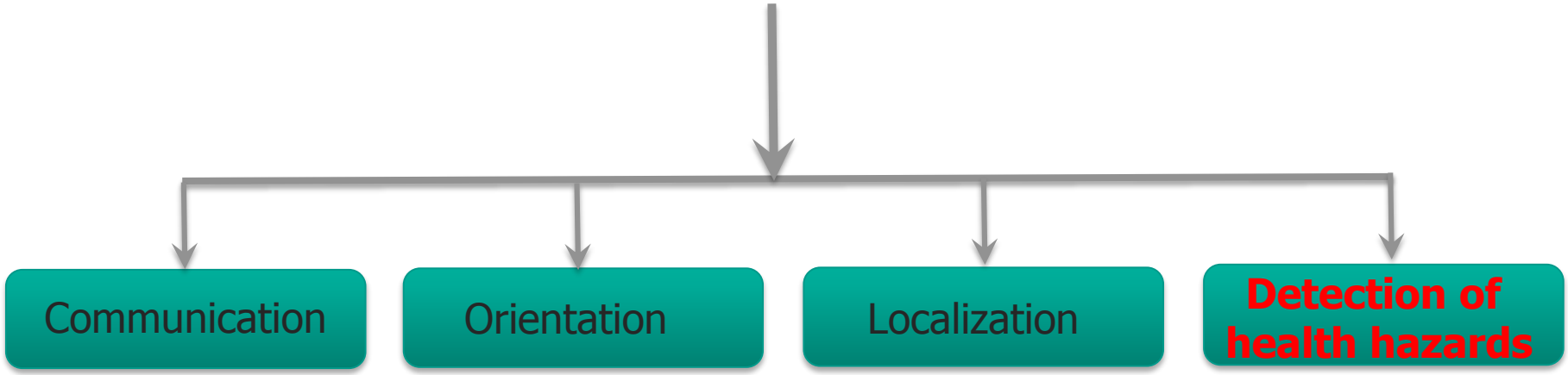
- CPU: 1 - 1,2 GHz DualCore,
  RAM: 512MB - 1GB,
  Flash Memory: 4GB – 8GB
- Display: 1,3" - 2" OLED, 320x320 bis 480x360 Pixel resolution., 250 – 300 ppi, capacitive touchscreen
- Sensors: Acceleration, Gyroscope, Compass, pulse meter, pedometer, , Barometer, GPS
- Audio: Microphone, loud speaker
- Programmable Vibration
- Communication: BT 4.0/4.1, WLAN, NFC, 3G/LTE Radio
- Battery: 300-400 mAh ≈ max. 1 Tag / 18h usage

Source: Rainer Lutze, lustcon, http://www.lustcon.de

- Pre installed **system apps** for communication, messaging, fitness and navigation
- via **Apps** programmable: Android Wear™, SWIFT™ , Tizen™ (Javascript), WebOS™
- **distributed SW-Architecture** – Smart watch and connected phone
- Voice Recognition via Google Now™, Siri, S-Phone™
- MP3-Player

Support Areas

The four support dimensions



- **Calls in emergency** with one button
- **Automatically started calls after unacknowledged pre alerts**

- **Day of week, date, month, year**
- **Holidays** (Christmas, Easter, ...)
- Own **birthday** plus birthday of relatives,
  ...

- Recognition of **leaving** and **returning** home
- Leaving agreed environment („geofencing")
- **Movement traces** (for emergency cases)

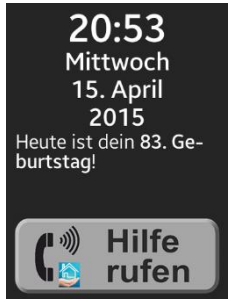
- **Tumble**
- **Insufficient fluid in-take**
- Detection of **significant deviations from learned ADLs**

