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PORTOROŽ, 15. DO 17. MAJ 2017

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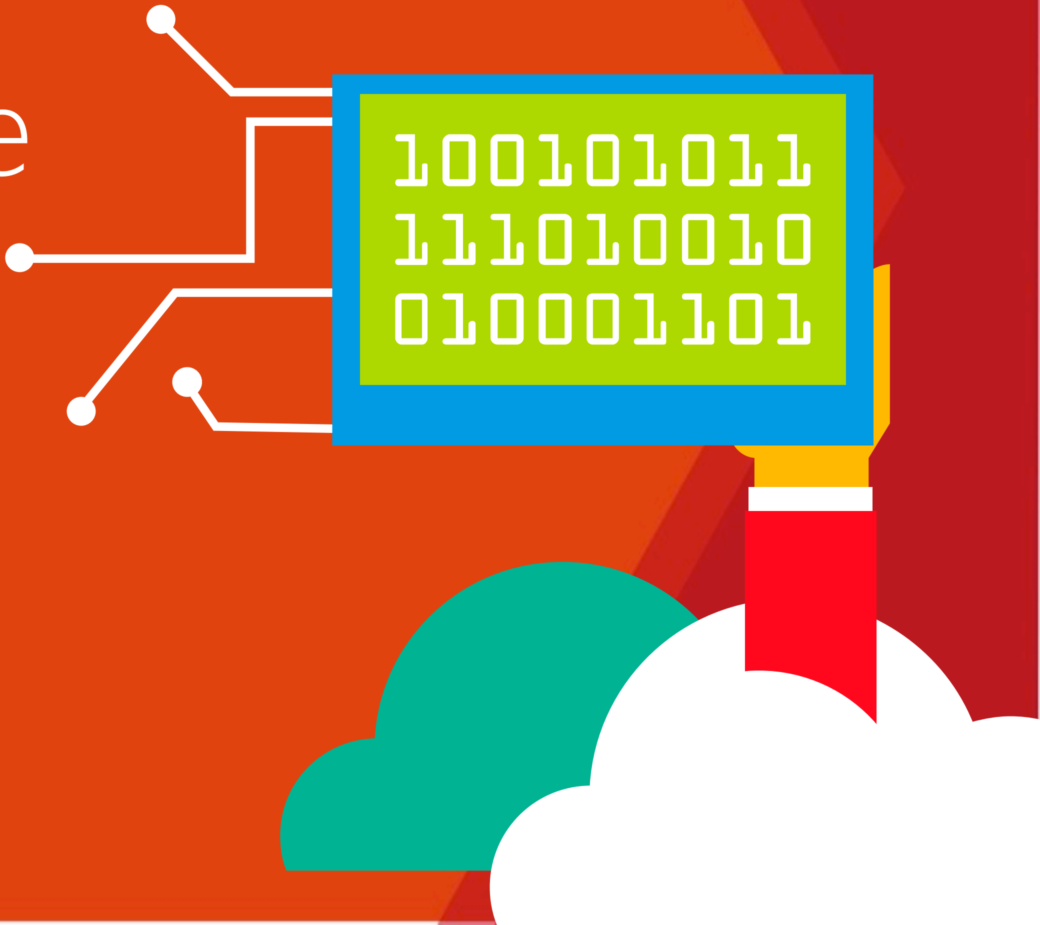
Artificial Intelligence in Mobile Health

Božidara Cvetković
Researcher at Jožef Stefan Institute



TEHNOLOGIJA

Human centred technology

Jean Luc - 66
Diabetes & Depression

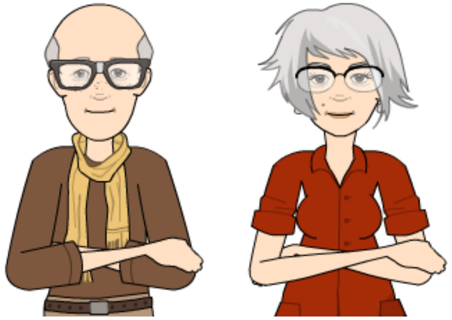
Simone - 62
Congestive heart failure

Edith - 33
Healthy

Émile - 36
?

Human centered …

Patients suffering from chronic diseases



Frequent check-ups with physician(s)

- Determine current state of the patients health
- Estimate the trend of the disease

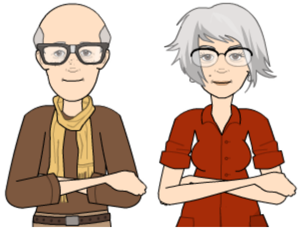
Self-reporting

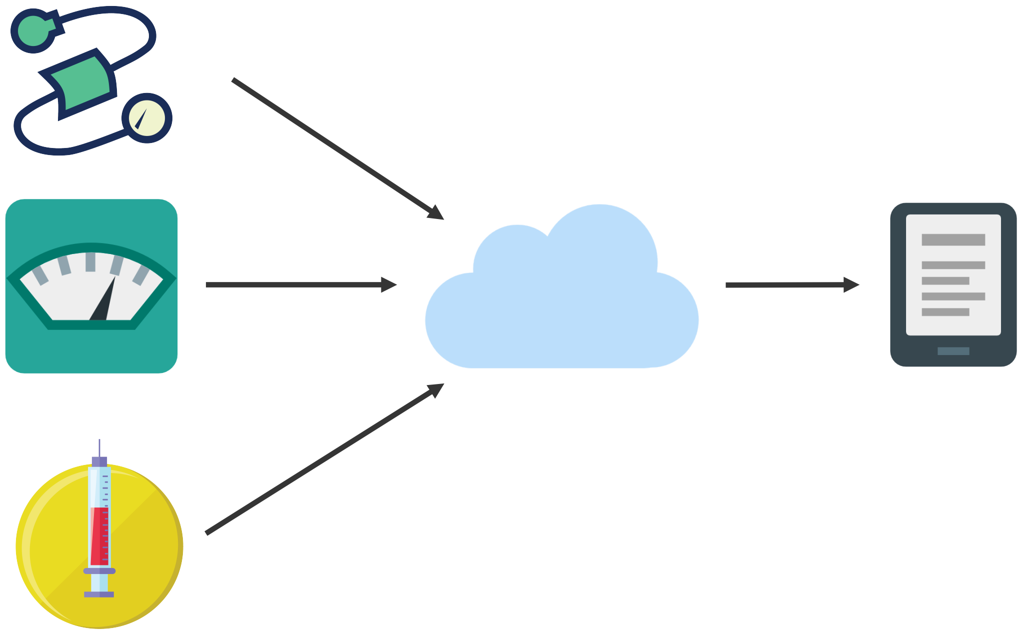
- Diabetes: glucose level, weight, activity, general feeling, …
- CHF: blood pressure, heart rate, weight, activity, fluid intake, general feeling, …

