

Machine Learning and Pervasive Computing

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Overview and Structure

- 22.10.2014 Organisation
- 22.10.2014 Introduction (Def.: Machine learning, Supervised/Unsupervised, Examples)
- 29.10.2014 Machine Learning Basics (Toolchain, Features, Metrics, Rule-based)
- 05.11.2014** A simple Supervised learning algorithm
- 12.11.2014 Excursion: Avoiding local optima with random search
- 19.11.2014 –
- 26.11.2014** Bayesian and decision-tree learner
- 03.12.2014 –
- 10.12.2014 Non-parametric methods
- 17.12.2014** Higher dimensional data (SVM, ANN, SOM)
- 07.01.2015 Classification (Single class, multi-class)
- 14.01.2015** Unsupervised learning
- 21.01.2015 Dimensionality reduction (Motivation, PCA)
- 28.01.2015** Anomaly detection
- 04.02.2015 Online learning and Recommender systems

Outline

Introduction

Toolchain

Projects

Conclusion

What is machine learning ?

What is machine learning ?

Wikipedia

Machine learning is a subfield of computer science and artificial intelligence that deals with the construction and study of systems that can learn from data, rather than follow only explicitly programmed instructions.

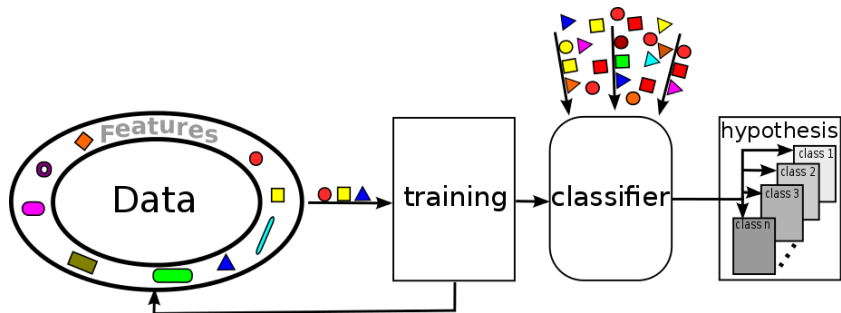
What is machine learning ?

Wikipedia

Machine learning is a subfield of computer science and artificial intelligence that deals with the construction and study of systems that can learn from data, rather than follow only explicitly programmed instructions.

Tom M. Mitchell, The Discipline of Machine Learning, 2006

Machine Learning seeks to answer the question how we can we build computer systems that automatically improve with experience, and what are the fundamental laws that govern all learning processes'