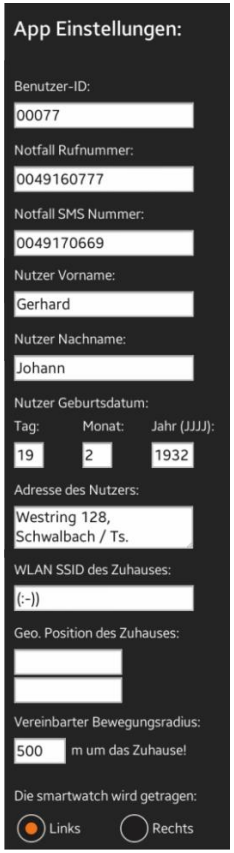
Example Realization

Example implementation Samsung Gear™ S

Communication, Orientation

Editor f. Service

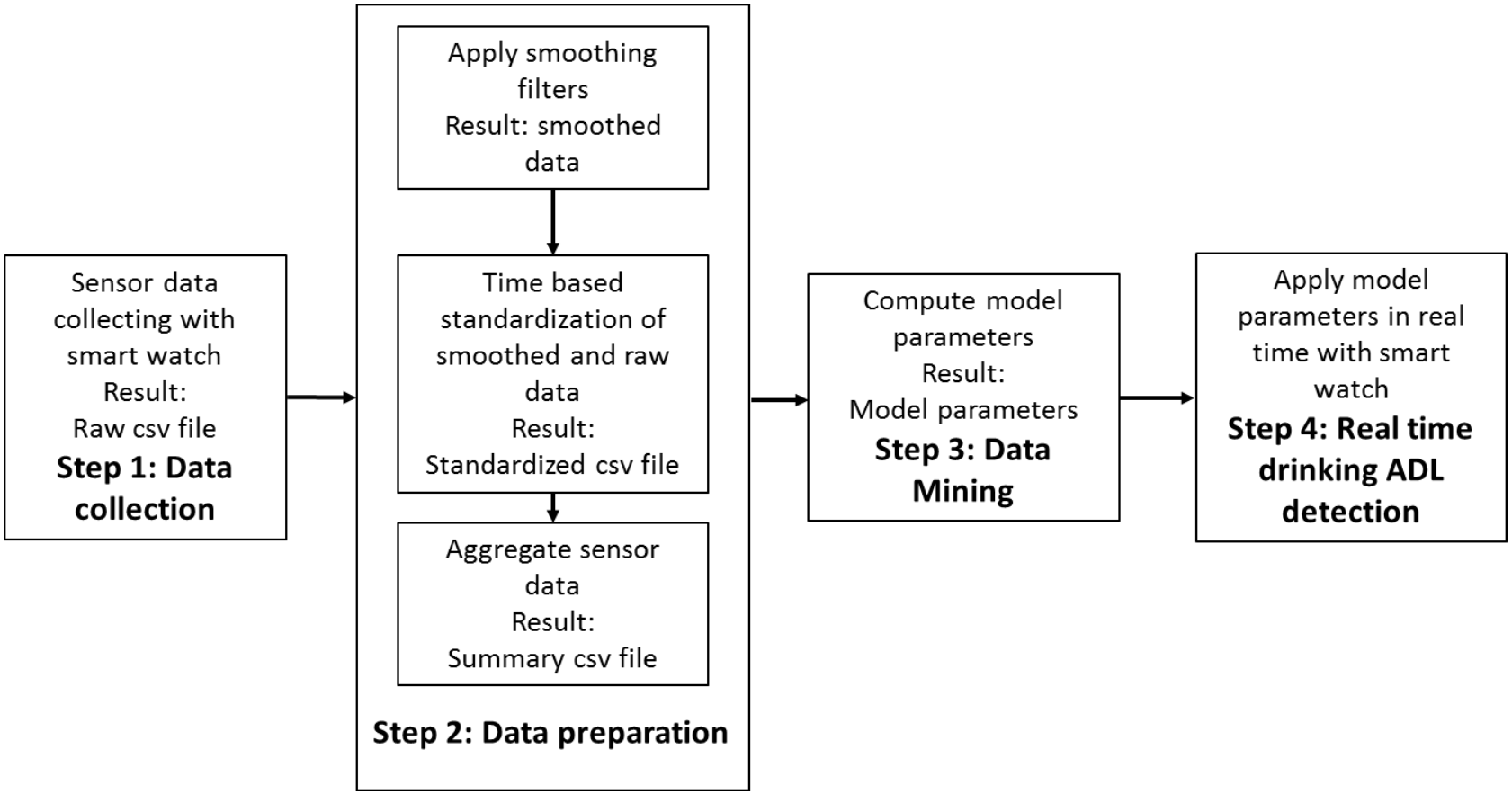




Source: Rainer Lutze, lustcon, http://www.lustcon.de

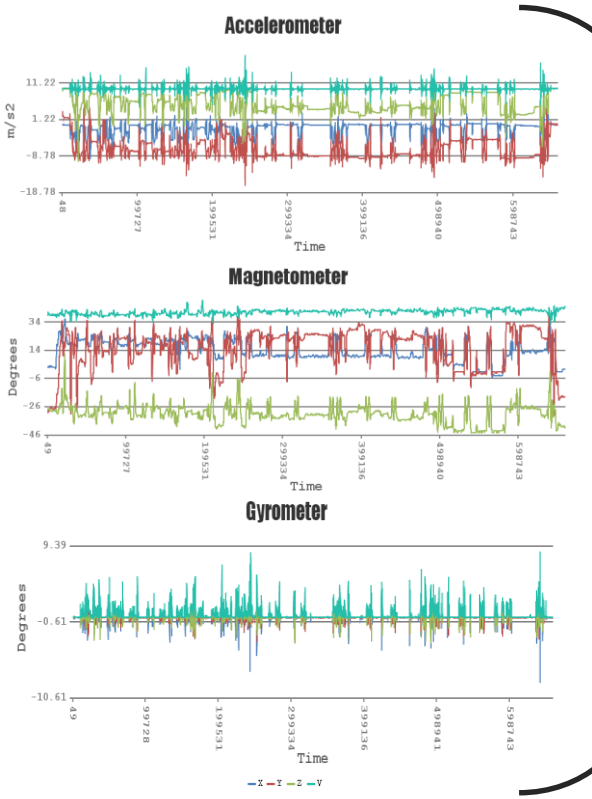
