Real-Time Body Temperature and Heart Rate Monitoring System for Classification of Physiological Response Patterns Using Wearable Sensor and Machine Learning Technology

Master Thesis
Final Presentation

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Motivation

- Mobile Devices are an integral part of our lives
- A subset of these devices has sensors that allow recording health data: Fitness trackers, smart watches

→ **Facilitates continuous monitoring and analysis of personal vital signs**

- Analysis and interpretation of this data is challenging:
  - Physiological response patterns (PRP) vary from person to person
  - PRP change based on activities, diseases or the environmental context
  - PRP depend on demographic factors: age, gender, fitness level

→ **PRP cannot be described in general terms**

→ **Machine learning algorithms which learn to interpret a person's individual PRPs**

Hypothesis

A real-time body temperature and heart rate monitoring system enables personalized classifications of physiological response patterns as either normal or abnormal.

Challenges

The accuracy, sensitivity and specificity of such a system depends on two main indicators:

1. The quality of the measurements generated by a sensor
2. The performance of the applied machine learning algorithms

→ **The thesis objectives must take this into account**

Objectives

(i) Evaluate the measurement quality of the chosen sensor and therefore its suitability for real-time detection of changes in vital signs

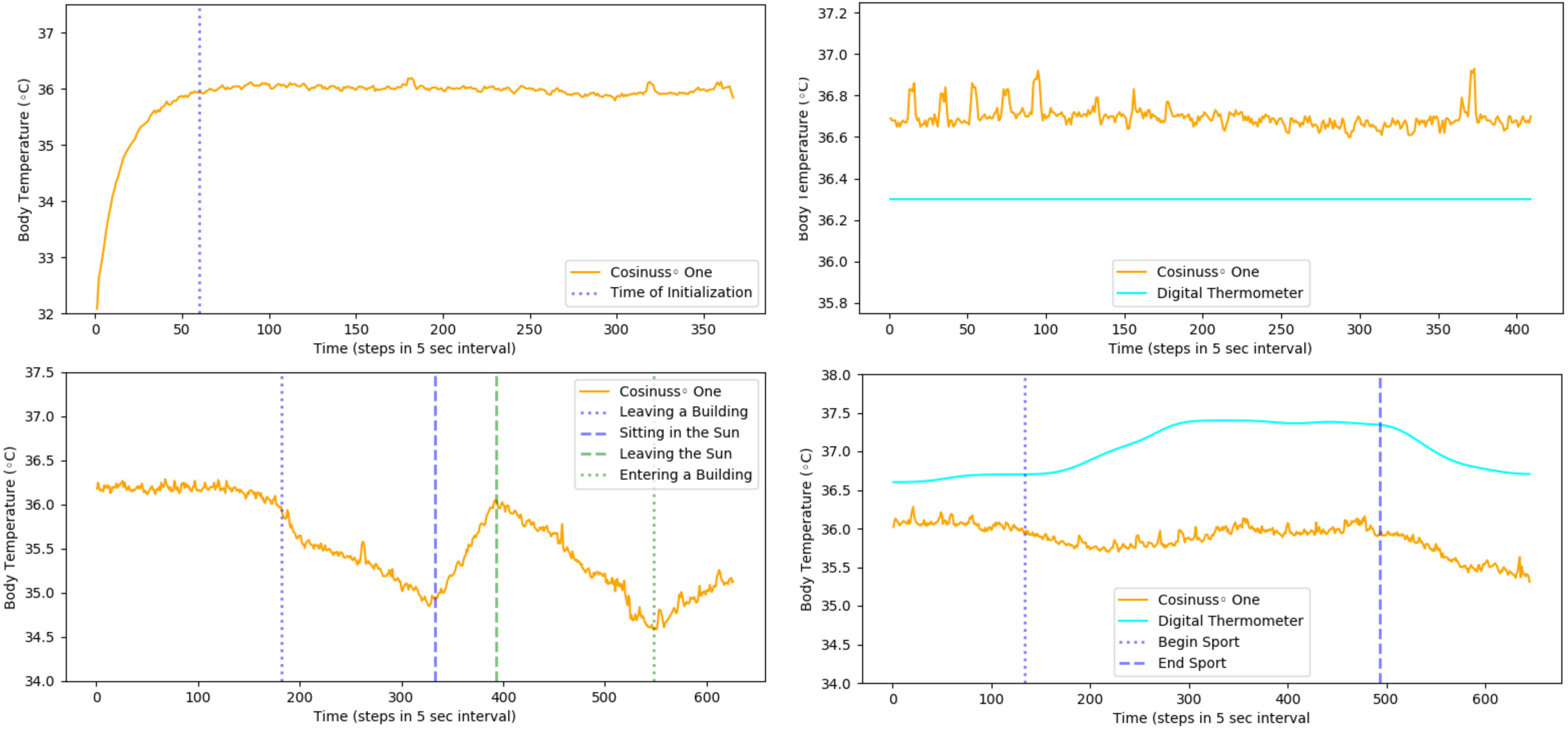
(ii) Develop an architectural concept of a distributed real-time monitoring and classification system

(iii) Implement this architectural concept as a proof-of-concept prototype

(iv) Show that MLAs can be used to learn the individual PRPs of a person's vital signs taking into account activities, demographic factors and the environmental context

(v) Show that MLAs can classify a tendency change of vital signs in response patterns as physiologically normal or abnormal

Cosinuss° One Body Temperature Evaluation



Discussion Cosinuss° One

Advantages:

- Two vital signs in one device
- High quality of heart rate measurements
- Reasonable body temperature measurements in a stable environment
- Open source Bluetooth API & long battery life