Artificial intelligence



Anomaly detection

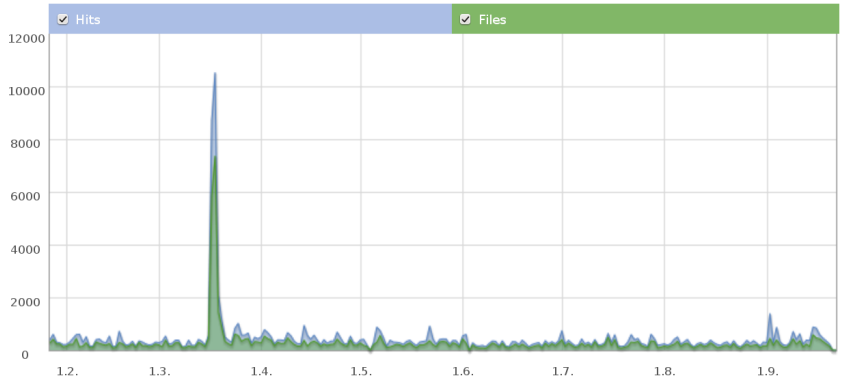


Image segmentation



Image segmentation

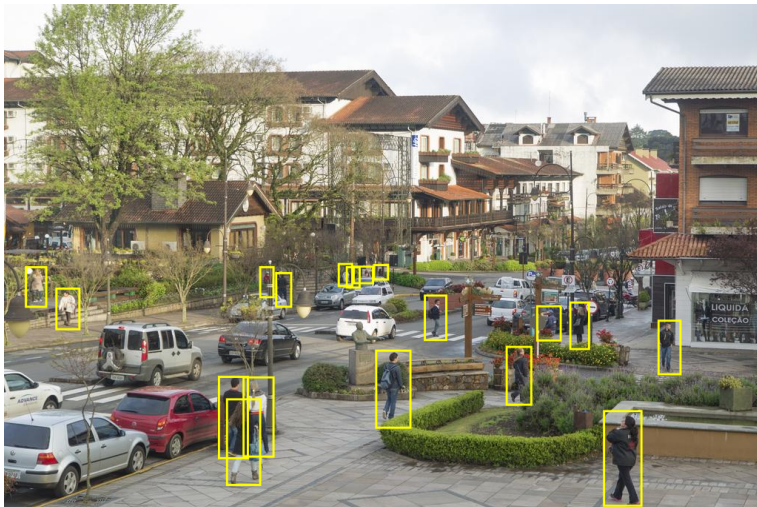


Image segmentation



Image segmentation



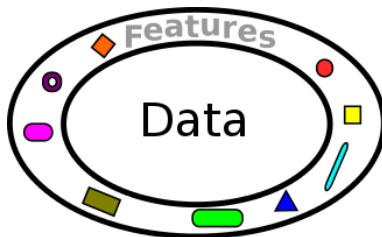
Image segmentation



Recommender systems

Here: <http://www.movielens.org>

Predictions for you ↴	Your Ratings	Movie Information
★★★★★	Not seen ▼	Black Christmas (1974) DVD VHS info imdb add tag Comedy, Horror, Mystery, Thriller
★★★★★	Not seen ▼	Blood of Heroes, The (1988) DVD info imdb Action, Sci-Fi [add tag] Popular tags: australia 📌, fighting 📌, delroy lindo 📌
★★★★★	Not seen ▼	Sisters (1973) DVD VHS info imdb add tag Horror, Thriller
★★★★★	Not seen ▼	Unsane (Tenebre) (1982) DVD VHS info imdb Crime, Horror, Mystery, Thriller - Italian, English [add tag] Popular tags: Giallo 📌, Italian 📌
★★★★★	Not seen ▼	Collector, The (1965) DVD VHS info imdb add tag Drama, Horror, Thriller
★★★★★	Not seen ▼	Howling, The (1980) DVD VHS info imdb Horror, Mystery [add tag] Popular tags: werewolf 📌
★★★★★	Not seen ▼	Dawn of the Dead (2004) DVD VHS info imdb Action, Drama, Horror, Thriller [add tag] Popular tags: mmm... brains... 📌, Zombie Movie 📌, bmovie 📌
★★★★★	Not seen ▼	Dark Water (Honogurai mizu no soko kara) (2002) DVD VHS info imdb Horror, Mystery, Thriller - Japanese

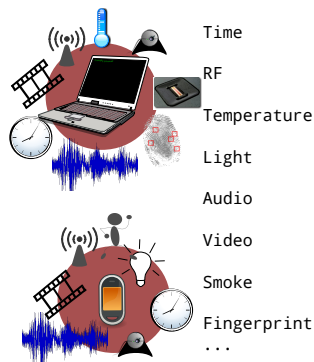


Sensors and sensor classes

- We are surrounded by a multitude of sensors

- Sensor readings utilised for

- Information provisioning
- Situation classification
- Authentication
- Cryptography