ADL Recognition

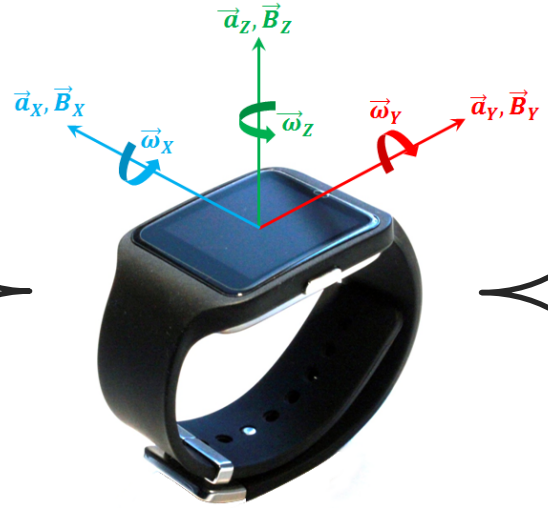
Global process

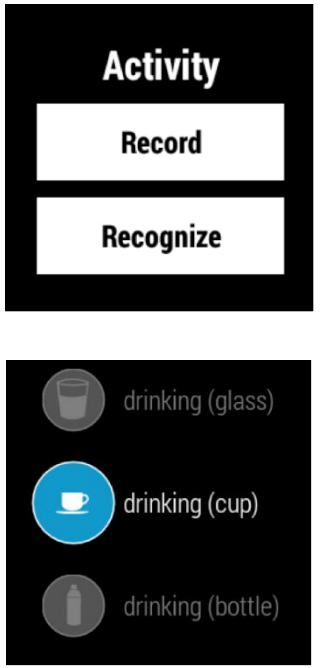


Data Collection

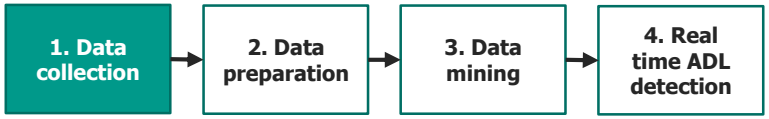
1. Data collection → 2. Data preparation → 3. Data mining → 4. Real time ADL detection