Disadvantages:

- Body temperature measurements effected by the environment
- Differences to commercially available thermometer
- Long time wearing comfort

→ **Heart rate measurements are reasonable**

→ **Body temperature measurements in the same environments behave mostly with the same tendency, i.e. have the same inaccuracy**

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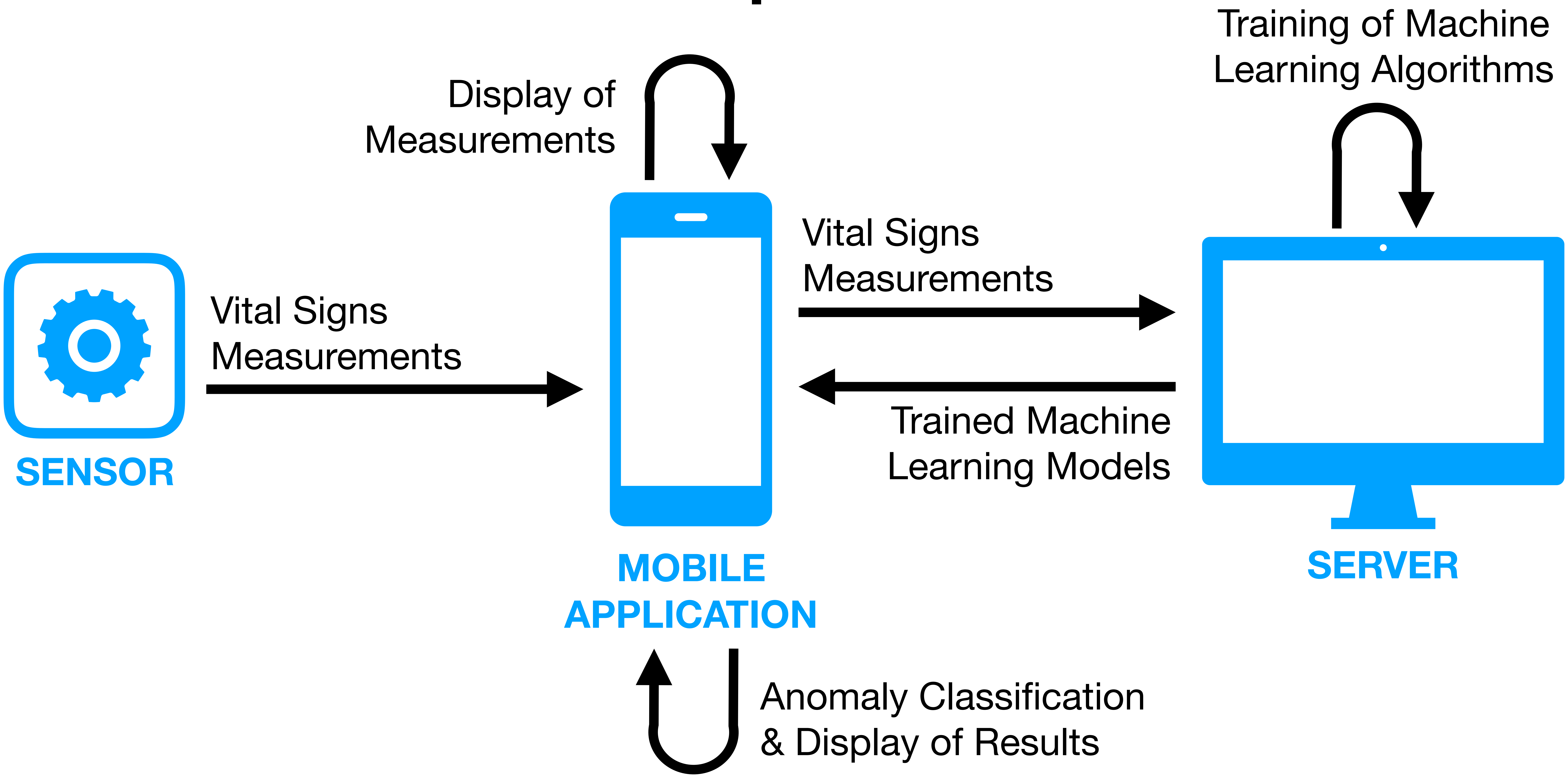
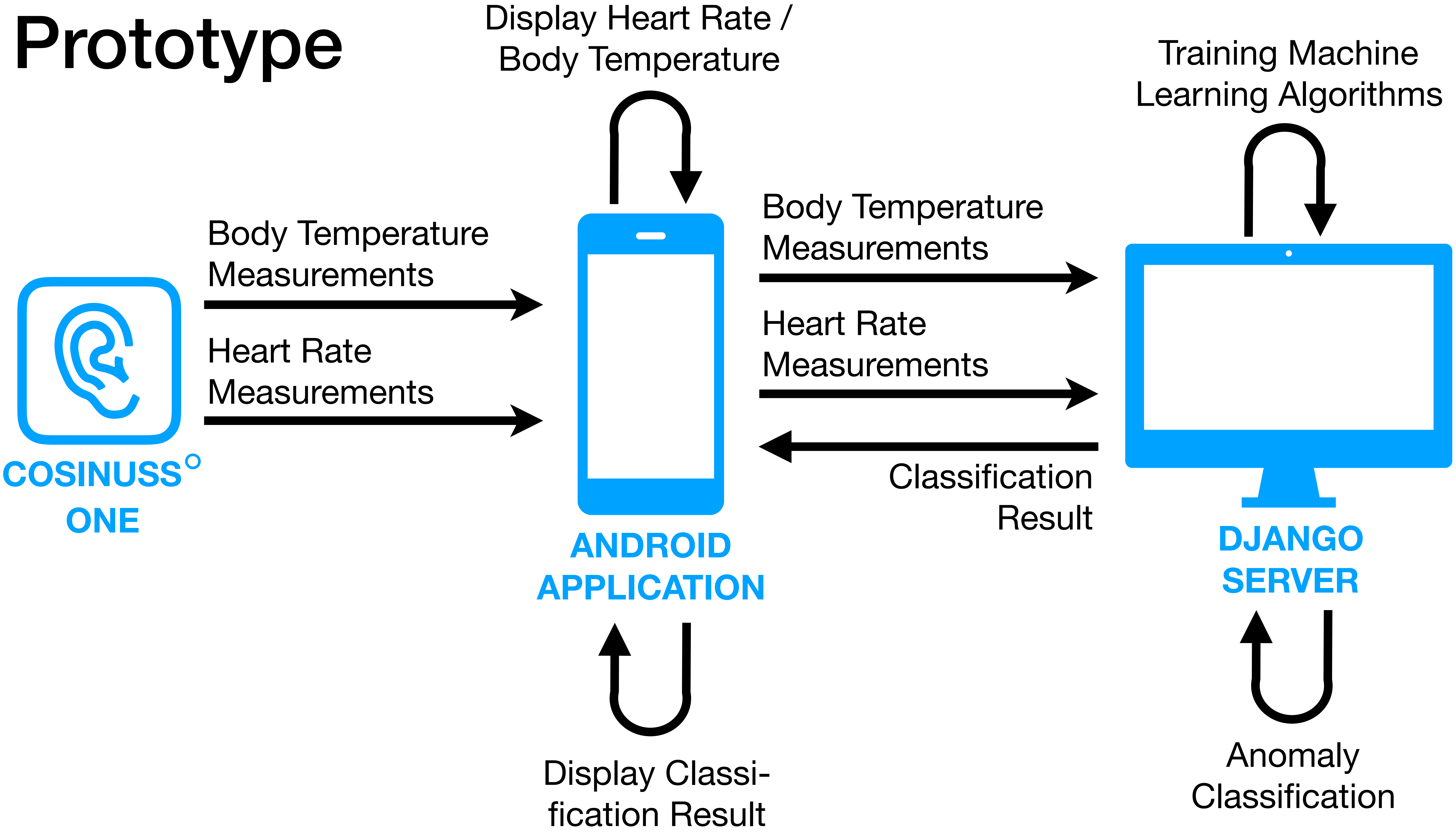
Architectural Concept