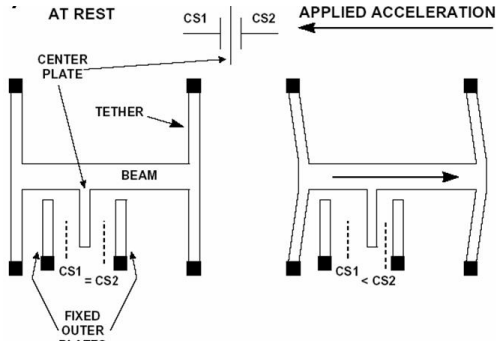


Sensors and sensor classes



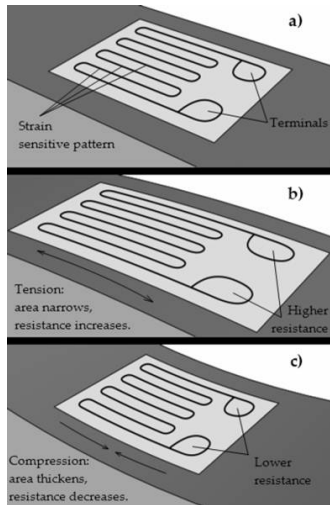
Sensors and sensor classes

- MEMS acceleration sensors
 - E.g. Analogue Devices ADXL
 - Low energy consumption, small, cheap, medium precision
 - MEMS = Micro-mechanical System: Mechanic in Silicon (Silizium)
 - Here: Comparison of capacity $CS1$ and $CS2$ leads to acceleration



Sensors and sensor classes

- Pressure sensors
 - Z.B. IEE about 3-10 Euro
 - Very imprecise



Sensors and sensor classes

- Output of sensors has to be interpreted typically
 - Raw electrical signals
 - Interpretation of signals as electric values
 - Binary or Real valued representation
 - Further identification of features
 - Feature extraction
 - Interpretation of features and classification



Data sampling

- Record sufficient training data
 - Annotated! (Ground-truth)
 - Multiple subjects
 - Various environmental conditions (time of day, weather, ...)



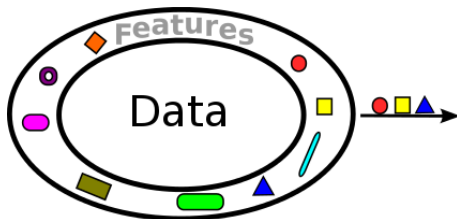
Data sampling

- Record sufficient training data
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Example

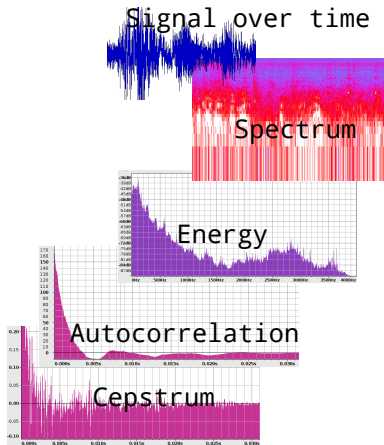
- Electric supply data over 15 years covers 5000 days but only 15 christmas days
- Especially critical events like accidents (e.g. plane, car, earthquake) are scarce



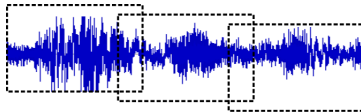


Features and feature extraction

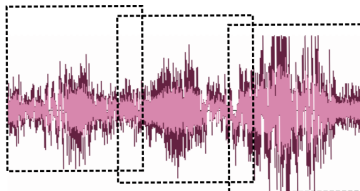
- What is a feature and why do we need it?
 - Captured data might be hard to interpret
 - Many aspects can be contained in a single data stream
 - Example: Audio
 - Loudness
 - Energy on frequency bands
 - Zero crossings
 - Direction changes



Feature subset-selection



- Pre-process data
 - Framing
 - Normalisation



Feature subset-selection

Domain knowledge?

→ better set of
ad-hoc features

Features commensurate?

→ normalise

Pruning of input required?

→ if no, create disjunctive
features or weighted
sums of features

- Pre-process data

- Framing
- Normalisation

Independent features?

→ construct conjunctive features
or products of features

Is the data noisy?