Lose, forget, to much work, manipulate

Human centered technology

Equipped with devices used in self-reporting

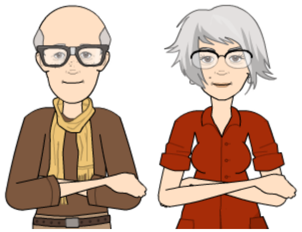


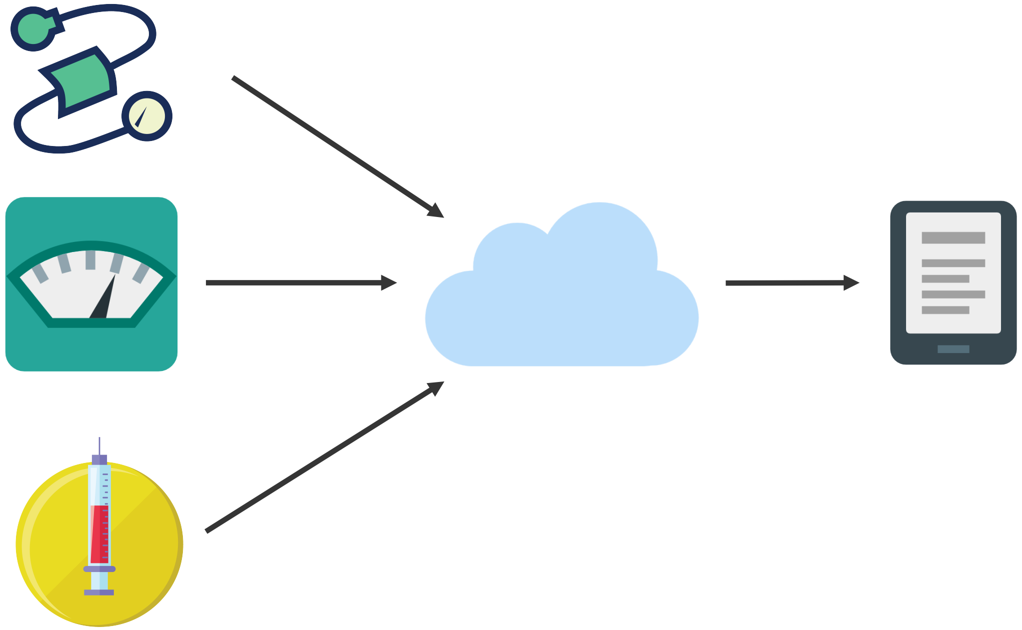


Physician sees raw data

Human centered technology

Equipped with devices used in self-reporting

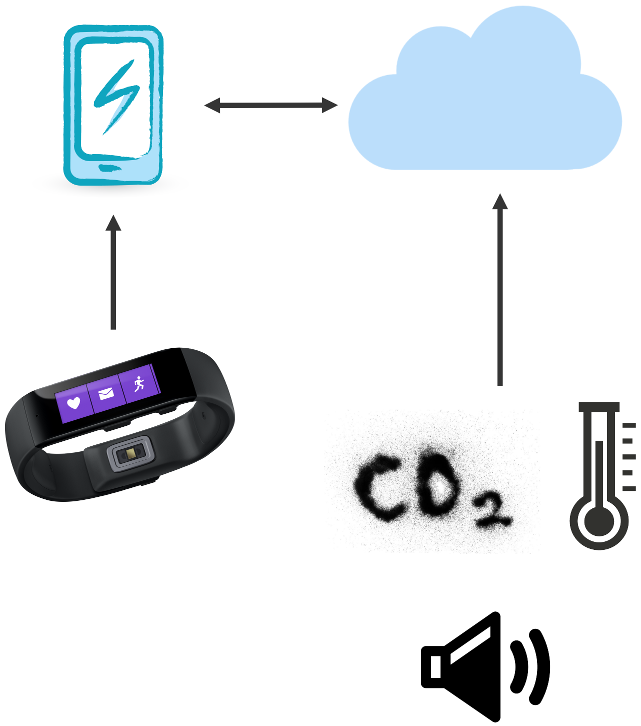




Aggregated data
Anomaly detection
Raw data

Human centered technology

Lifestyle monitoring and management



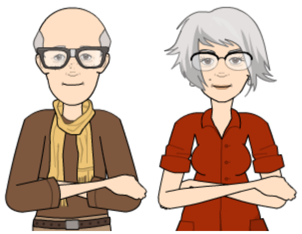
Physical activity monitoring
Mental stress monitoring
Quality of sleep monitoring
Environment monitoring
Anomaly detection
- Fall detection
- Visual recognition of skin anomaly – skin cancer, Lyme disease

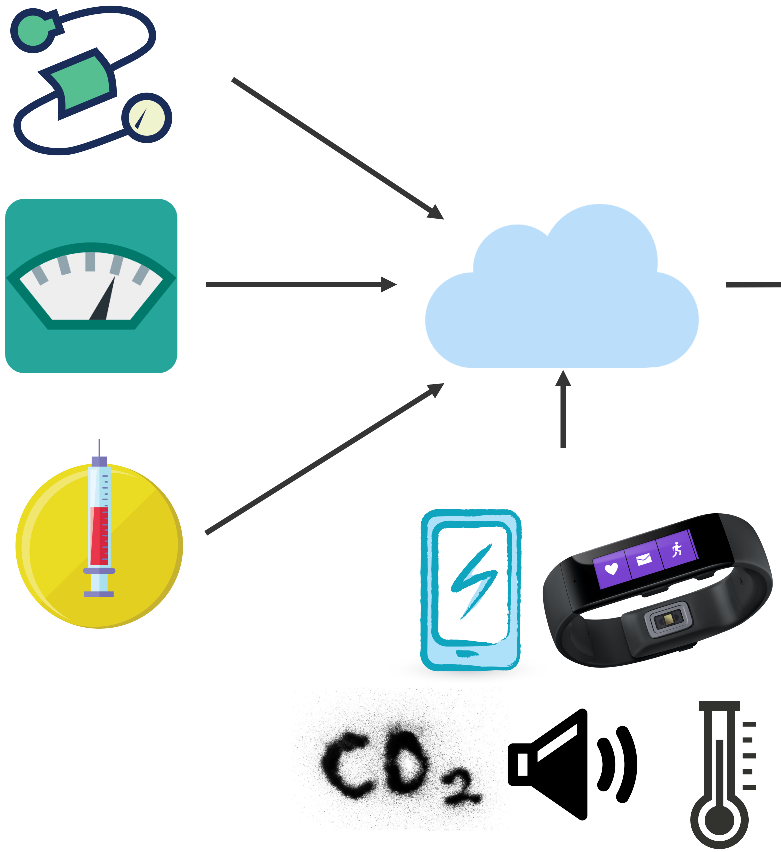
…

Fast unobtrusive diagnosis

Human centered technology

Equipped with devices used in self-reporting





Enriched data

Better insight into daily living

Improved monitoring and detection

Artificial Intelligence in Mobile Health

Recognition of person's contexts

Model and monitor raw or virtual parameter trends

Detect and predict anomalies in patterns

Personalize the machine-learning models

…

Aggregate the data in understandable way

Give appropriate recommendations

…

"Life is the sum of all your choices.
So, what are you doing today?"
Albert Camus

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General Contexts

Clues that help us solve a puzzle

Recognize single or multiple current or historical states of the person

Contexts:

At the office

Prolonged sitting

Increased stress

Leaves office at 5 PM

State of the person:

Working

Anticipate leaving around 5 PM

Anticipate stress relief

Anticipate walking a dog around 9PM

How do we do this with machine-learning?

Physical Activity Monitoring

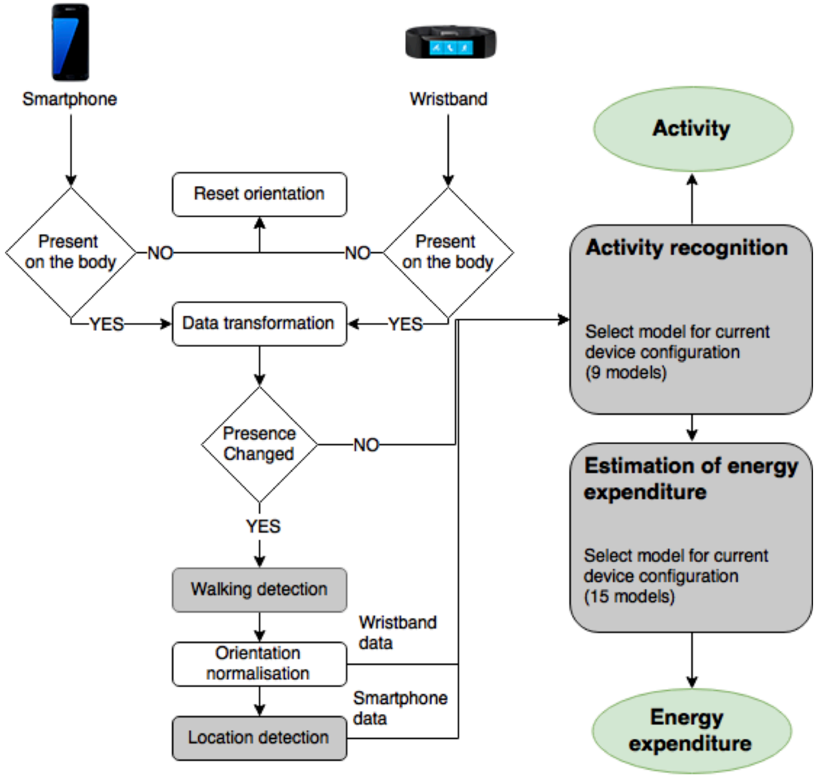
Recognize what the person is doing and estimate its intensity

Supervised machine-learning technique

- 4 machine-learning tasks: 3xclassification, 1xregression
- Accelerometers, physiological signals

1. Dataset collection

2h of data per person



Cvetkovic et al. (2017) Real-Time Activity Monitoring with a Wristband and a Smartphone, Information Fusion, In review.