Prototype



Display Heart Rate / Body Temperature
Training Machine Learning Algorithms
Body Temperature Measurements
Heart Rate Measurements
Body Temperature Measurements
Heart Rate Measurements
Classification Result
COSINUSS° ONE
ANDROID APPLICATION
DJANGO SERVER
Display Classi-fication Result
Anomaly Classification

Discussion System Concept & Prototype

Advantages:

- System allows continuous monitoring of vital signs
- Resilience against network failures and user feedback as part of the concept
- REST and Bluetooth architecture in the prototype allow modularity, changeability and extensibility

Disadvantages:

- Mobile phone needed which can decrease freedom of movement
- Difference between concept and prototype:
  - No classification on the mobile device
  - Missing user feedback

→ **The system can continuously analyze and learn in real-time changes in PRP**

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Machine Learning Algorithms

Problem:

Abnormal health data cannot be generated by pressing a button, is different for every person and every circumstance, and is therefore unknown during training.

Consequence:

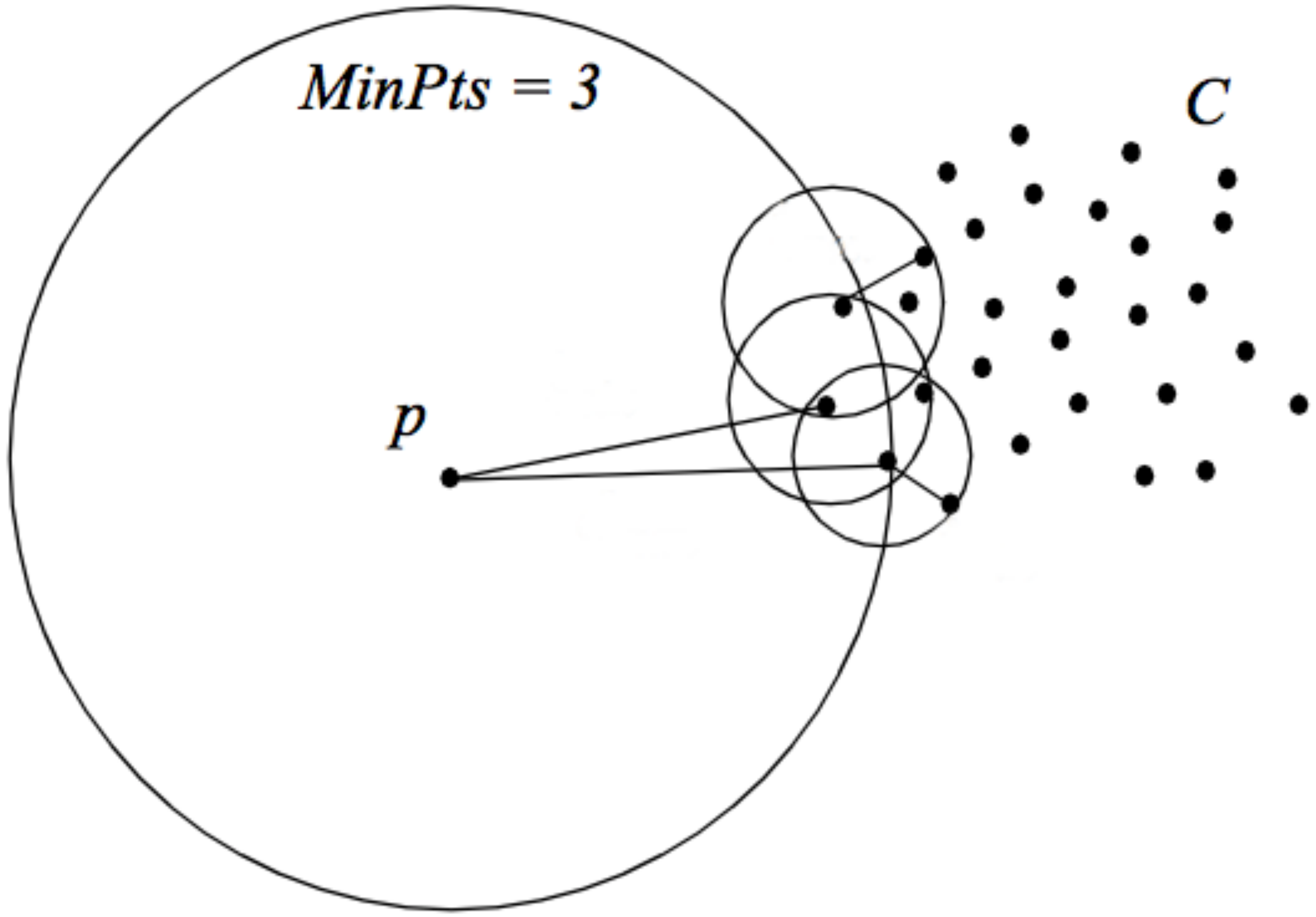
Supervised machine learning algorithms cannot be used. Only semi- and unsupervised algorithms for anomaly detection can be applied.

Algorithms:

- Local Outlier Factor
- Isolation Forest
- One-Class Support Vector Machine
- Autoencoder