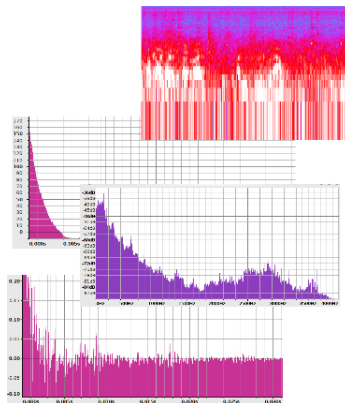
→ detect outlier examples

Do you know what to do first?

→ If not, use a linear predictor

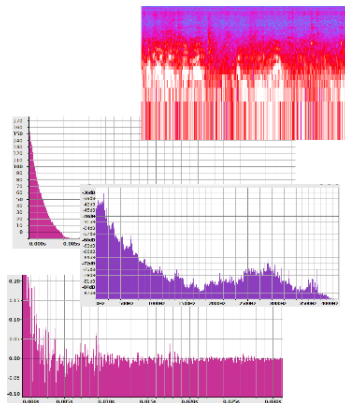
Feature extraction

- Identify meaningful features
 - remove irrelevant/redundant features



Feature extraction

- Identify meaningful features
 - remove irrelevant/redundant features
- Features can be contradictory!



Feature subset-selection

Simple ranking of features with correlation coefficients

Example: Pearson Correlation Coefficient

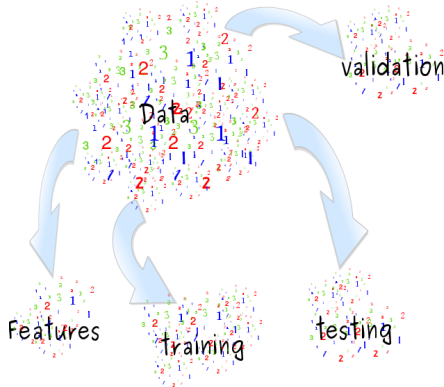
$$\varrho(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} \quad (1)$$

- Identifies linear relation between input variables x_i and an output y

Feature subset-selection

How to do reasonable feature selection

- Utilise dedicated data sets for feature selection and classifier training
- Pay attention that a single raw-data sample could not impact features in both these sets
- Don't train the features on the training- or test-data-set



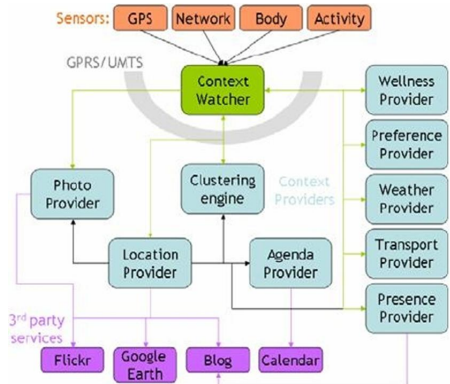
Examples and case studies: Media Cup

- Media Cup: Context recognition
 - Activity: Trigger sleep mode (save energy)
 - Level of activity
 - Own context: Object movement, person is nervous, specific handling of objects
 - Environmental context: Vibration, earthquake
- Sensor: Ballswitch
 - (nearly) no quiescent current
 - Various types, filled with gas/liquid
 - e.g. Acceleration with fixed value (liquid)
 - Vibration (filled with gas)



Examples and case studies: Context Watcher

- Context Watcher
 - Location
 - GSM cell-ID; GPS
 - Mood
 - user input
 - Activity
 - calendar based
 - Bio-data
 - heart and foot sensors
 - Weather
 - location based over internet
 - Photo/picture
 - camera



Examples and case studies: Context Watcher



Picture	Context Data
	cell id: 10571 altitude: 59.4 speed: 115.1 km/h course: 246.6 pos: (52.279, 6.503) range: 1 m street: E30 postal code: 7462 city: Rijssen (NL)