Data Collection



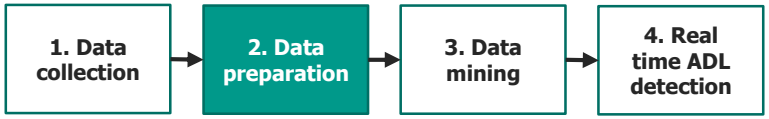
- 1 recording =
  - 10 sec. intervall
  - 1800 sensor values
  - 1 CSV file
- ~ 1200 recorded ADLs
  - ~ 300 drinking Activities
  - ~ 900 other ADLs
- 28 test subjects used for recording

```
-5;-1;1420537162191;WEAR;SmartWatch 3
-5;-2;1420537162191;TEXT;Trinken
0;1;1420537162281;WA;0.22500217;-4.495256;8.478273
0;2;1420537162288;WA;0.22500217;-4.437809;8.305931
0;3;1420537162304;WA;0.12925656;-4.8973875;8.305931
0;4;1420537162314;WG;-0.005326745;0.0;-0.018643608
0;5;1420537162318;WA;0.30159867;-4.5144053;8.612317
…
0;16;1420537162368;WG;-0.039950587;0.0026633726;-0.029297099
0;17;1420537162369;WA;0.32074776;-4.5527034;8.439975
0;18;1420537162374;WG;0.031960472;0.069247685;-0.5619716
0;19;1420537162387;WA;0.22500217;-4.5718527;8.056993
0;21;1420537162387;WG;0.045277335;0.07191106;-0.5619716
0;22;1420537162398;WG;0.058594197;0.07191106;-0.56729835
```

Example raw data retrieved from the smartwatch

Data Preparation

Applying Filters



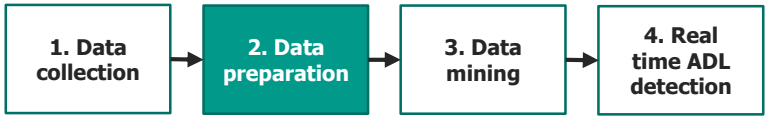
- Applying filters
  - High/low pass
  - Median filter
- Spline Interpolation
  - to handle recordings that are not time-equidistant
- Implementation in R

```
s_A;time_A;x_A;y_A;z_A;s_G;time_G;x_G;y_G;z_G;s_M;time_M;
x_M;y_M;z_M;s_R;time_R;x_R;y_R;z_R
A;40;0.28950448578947;-
4.5174288736842;8.5609167368421;G;40;-
0.0084340129166667;0.0015536340166667;-
0.020197241666667;M;40;;;;R;40;;;
A;60;0.21064033;-4.6484492;8.2963565;G;60;-
0.033292156;0.005326745;-0.0292970985;M;60;;;;R;60;-
0.109693386;0.6582455;-0.72389895
A;80;0.244151285;-4.7729182;8.3825275;G;80;-
0.043679308733333;0.00390627972;-
0.0305400064;M;80;;;;R;80;-0.109693386;0.6582455;-
0.72389895
A;100;0.25691736666667;-
4.5654696;8.1846536666667;G;100;0.039131090538462;0.07068
181;-0.5619716;M;100;-62.011962686567;-
70.799604477612;0.86492537313433;R;100;-
0.12131360294737;0.57195355263158;-0.79768584157895
```

Example time standardized data retrieved from the smartwatch.

Data Preparation

Feature extraction



- 39 basic statistical features for each sensor (13 for each sensor axis)
  - ➢ mean, standard deviation, …
- FFT
  - ➢ 118 frequency-based features
- Implementation in R
- Result:
  - ➢ CSV file including all extracted features for all recordings