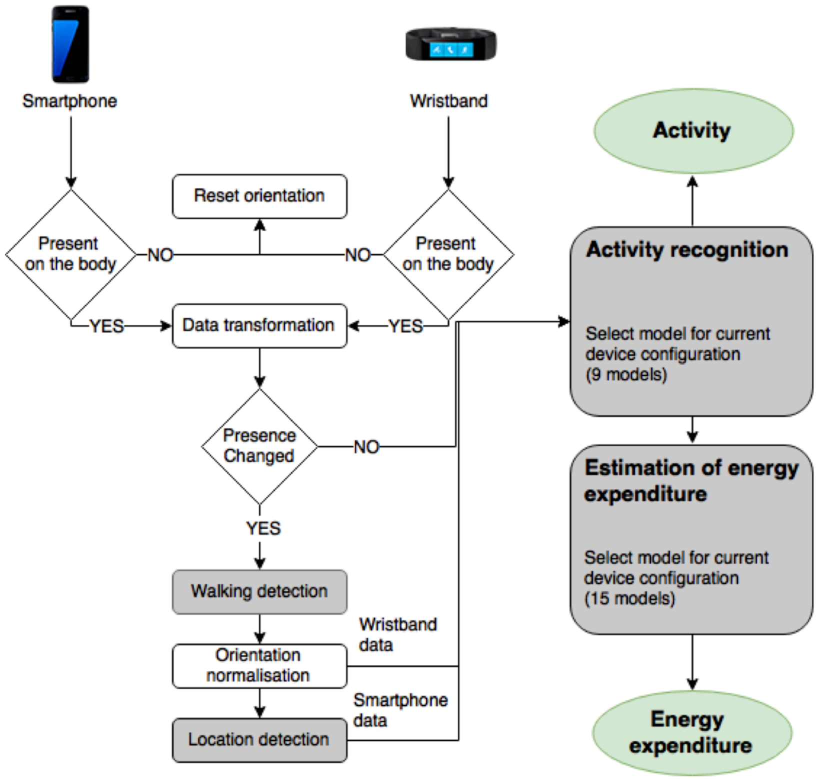
Physical Activity Monitoring

Recognize what the person is doing and estimate its intensity

Supervised machine-learning technique

- 4 machine-learning tasks: 3xclassification, 1xregression
- Accelerometers, physiological signals

1. Dataset collection
2. Preprocessing and feature extraction
3. Feature selection and training the models



Cvetkovic et al. (2017) Real-Time Activity Monitoring with a Wristband and a Smartphone, Information Fusion, In review.

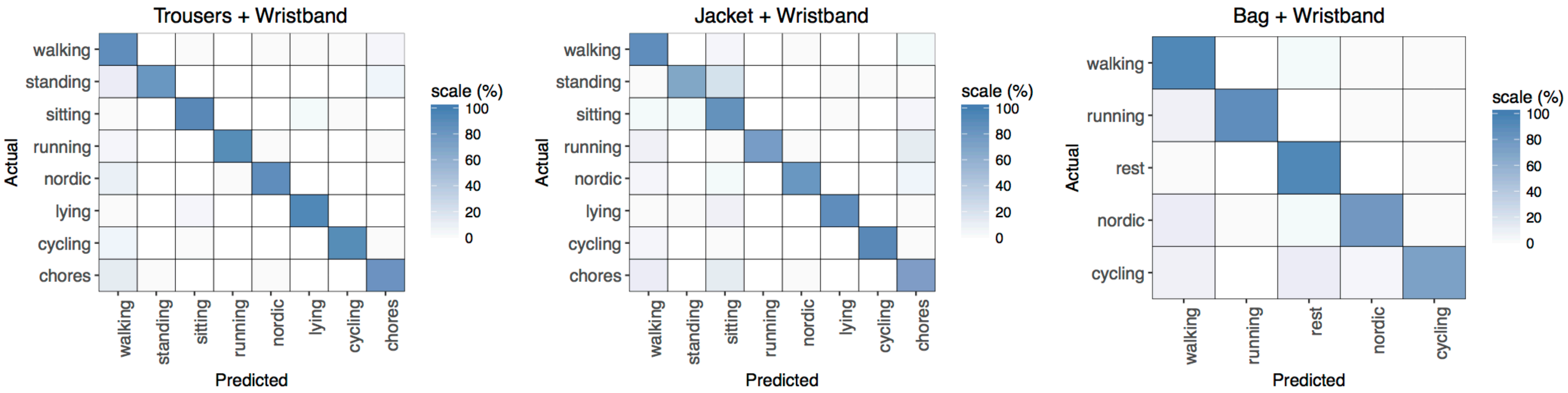
Physical Activity Monitoring

Recognize what the person is doing and estimate its intensity

Evaluation

Walking and location recognition – 91%

Activity recognition – 87% on average over all locations



Cvetkovic et al. (2017) Real-Time Activity Monitoring with a Wristband and a Smartphone, Information Fusion, In review.

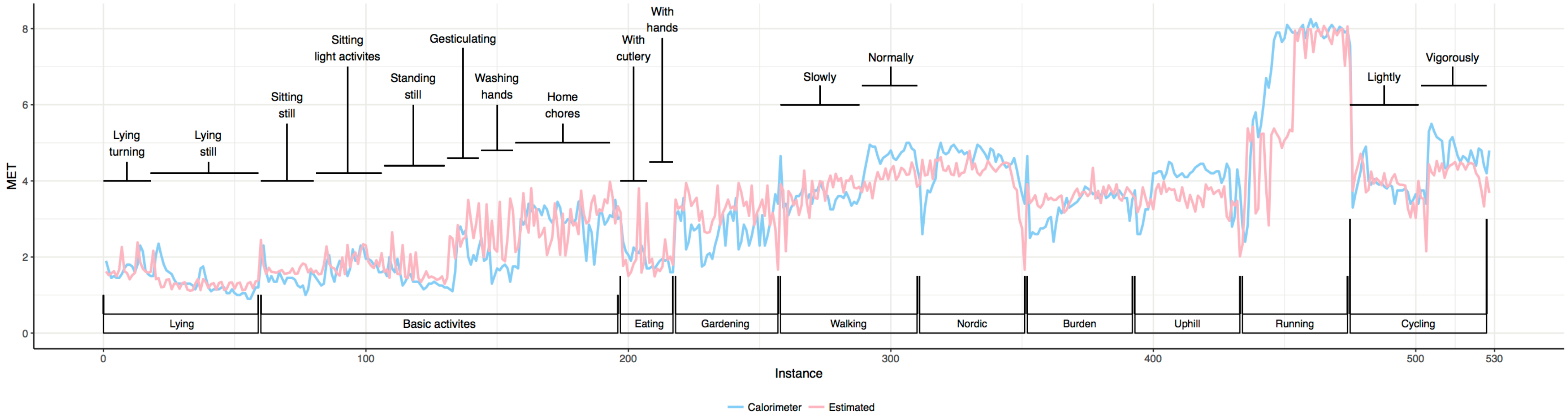
Physical Activity Monitoring

Recognize what the person is doing and estimate its intensity

Evaluation – Estimation of energy expenditure

In MET: 0.64 MET over all locations

In kCal: error of 2 kCal (Bodymedia 4kCal, MS Band 22kCal)



Cvetkovic et al. (2017) Real-Time Activity Monitoring with a Wristband and a Smartphone, Information Fusion, In review.