Johan's blog

📅 Saturday, March 24, 2007

A day in Papendrecht

The weather that I enjoyed today: it has been rather cloudy in Alblasterdam, 1/9°C, with a relative humidity of 93%, a gentle breeze was blowing from north to northeast. The cities that I visited today: Papendrecht (7.4h), Dordrecht (1.6h), Alblasterdam (4.5h). The max of speed that I had today: 104.9. The photos that I took today:



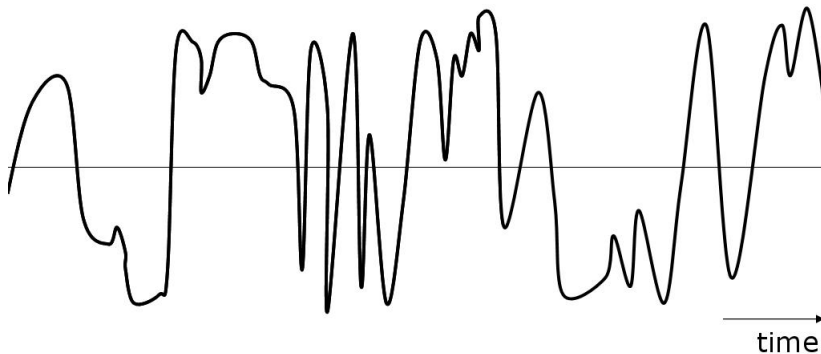

Examples and case studies: TEA

TEA-Audio

- Requirements
 - Restricted memory space
 - Computing power restricted
- Benefit
 - Many sensors → Many features
- Example approach
 - Utilise time domain (no transformation)
 - Utilise statistic measures
 - Feature extraction based on small amount of data

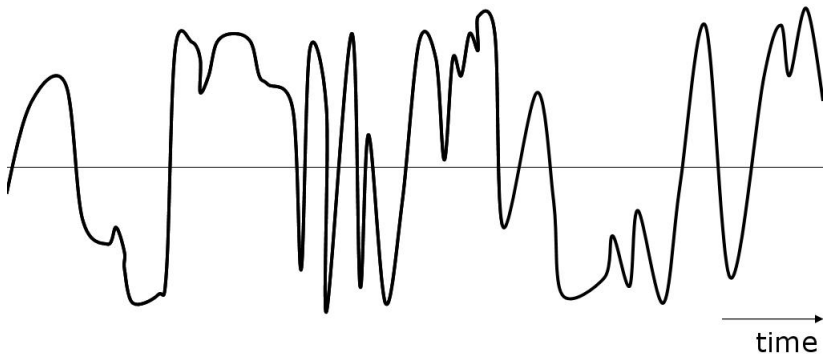
Examples and case studies: TEA

- Audio data in time domain



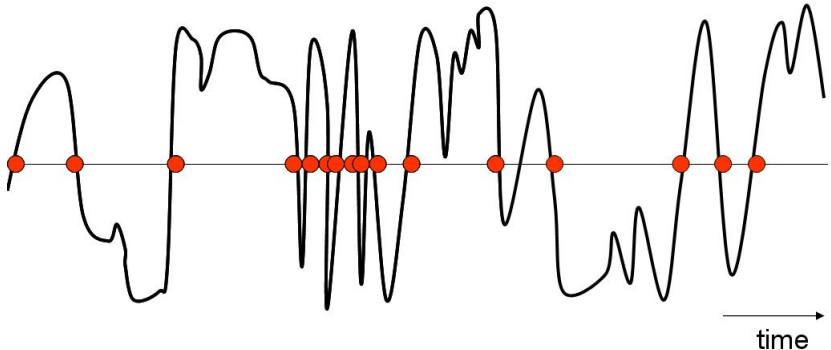
Examples and case studies: TEA

- Audio data in time domain
- Features?