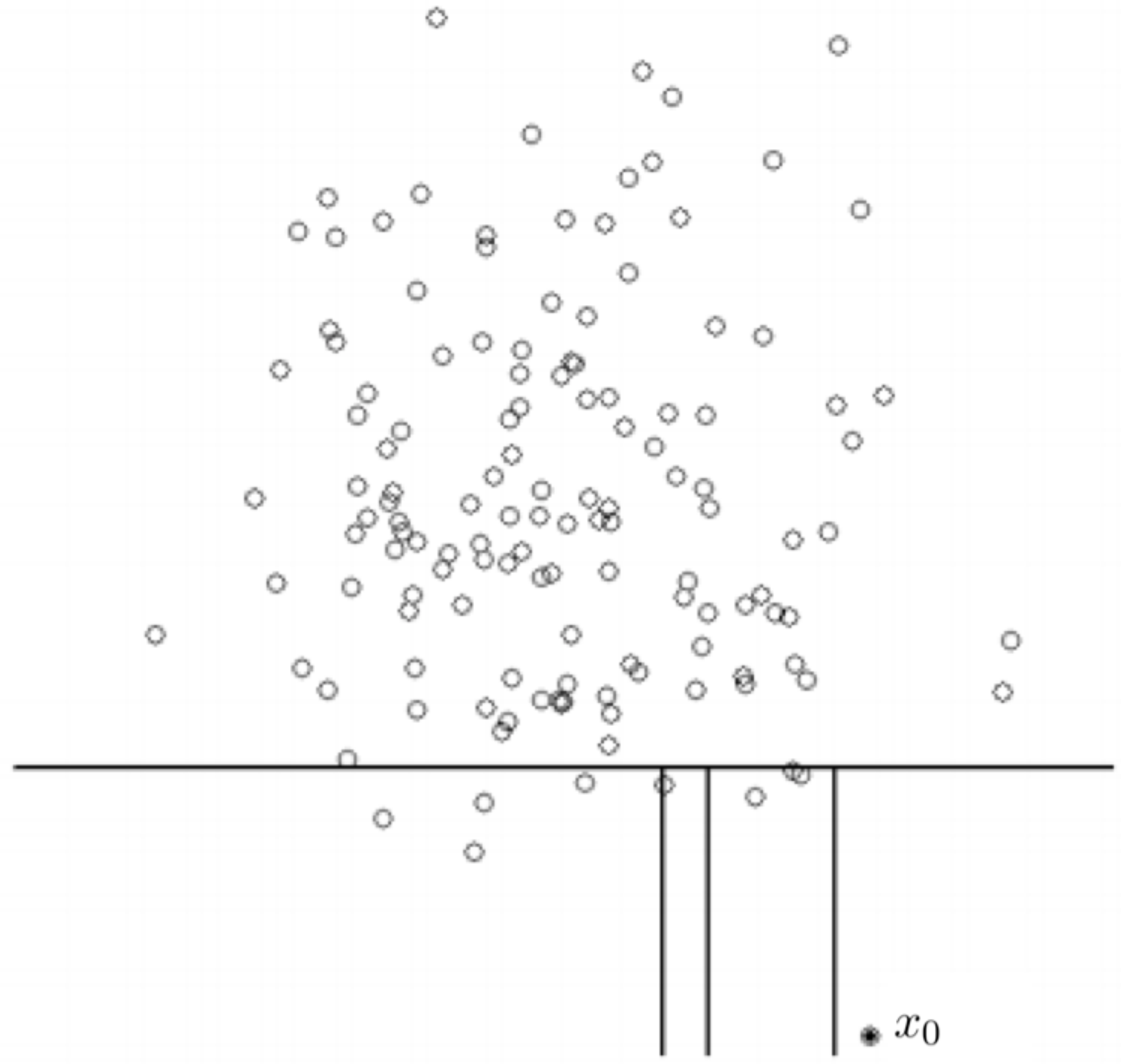
Local Outlier Factor

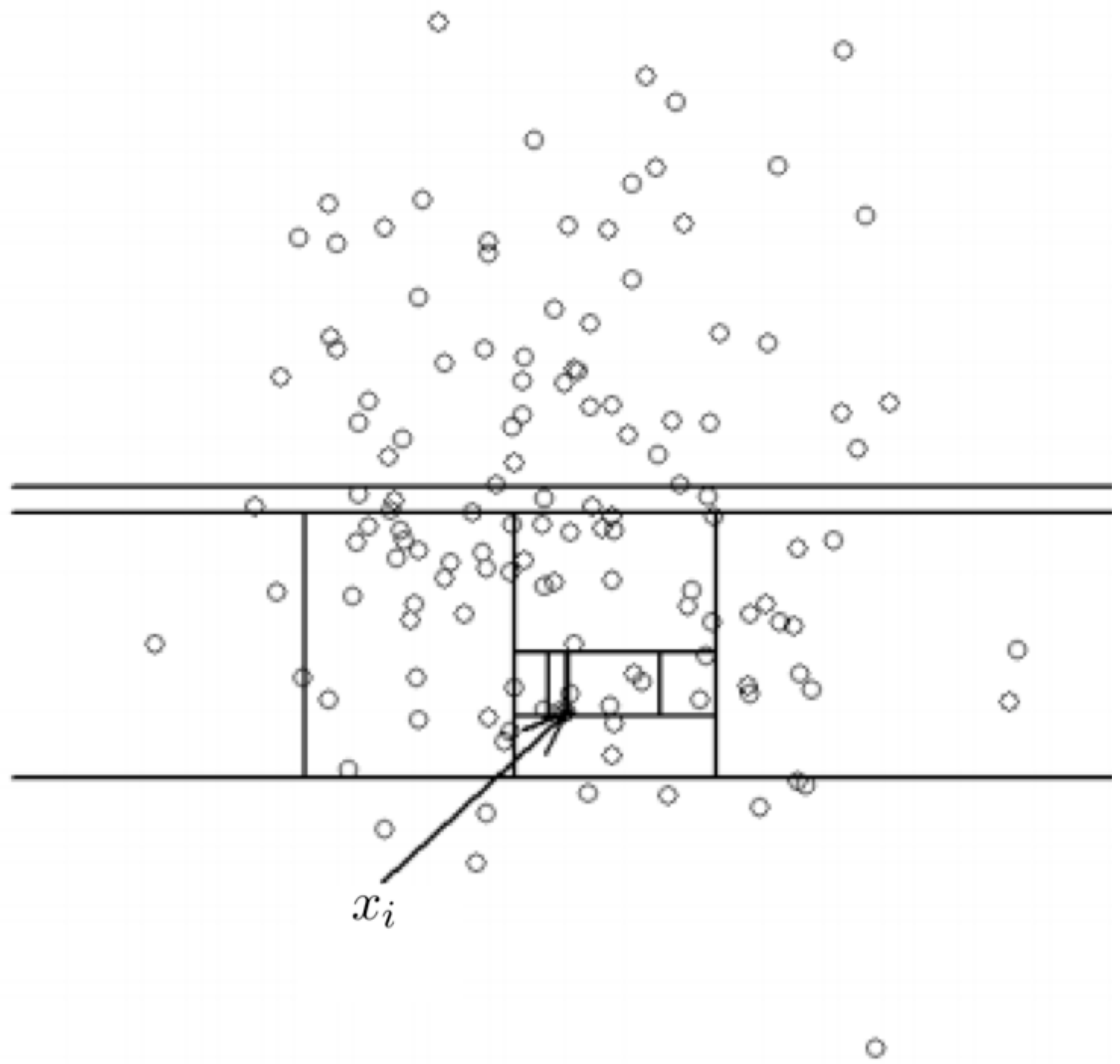
- Density based approach
- Compare the local density of a point with the average density of the point's *k* nearest neighbors
- Low density ➡ point is an anomaly
- High density ➡ point belongs to the cluster



Isolation Forest

- Distance based approach
- Assembly of decision trees which isolate an instance from the rest of the other instances
- Short path (< average path) ➡ anomaly, since chance of isolation is higher
- Long path (>= average path) ➡ normal data