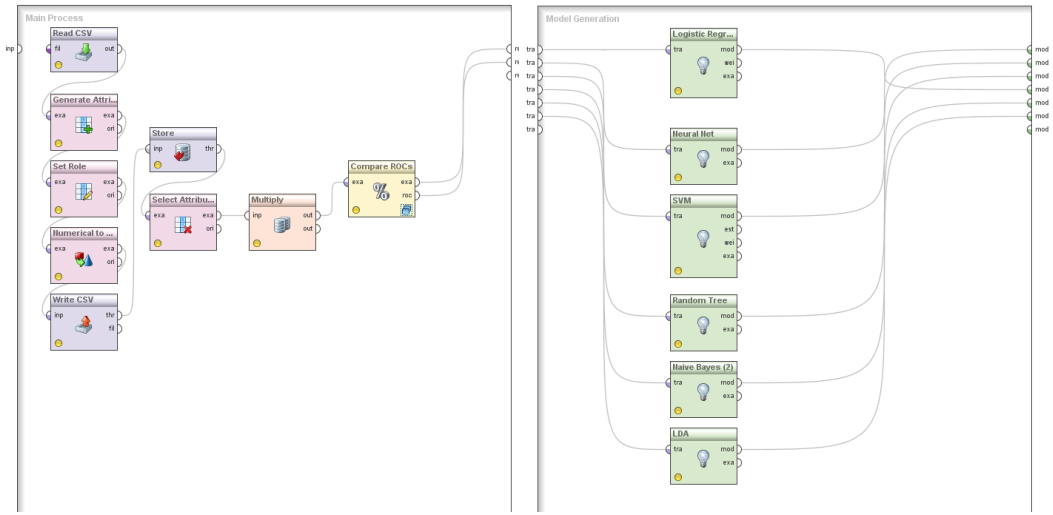
DRINKBINOMIAL	ACC.IQR_Y	MAG.IQR_Y	ACC.SD_Y	MAG.SD_Y	ACC.FFT.Y1	ACC.FFT.X1	…	ACC.FFT.X9	ACC.FFT.Y6
true	2.0994	1.5363	1.2400	1.0655	-0.9445	-1.0141		-0.4631	-0.9172
true	2.1193	2.3964	1.8756	1.9786	-0.9956	-1.0771		-0.4101	-0.7378
true	1.2783	1.7784	0.8747	1.2040	-0.8423	-1.0771		-0.5690	-0.5585
true	2.3568	1.4780	1.7417	1.5552	-0.9956	-1.0141		-0.6749	-0.8275
true	3.0261	2.8665	2.6088	2.5032	-0.8934	-0.7622		-0.5690	-0.2895
false	-0.1873	-0.5898	0.1821	-0.8790	2.1726	-0.1955		0.0665	-0.4689
false	-0.5784	0.0607	-0.5854	-0.1924	-0.1269	-0.1325		-0.3042	2.9831
false	0.0394	0.2638	0.0024	-0.0594	-0.1269	1.1270		0.6490	0.3829
false	-0.1460	-0.0487	0.2727	-0.1846	-0.1780	-0.0695		-0.3572	0.8760
false	1.1509	0.8260	0.7655	0.3184	0.0775	-0.0695		-0.0924	1.2347
false	1.3691	1.4679	0.9200	0.9849	0.4352	-0.8252		-0.1983	-0.9620

Data Modelling

Apply different data mining techniques

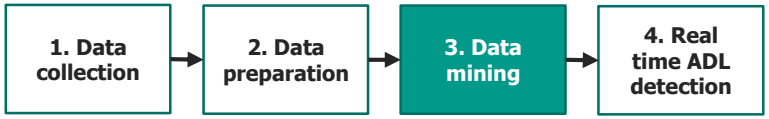
1. Data collection → 2. Data preparation → **3. Data mining** → 4. Real time ADL detection

- Logistic regression
- Clustering analysis
- Neural networks
- Random tree
- Discriminant analysis



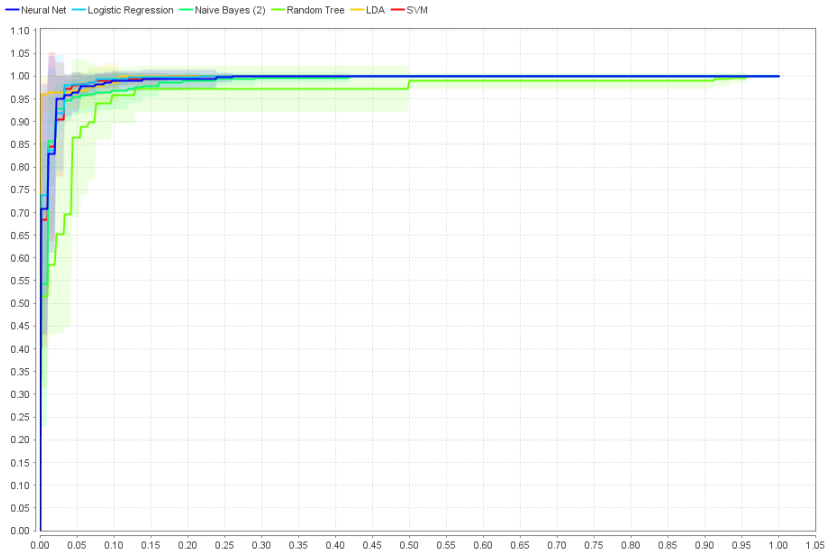
Data Modelling

Logistic Regression vs. Neural Net



LogReg - time only	true false	true true	class precision
pred. false	**279**	**6**	97.89%
pred. true	5	**72**	93.51%
class recall	98.24%	92.31%	**362**
Neuralnet - time only	true false	true true	class precision
pred. false	**277**	4	98.58%
pred. true	7	**74**	91.36%
class recall	97.54%	94.87%	**362**