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Mental Stress Monitoring

Detect and estimate the level of mental stress

Supervised machine-learning technique

- 2 classification machine-learning tasks
- Activity, its intensity, physiological signals

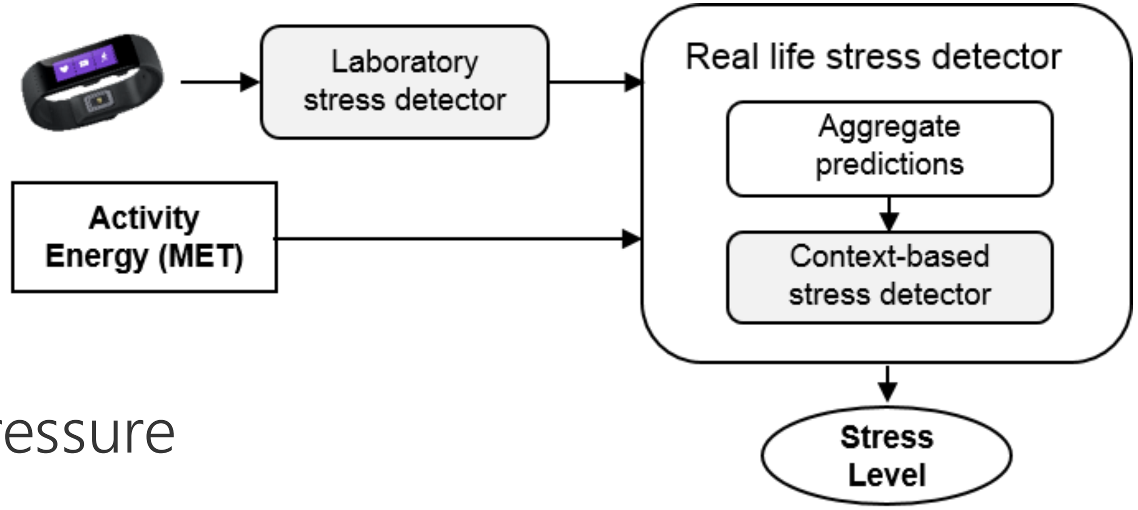
1. Dataset collection

Laboratory stress dataset

- People solving math problems under time pressure

Real-time stress dataset

- People were labeling stressful events over period of two weeks



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Gjoreski et al. (2016) Continuous stress detection using a wrist device: – In laboratory and real life. In: UbiComp Adjunct,.

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Mental Stress Monitoring

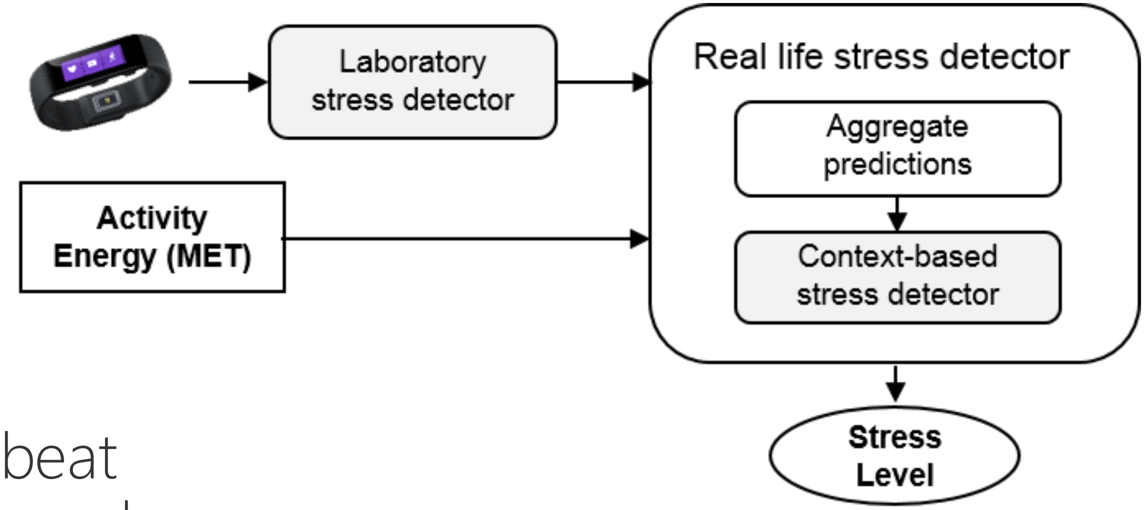
Detect and estimate the level of mental stress

Supervised machine-learning technique

- 2 classification machine-learning tasks
- Activity, its intensity, physiological signals

1. Dataset collection
2. Preprocessing and feature extraction

    Blood volume pulse, heart rate, beat-to-beat intervals, skin temperature and electrodermal activity



Gjoreski et al. (2016) Continuous stress detection using a wrist device: – In laboratory and real life. In: UbiComp Adjunct,.

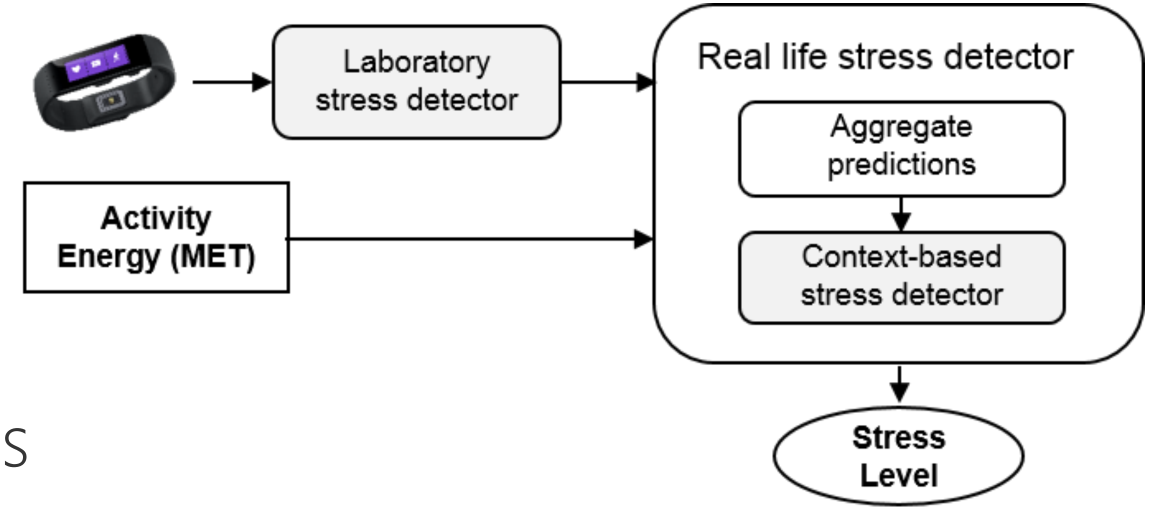
Mental Stress Monitoring

Detect and estimate the level of mental stress

Supervised machine-learning technique

- 2 classification machine-learning tasks
- Activity, its intensity, physiological signals

1. Dataset collection
2. Preprocessing and feature extraction
3. Algorithm design and training models



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Mental Stress Monitoring

Detect and estimate the level of mental stress

Evaluation

55 days of real-life data

- 72% without context and 92% with context

	No Context		With Context	
	NO STRESS	STRESS	NO STRESS	STRESS
NO STRESS	638	175	790	23
STRESS	44	70	51	63

Gjoreski et al. (2016) Continuous stress detection using a wrist device: – In laboratory and real life. In: UbiComp Adjunct,.