One-Class SVM

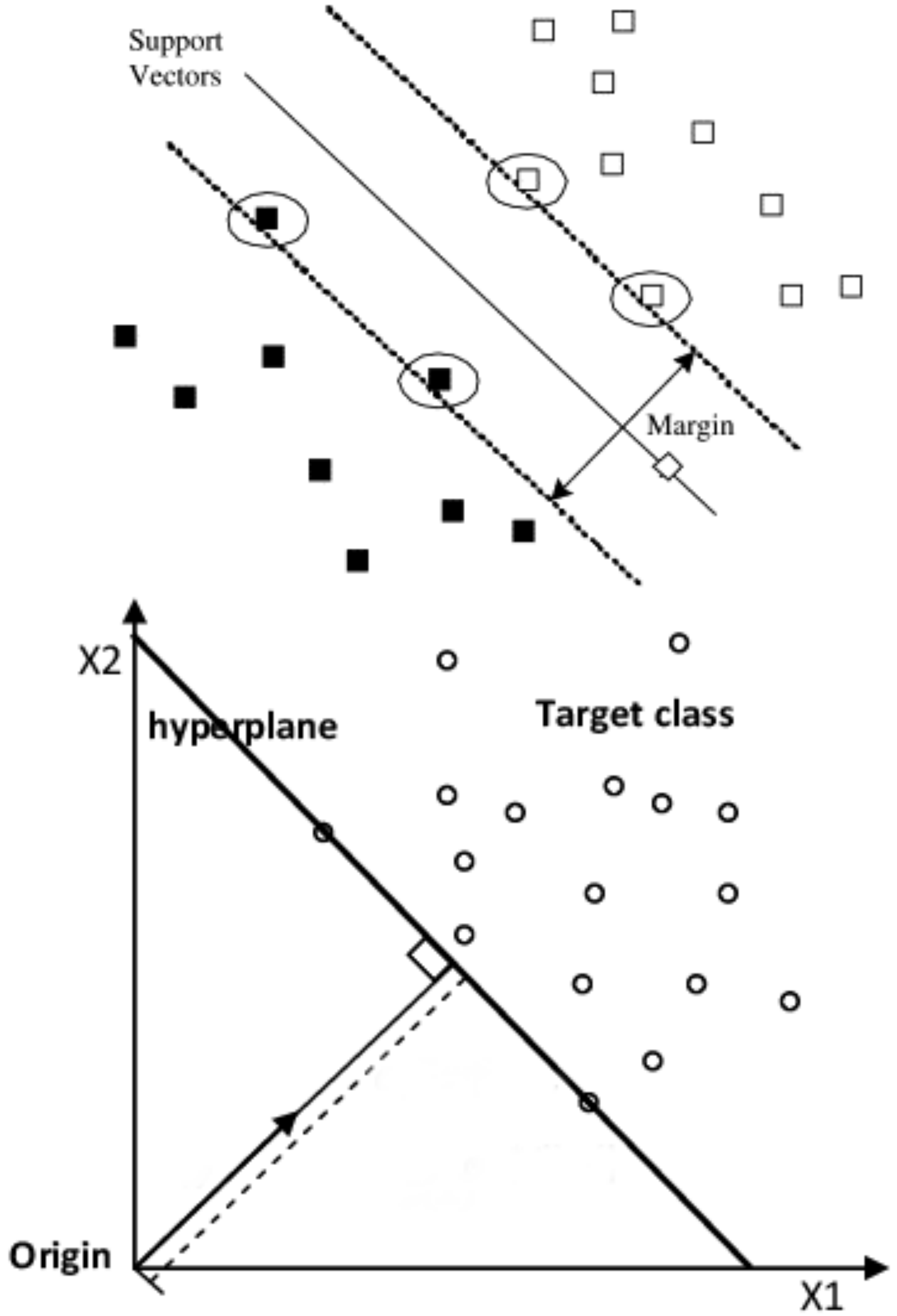
- Based on normal SVM approach

SVM:

- Map nonlinear separable data from the input space to a higher dimensional feature space using a kernel function
- Linearly separate data by searching a hyper-plane which optimizes the margin between the hyperplane and the support vectors

One-Class SVM:

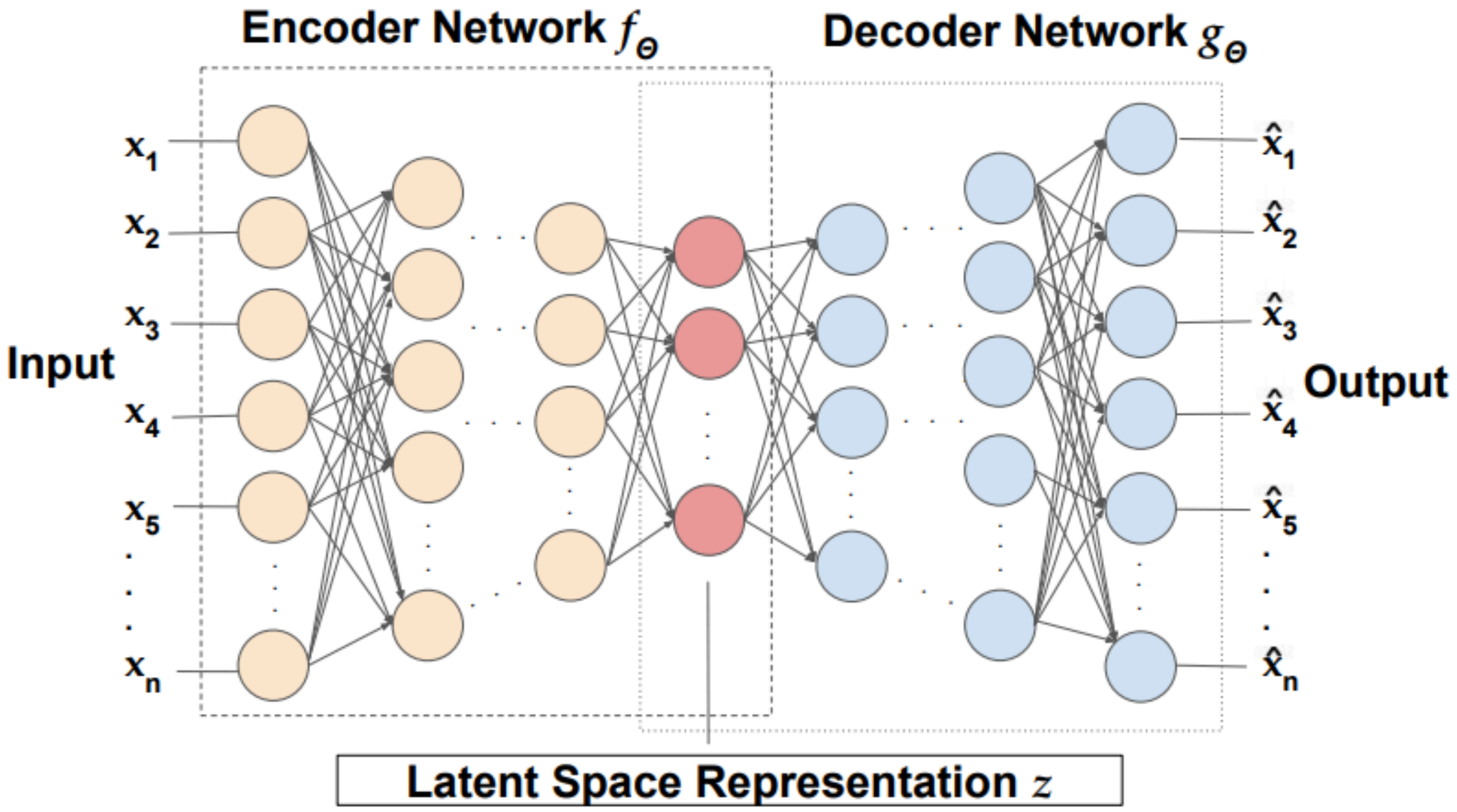
- Search for a hyperplane that maximizes the distance between the data points and the origin