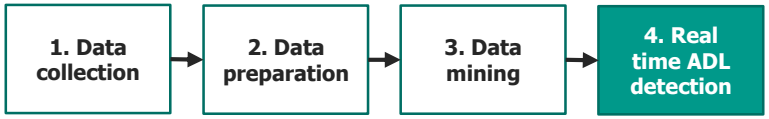
Classification percentages with the logistic regression and neural net model (RapidMiner output) for 362 test cases (about 1000 examples used for training)

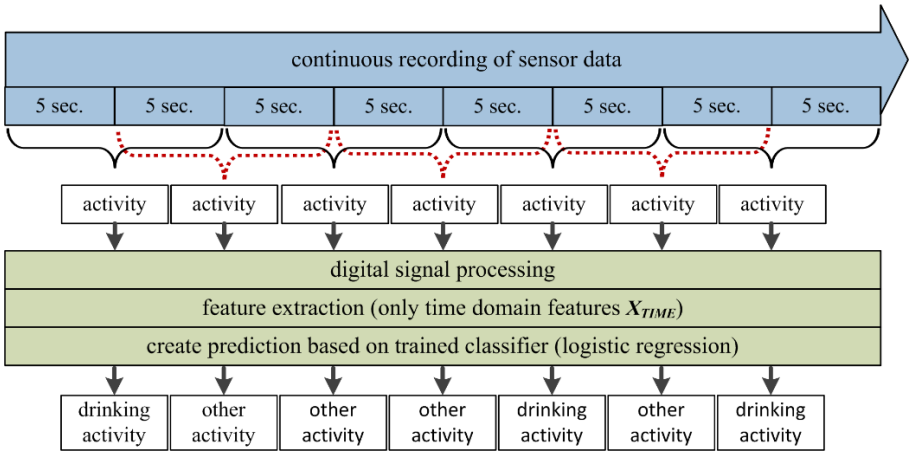


ROC using neural nets (dark blue), logistic regression (light blue), SVM (red), a random tree (green) and discriminant analysis (yellow)