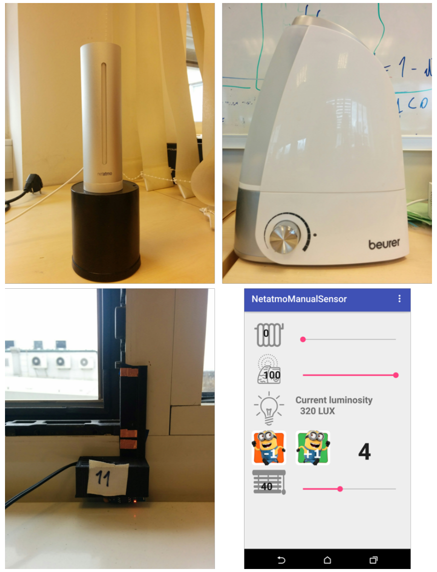
Environment Monitoring

Detect low environment quality and recommend actions

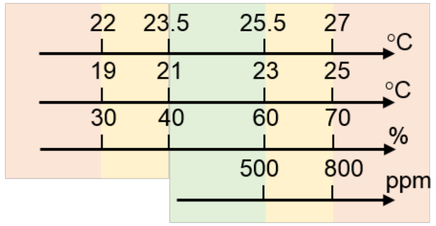
Supervised machine-learning technique + ontology

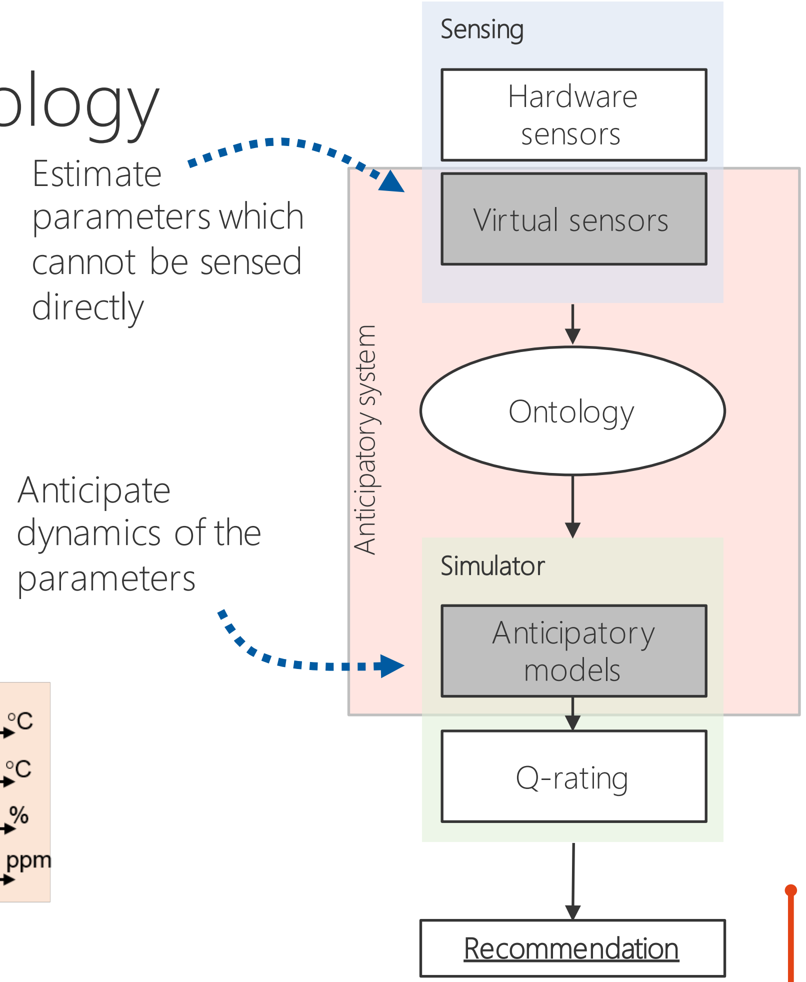
1. Dataset collection + Expert knowledge

   1 year three offices



Temperature - Summer
Temperature - Winter
Humidity
CO_2





Frešer, M. et al. (2016) Anticipatory system for T-H-C dynamics in room with real and virtual sensors. ACM UbiComp '16.

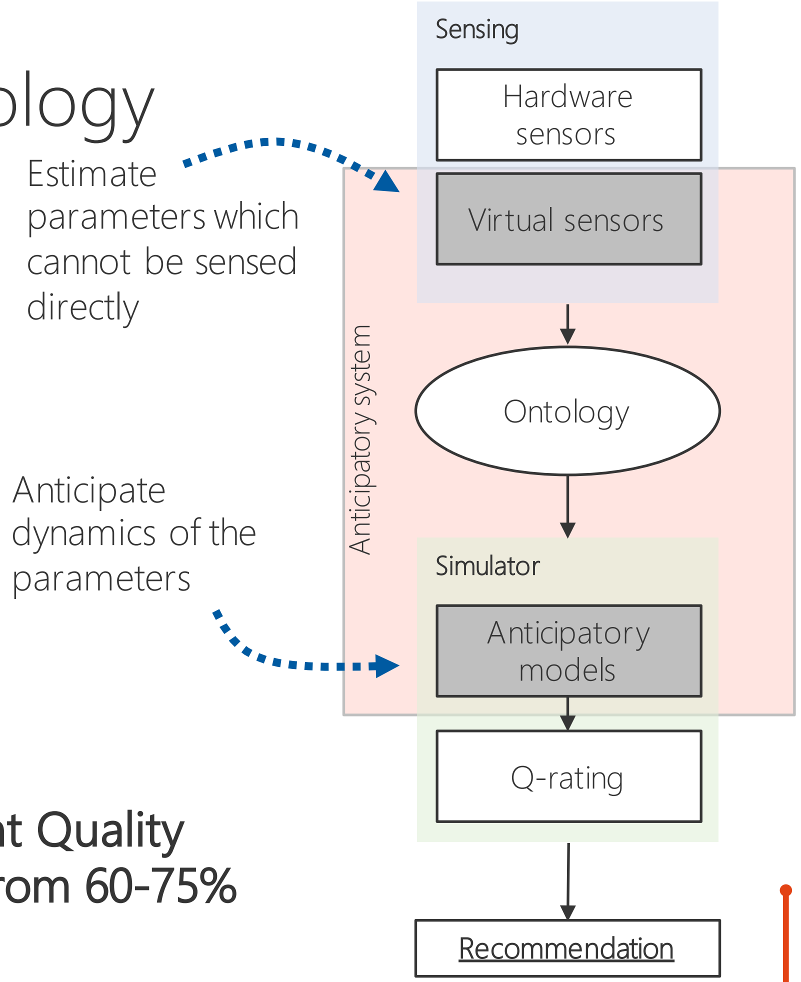
Environment Monitoring

Detect low environment quality and recommend actions

Supervised machine-learning technique + ontology

1. Dataset collection + Expert knowledge
2. Preprocessing and feature extraction
3. Feature selection and training the models

	ACC (%)	MAE	RMSE
Window state	91		
Number of occupants		0.6	1.2
Predict T [°C]		0.4	0.5
Predict H [%]		0.6	0.9
Predict CO_2 [ppm]		55	104



Environment Quality Increased from 60-75%

Frešer, M. et al. (2016) Anticipatory system for T-H-C dynamics in room with real and virtual sensors. ACM UbiComp '16.

"We are all special cases"

Albert Camus

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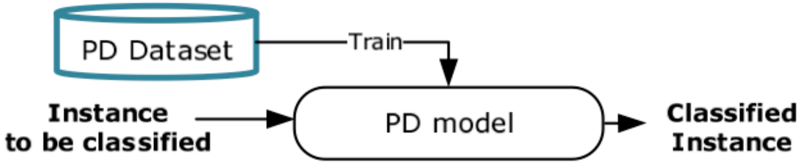
Personalization

Adapt the model to the particular person

Supervised machine-learning

If we have labeled data of the person



Cvetkovic et al. (2016) Activity Recognition for Diabetic Patients Using a Smartphone. Journal of Medical Systems.