Autoencoder

- Lossy compression technique based on feedforward multilayered artificial neural networks
- Consists of an encoder and decoder network with symmetrical design
- Encoder: tries to find a reduced representation *z* which stores the most important information
- Decoder: tries to reconstruct the original data from *z*
- Reconstruction error: represents the difference between input and output of the network
- Low reconstruction error → normal data
- High reconstruction error → anomaly, since this data type is not known during training

Autoencoder



System & Algorithm Evaluation

Data Generation:

- Measuring heart rate and body temperature for 72 hours every 5 seconds
- Generation of time series with length of 2 minutes:
  - Each time-series consist of 25 values of each vital sign
  - Supplemented by mean, standard deviation, hour and minute
  - Overlap of 30 seconds to not miss boundary events

→ **Abnormal health data cannot be generated by pressing a button…**
What should be used as anomalous data?

Normal Labels:

- Sleeping
- Lying
- Sitting
- Walking

Abnormal Labels:

- Sport
- Metro
- Eating

System & Algorithm Evaluation

Training of Algorithms:

- Data driven approach supplemented by statistical features
- All normal labeled data as training data, except the same amount of abnormal data
- All abnormal labeled data as test data plus the same amount of normal data held out for training → ratio 1:1 for normal and abnormal data
- Grid search for finding the best parameters

Evaluation of Algorithms:

- Calculation of accuracy, sensitivity and specificity using confusion matrices
- Overall result using all abnormal labeled data together
- Specific results for each type of abnormal data

Overall Results

		Local Outlier Factor		Isolation Forest		One-Class SVM		Auto-encoder	
		-1	$+1$	-1	$+1$	-1	$+1$	-1	$+1$
Confusion Matrix	-1	142	22	148	16	144	20	125	39
	$+1$	14	150	24	140	13	151	19	145
Accuracy		89.02 %		87.80 %		89.94 %		82.32 %	
Sensitivity		86.59 %		90.24 %		87.80 %		76.22 %	
Specificity		91.46 %		85.37 %		92.07 %		88.41 %	

→ **One-Class SVM performed best**

Specific Results

Local Outlier Factor		Sport		Metro		Eating	
Confusion Matrix		−1	+1	−1	+1	−1	+1
	−1	63	1	37	15	42	6
	+1	6	58	5	47	3	45
Accuracy		94.53 %		80.77 %		90.63 %	
Sensitivity		98.44 %		71.15 %		87.50 %	
Specificity		90.63 %		90.38 %		93.75 %	

One-Class SVM		Sport		Metro		Eating	
Confusion Matrix		−1	+1	−1	+1	−1	+1
	−1	64	0	45	7	35	13
	+1	5	59	5	47	3	45
Accuracy		96.09 %		88.46 %		83.33 %	
Sensitivity		100 %		86.54 %		72.92 %	
Specificity		92.19 %		90.38 %		93.75 %	

Isolation Forest		Sport		Metro		Eating	
Confusion Matrix		−1	+1	−1	+1	−1	+1
	−1	64	0	51	1	33	15
	+1	9	55	8	44	7	41
Accuracy		92.97 %		91.35 %		77.08 %	
Sensitivity		100 %		98.08 %		68.75 %	
Specificity		86.15 %		84.62 %		85.42 %	

Auto-encoder		Sport		Metro		Eating	
Confusion Matrix		−1	+1	−1	+1	−1	+1
	−1	64	0	29	23	32	16
	+1	7	57	6	46	6	42
Accuracy		94.53 %		72.12 %		77.08 %	
Sensitivity		100 %		55.77 %		66.67 %	
Specificity		89.06 %		88.46 %		87.50 %	

→ **Sport: One-Class SVM performed best**
Metro: Isolation Forest performed best
Eating: Local Outlier Factor performed best