ADL Real Time Detection

Basic Procedure: Logistic Regression parameters



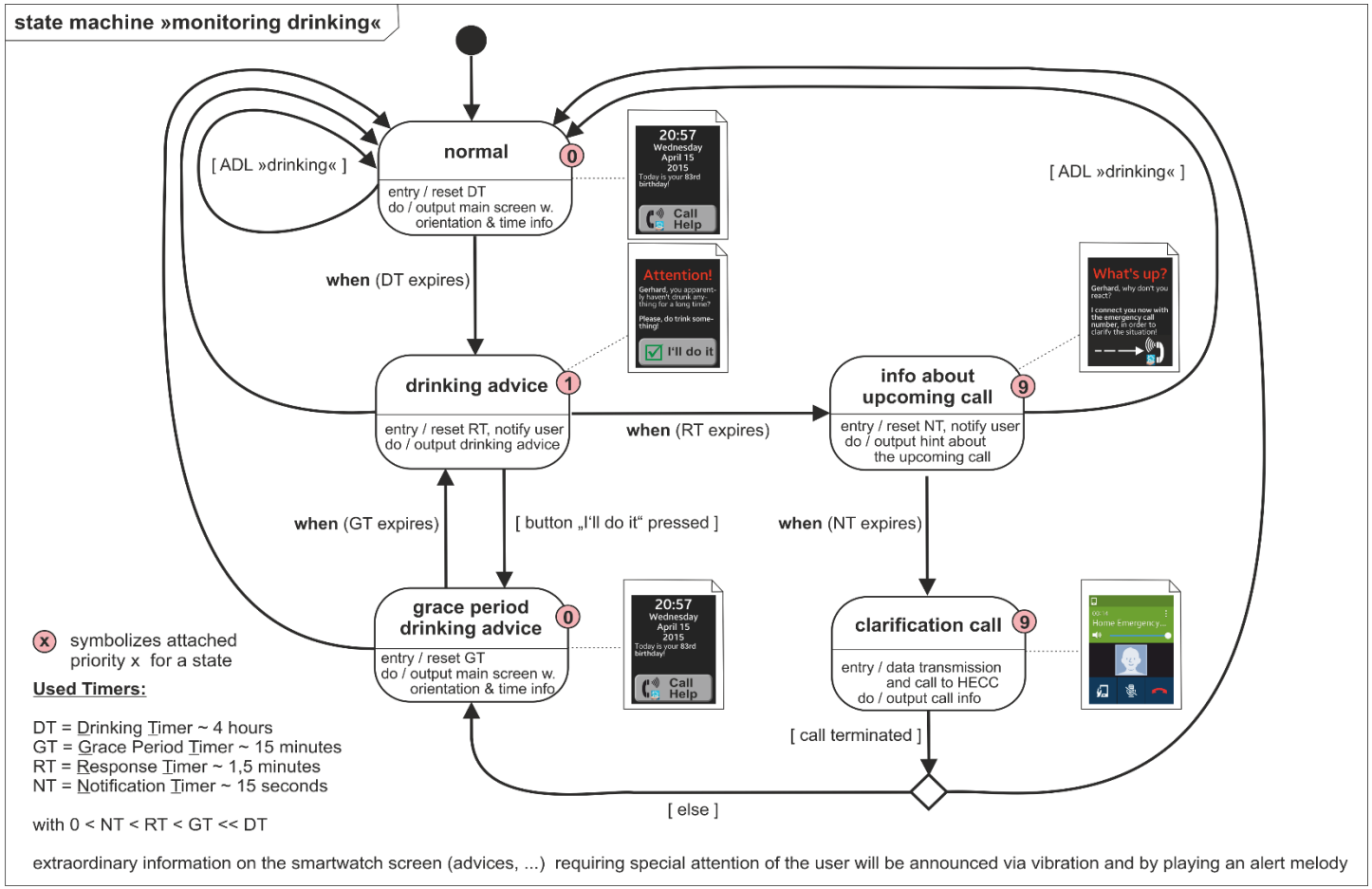


		Executed ADL	
		Drinking ADL	**Non-drinking AD**
Classified ADLS	**Drinking ADL**	30 (96.7 %)	12 (16.2 %)
	Non-drinking ADL	1 (3.3%)	62 (83.8 %)

Example classifications with the real time app.

ADL Real Time Detection

Real live integration: Integration into a state machine



Source: Rainer Lutze, lustcon, http://www.lustcon.de

ADL Real Time Detection

Real live scenario: User interaction

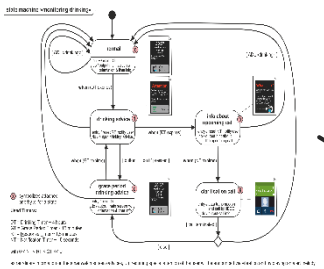
(a) Pre alert (b) Alert call

Source: Rainer Lutze, lustcon, http://www.lustcon.de

Emergency call app warning the user that for a longer time periods no drinking ADLs have been detected.

Usage in real life

Integration into client / server environment



Home Auto-matization

Smartwatch with App

Signalizing **Departure** from, Upcoming **Arrival** at Home (SMS)

Backup, Recovery, Update Configu-ration-Data

Con-densed Sensor Data

Voice Connection

Localization Data (SMS): Geographic **Place,** Movement Speed, Movement Direction

Reporting of Activities to Relatives

Situation Analysis

Longterm Analysis Server (LTAS)

Home Emergency Call Center (HECC)

Source: Rainer Lutze, lustcon, http://www.lustcon.de

Practical experiences

Problems and limits

- **Energy management**
- **Processing power :** distributed processing
- **Ethical / legal questions:** profiling!
- **Interfaces** with house automation (HA): Standards, open interfaces, esp.: State HA ➔ Smartwatch
- **Medical Device**: Certification(FDA), precision
- **Acceptance**: tests…

Summary

- Smartwatches can detect ADLs!
- Smartwatches are accepted by elderly
- To do: *detect more different types of ADLs*
- Daily report generation
- Long term detection of ADLs
- Additional field tests
- Usability of Smartwatches must be improved*: special usability guide lines for target groups*, ...

Example: Prototype ADL drinking recognition

Source: Rainer Lutze, lustcon, http://www.lustcon.de

More information: klemens.waldhoer@fom.de

wearables \at \work 2016

Conference 2016
FOM München
17.02.2016

http://www.wearables-at-work.info

Source: https://www.fom.de/studienorte/studium-in-muenchen.html

Blog: http://www.wearables-at-work.de

Thanks for your time and interest!