Personalization

Adapt the model to the particular person

Supervised machine-learning

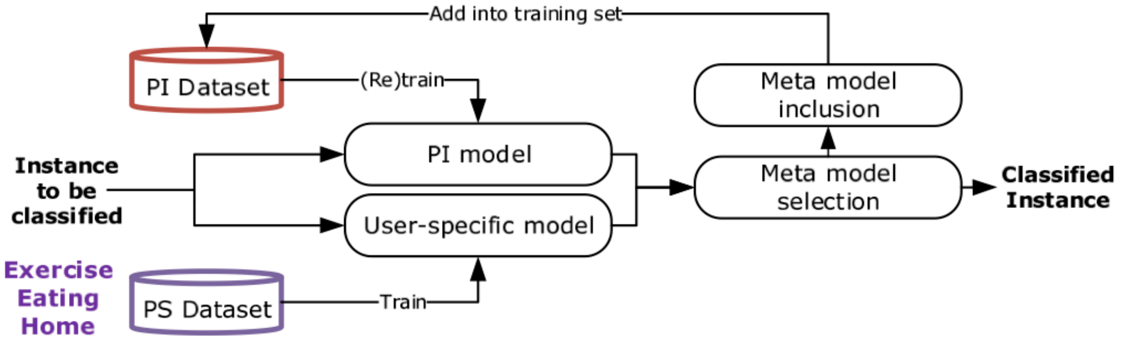
If we have labeled data of the person

Semi-supervised machine-learning

If we have some labeled data

Unsupervised machine-learning

If we have no labeled data



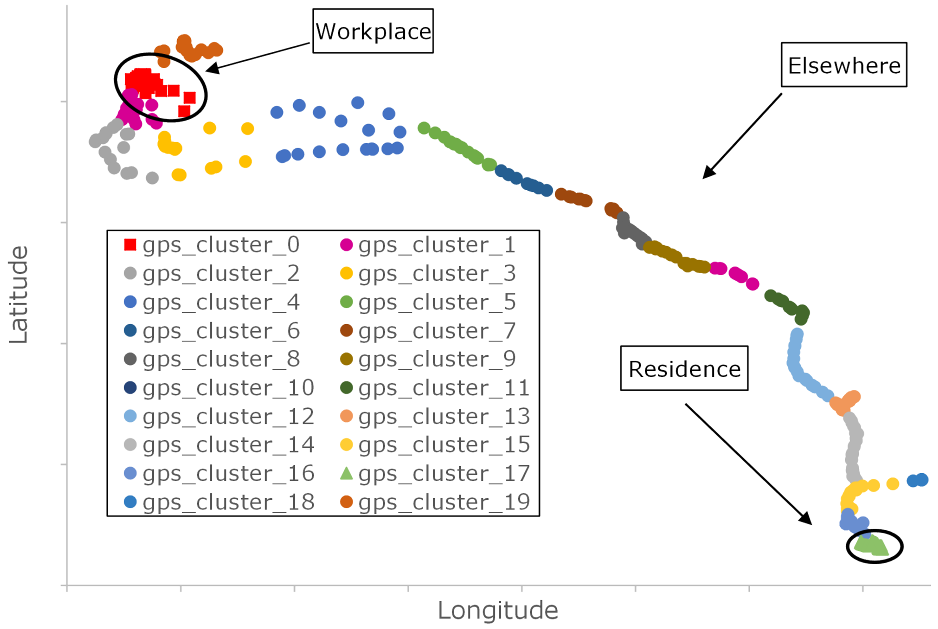
Cvetkovic et al. (2016) Activity Recognition for Diabetic Patients Using a Smartphone. Journal of Medical Systems.

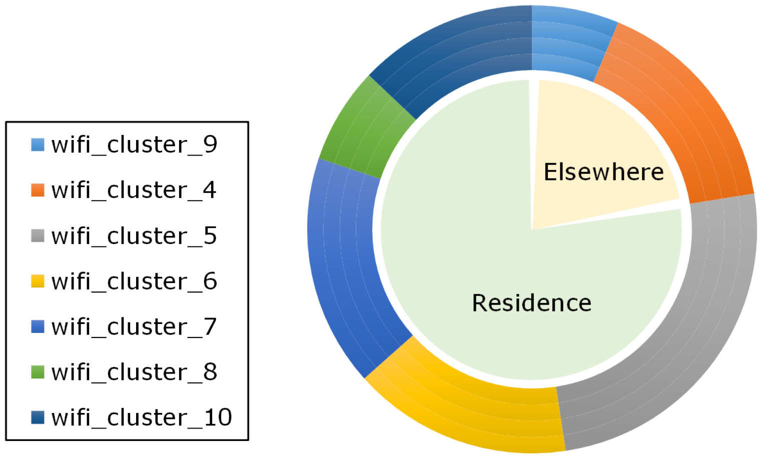
Personalization

Unsupervised machine-learning technique

Personalization of semantic location from WIFI and GPS traces

- Contexts: Time of day and day of the week





Home, Sleep, Eating: wifi_cluster_5, wifi_cluster_7
Home, Eating: wifi_cluster_8, wifi_cluster_9,
Out, Transport: wifi_cluster_4
Home, Sleep: wifi_cluster_10

Cvetkovic et al. (2016) Activity Recognition for Diabetic Patients Using a Smartphone. Journal of Medical Systems.

Use cases – Lifestyle monitoring

Monitor

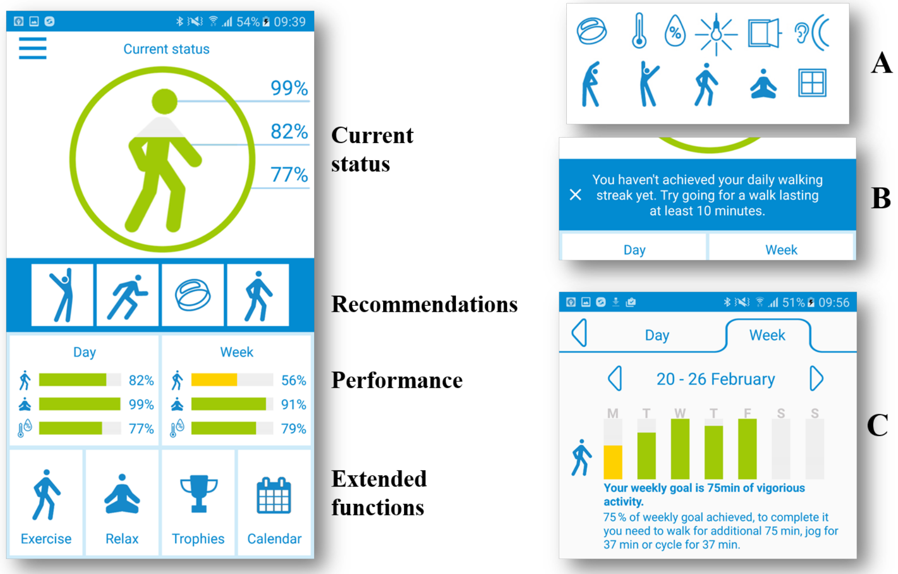
Physical activity, sleep, mental stress, environment

Recommend

Physical activities to reach daily goals (WHO recommendations)

Stress relief exercises (e.g., breathing)

Actions to improve the environment



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Use cases – Depression and Diabetes

Anomaly in physical activity can be a sign of a depression

Blood glucose depends on the balance between food intake and physical activity

1. We can use physical activity monitoring to estimate the balance between the two
2. We can use physical activity monitoring as a machine-learning feature for prediction and recognition of glycemias

Cvetkovic et al. (2016) Activity Recognition for Diabetic Patients Using a Smartphone. Journal of Medical Systems.
Cvetkovic et al. (2017) Predicting glycaemia in patients with diabetes using ECG and other wearable sensor data. Artificial Intelligence in Medicine