Discussion Machine Learning Algorithms

Advantages:

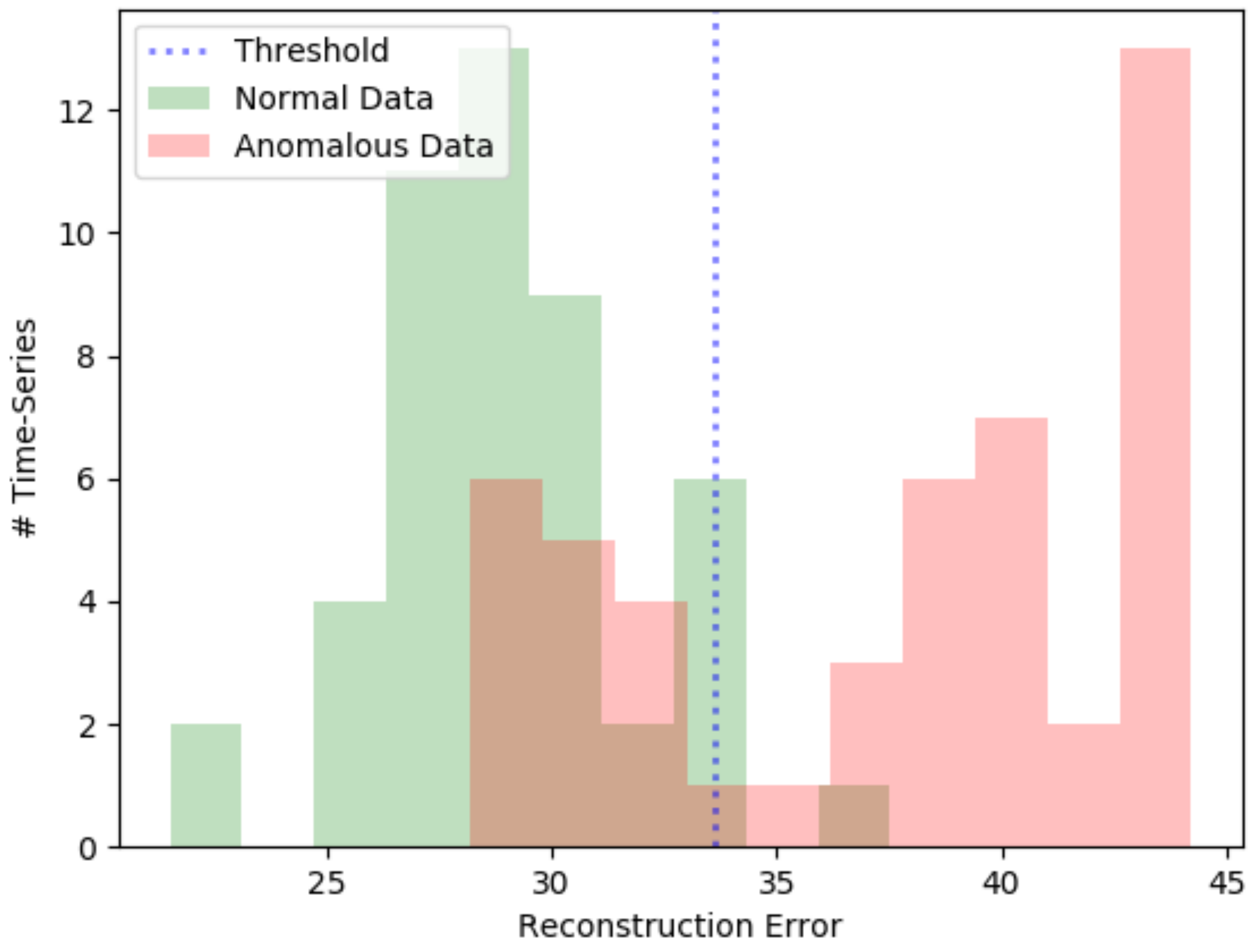
- Algorithms consider inequality of data distribution
- Fast computation using data driven approach allows time critical analysis
- Algorithms based on different mathematical approaches can be applied
- High accuracy, sensitivity and specificity for all types of anomalous data

Disadvantages:

- Most errors on the boundaries of activity change
- At least 1 minute (half of a time-series) of new activity measurements until a change is detected → delayed correct classifications
- Threshold for anomalies can not be shifted and therefore there is no control over sensitivity and specificity (except for the Autoencoder)

→ **Accuracy of all algorithms over 80 %**

Discussion Machine Learning Algorithms



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Hypothesis

A real-time body temperature and heart rate monitoring system enables personalized classifications of physiological response patterns as either normal or abnormal.

But…

→ **This thesis is subject to two limiting factors**

Experiments:

- The experiments to evaluate the Cosinuss° One sensor and the MLAs were only conducted on one person (N = 1)
- In order to obtain statistically meaningful results, the evaluations have to be conducted during the same scenarios on a bigger sample size (N > 1)

Machine Learning Algorithms:

- Accuracy, sensitivity and specificity of the MLAs have only been evaluated on regular medical data using different activities as the artificial anomalous counterpart
- This does not imply that the system will work for diseases as well

Outlook

Data Sources:

- Use more medical and non-medical data sources
- More available data for irregularity detection could improve algorithm results

System Extensions:

- Implement differences between prototype and concept
- Use smart watch instead of mobile phone
- Alarm hierarchy including third parties

Machine Learning Algorithms:

- Computing and using more statistical features
- Testing other algorithms and more sophisticated neural networks
- Playing with the analysis time frame

Thank You! Questions?