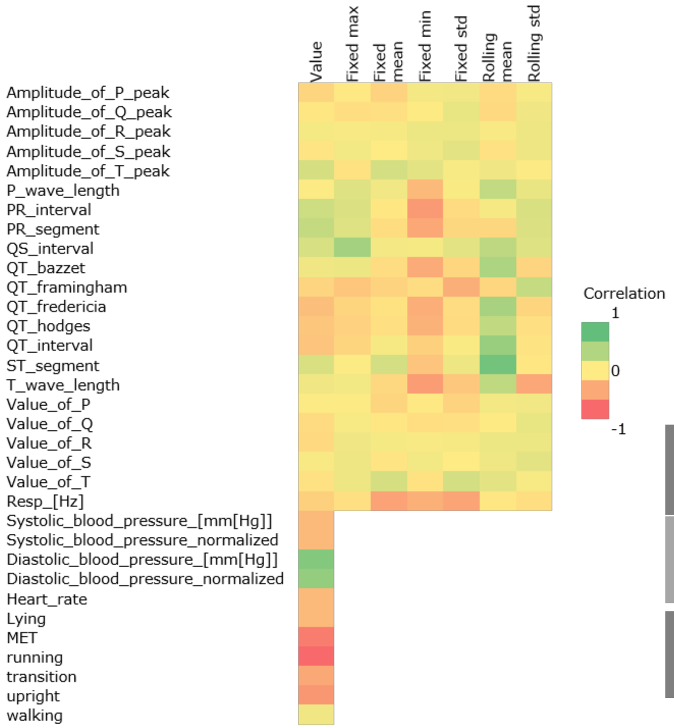
Detection and prediction of glycaemias

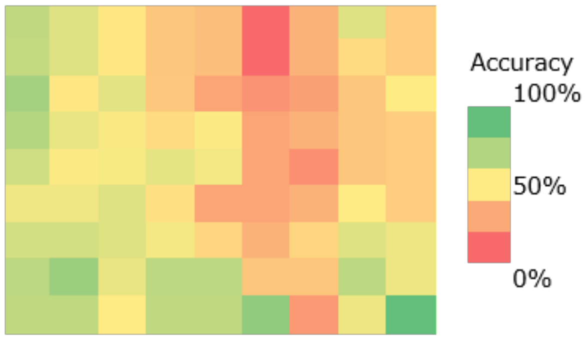
- Diabetes (I, II) patients
- They were equipped with smartphones and Zephyr bio-harness (ECG, breathing rate), glucometer, blood pressure monitor

Cvetkovic et al. (2017) Predicting glycaemia in patients with diabetes using ECG and other wearable sensor data. Artificial Intelligence in Medicine

Detection and prediction of glycaemias

- Data was divided in 5 minute segments 45 minutes before glucose measurement
- 296 extracted features (ECG, breath rate, activity, blood pressure, weight)





	0	1	2	3	4	5	6	7	8	AVG
Accuracy (%)	85	86	86	83	85	83	85	92	88	86
Correct event detected	31	32	26	21	18	15	12	15	9	
All events	40	39	32	28	23	19	16	17	11	

Cvetkovic et al. (2017) Predicting glycaemia in patients with diabetes using ECG and other wearable sensor data. Artificial Intelligence in Medicine

Hospitalization prediction in CHF patients

141 CHF patients were equipped with telemonitoring devices

- Trial duration 369 ± 134 days
- 9 hospitalizations suitable for analysis
  - Because telemonitoring alone reduced hospitalizations by 70 %

	created_at	patient_id	sys	dia	pulse	arr	weight	so2	hospit	visited	phone	note	therapy
1	2014-08-10 06:24:26 UTC	24	116	72	72	0	84.1	98	0	0	0	0	0
2	2014-09-01 07:18:42 UTC	24	120	79	80	1	80.2	96	0	0	0	0	0
3	2014-10-01 05:26:30 UTC	24	127	78	76	0	79.9	97	0	0	0	0	0
4	2014-10-18 05:51:19 UTC	24	105	72	78	1	81.6	97	0	0	0	0	0
5	2014-11-29 05:14:16 UTC	24	114	72	67	1	83.4	97	0	0	0	0	0
6	2014-12-25 06:25:17 UTC	24	121	76	59	1	81.7	97	0	0	0	0	0
7	2015-01-11 07:45:39 UTC	24	120	76	83	1	81.9	96	0	0	0	0	0
8	2015-01-23 06:13:55 UTC	24	117	66	75	1	80.9	95	0	0	0	0	0
9	2015-03-31 06:20:13 UTC	24	119	87	81	1	81.5	94	0	0	0	0	0

Cvetkovic et al. (2016) Hospitalisation prediction from telemonitoring data in congestive heart failure patients. IJCAI.

Hospitalization prediction in CHF patients

Data sample

Non-hospitalized patient

Cvetkovic et al. (2016) Hospitalisation prediction from telemonitoring data in congestive heart failure patients. IJCAI.

Hospitalization prediction in CHF patients

168 features were extracted from raw data without and with context (expert knowledge)

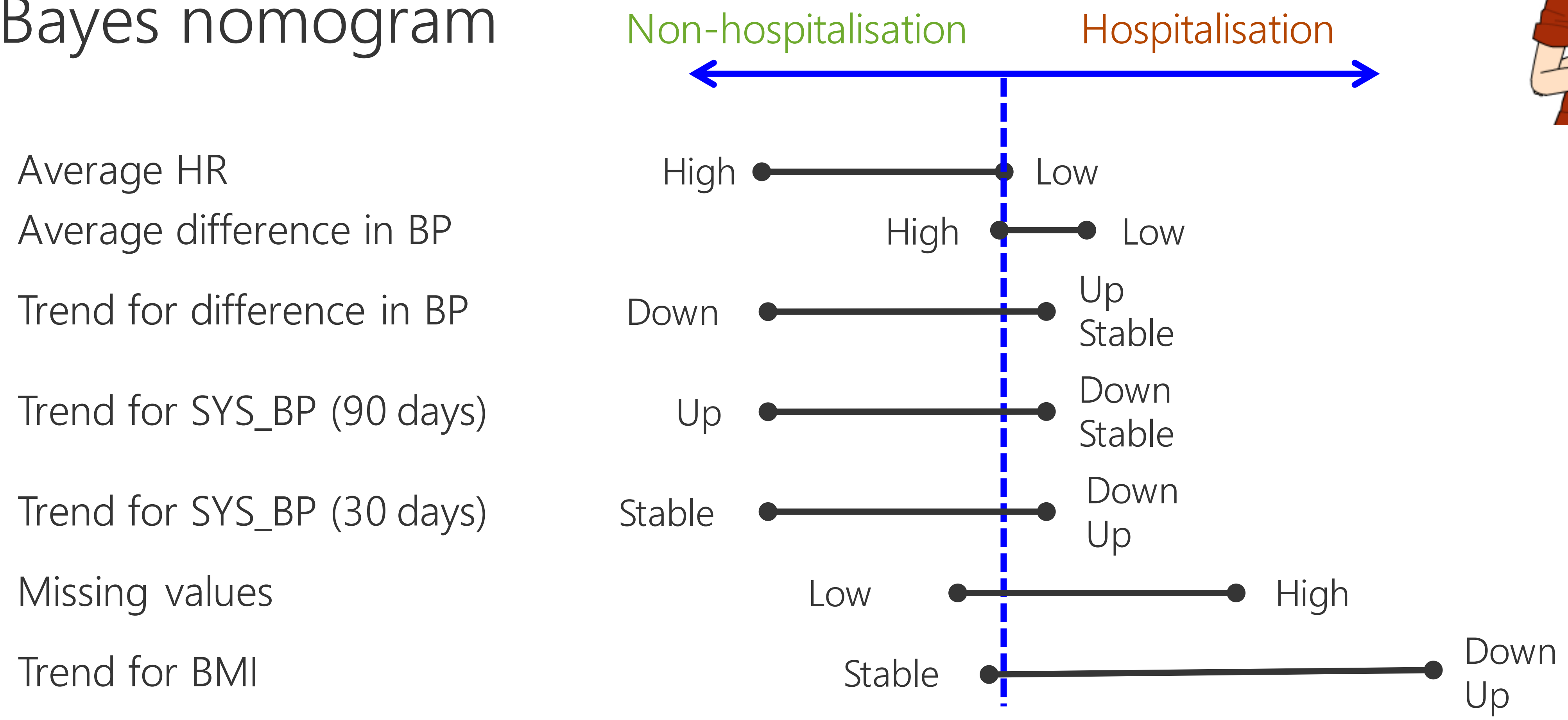
- Raw, statistical, demographical, discretized, …

	Recall	Precision	F-measure	AUC
J48	0.33	0.60	0.43	0.71
Random Forest	0.22	0.67	0.33	0.58
SVM	**0.89**	0.62	0.73	0.82
Naive Bayes	0.78	**0.88**	**0.82**	**0.98**

Cvetkovic et al. (2016) Hospitalisation prediction from telemonitoring data in congestive heart failure patients. IJCAI.

Hospitalization prediction in CHF patients

Naïve Bayes nomogram



Cvetkovic et al. (2016) Hospitalisation prediction from telemonitoring data in congestive heart failure patients. IJCAI.

Hospitalization prediction in CHF patients

We thought the model was likely to overfit so we tested on newly obtained data

	OLD		NEW	
	Hospitalized	Non-hospitalized	Hospitalized	Non-hospitalized
Hospitalized	7	2	7	2
Non-hospitalized	1	116	4	46

Cvetkovic et al. (2016) Hospitalisation prediction from telemonitoring data in congestive heart failure patients. IJCAI.

CHF detection from heart sound

Patient records the sound of heart and receives a feedback weather it is healthy or not with accuracy 96%

- Seven stacked machine-learning models

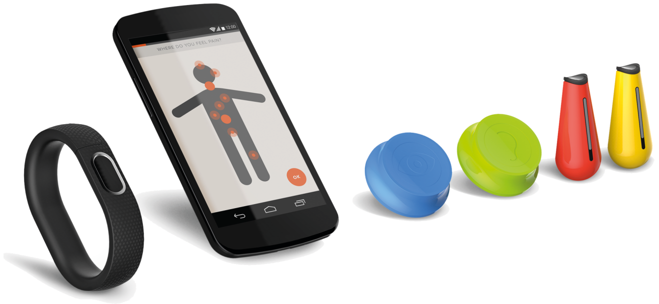
	Healthy	Unhealthy
Hospitalized	0.97	0.03
Non-hospitalized	0.13	0.87

Gjoreski et al. (2017) Chronic Heart Failure Detection from Heart Sounds Using a Stack of Machine-Learning Classifiers, IE.

Unobtrusive diagnosis

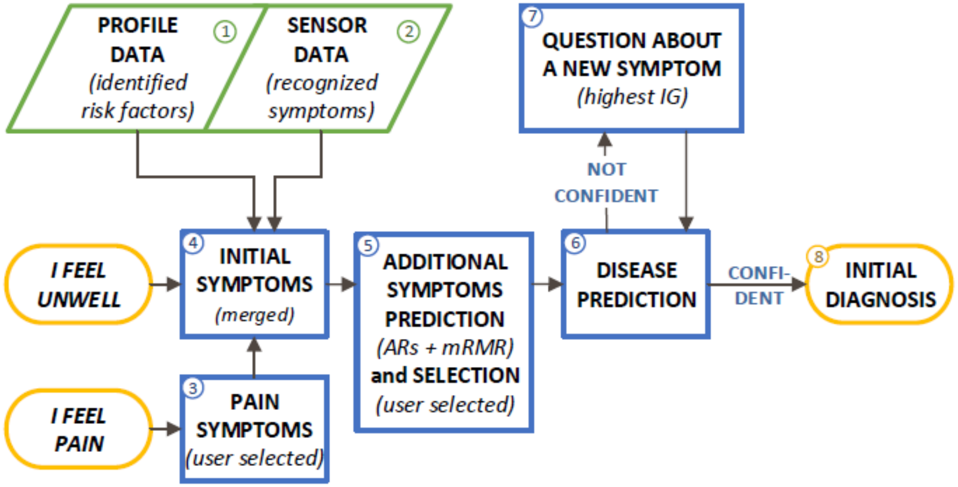
Tricorder XPRIZE competition

Team from Slovenia was selected among top 10



Diagnose 14 conditions:

- Healthy, Hypertension, Atrial fibrillation, Acute haemorrhagic stroke , Obstructive sleep apnoea, Otitis media, Microcytic iron deficiency anaemia, Streptococcal pharyngitis, Lower urinary tract bacterial infection, COPD, Acute viral pneumonia, Leucocytosis, Tuberculosis, Hepatitis A, Diabetes type 2



Abdominal pain
Fever

Somrak et al. (2015) Medical diagnostics based on combination of sensor and user-provided data, ECAI.

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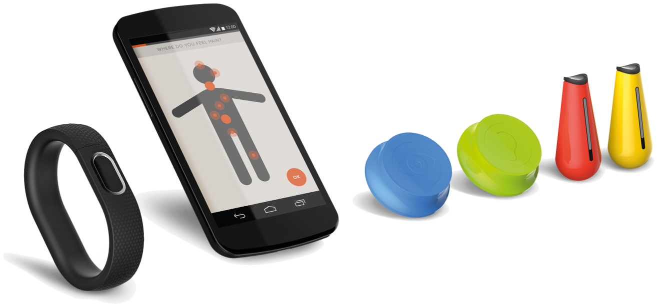
Unobtrusive diagnosis

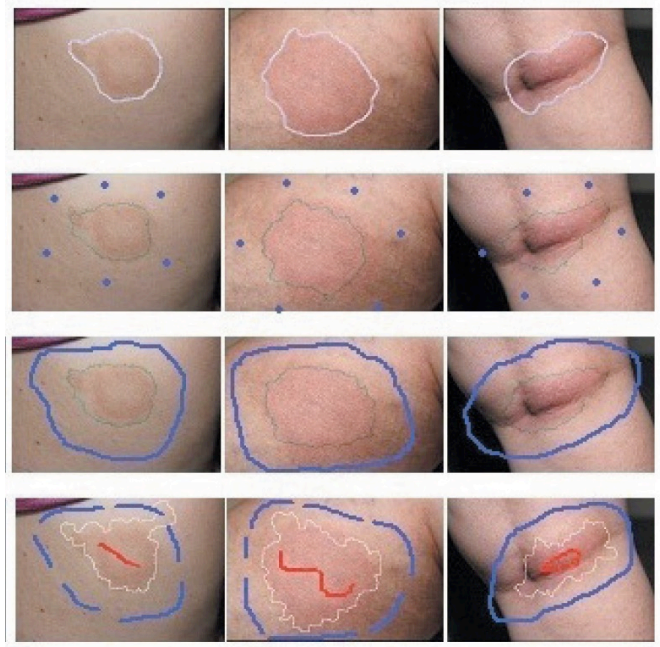
DEMO



Somrak et al. (2015) Medical diagnostics based on combination of sensor and user-provided data, ECAI.

...and...

Smartwatch with fall detection for elderly
Lyme borreliosis recognition from smartphone pictures



Current challenges

Estimate blood pressure from wristband's PPG sensor

Decision support system for CHF physicians

Migraine prediction

COPD monitoring

Sleep analysis using wearable and ambient sensors

Monitor patients with neurodegenerative disease

....

Conclusion

Trend of wearable sensors development is high and still increasing

Many challenging mHealth modules have been developed and even implemented and validated in pilots

mHealth will soon be part of us either through mobile applications or through health services

We are not trying to spy (on you), our research aims at helping (you)

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