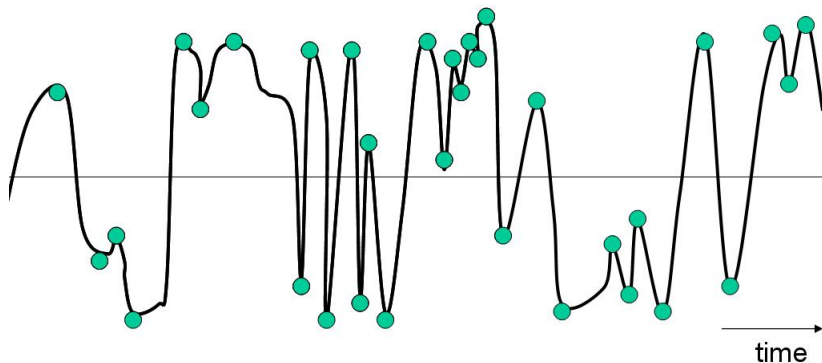
Examples and case studies: TEA

- Count zero crossings
- Distance between zero crossings



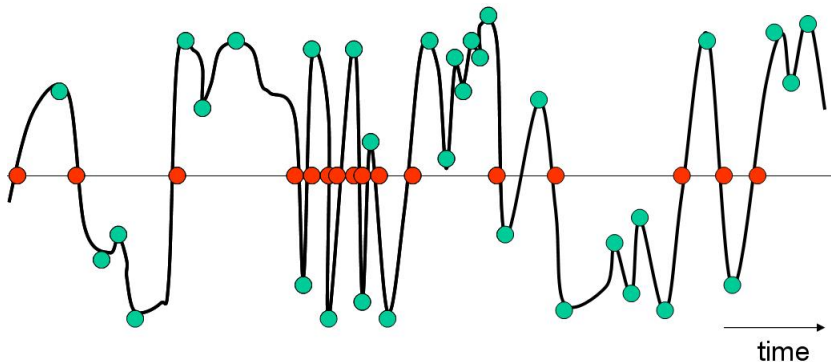
Examples and case studies: TEA

- Count of direction changes



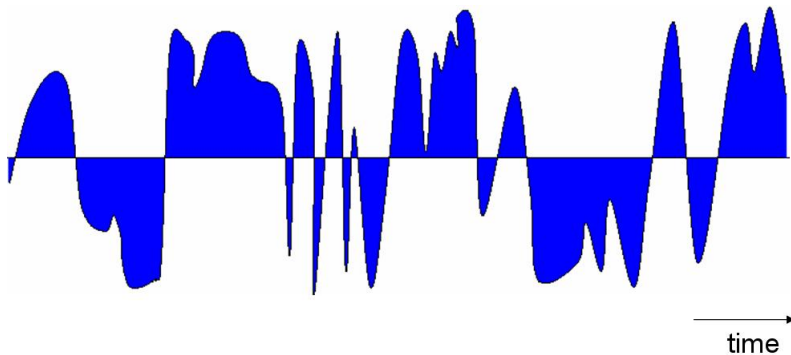
Examples and case studies: TEA

- ratio: $\frac{\text{direction changes}}{\text{zero crossings}}$



Examples and case studies: TEA

- Integral



Examples and case studies: TEA

- Several chunks for speech

whistling


```
Raw - Avg: 163.7 ; Abs Avg: 2368.5 ; ratio: 1.857 ; sd: 1.04  
Spec - avg: 8.1 ; sd: 2055.67 ; avg dis: 315.8 ; sd dis: 102655.69  
Prof - avg: 7954.4 ; sd: 2.15 ;
```

A spectrogram visualization for whistling. It shows a single, continuous, horizontal line of energy across the frequency spectrum, indicating a sustained tone. The x-axis represents time and the y-axis represents frequency.

Whistling

speech

```
Raw - Avg: 170.5 ; Abs Avg: 471.0 ; ratio: 12.190 ; sd: 566179.8  
Spec - avg: 12.5 ; sd: 4447.67 ; avg dis: 115.4 ; sd dis: 13669.85  
Prof - avg: 1411.2 ; sd: 1673821.1 ;
```

A spectrogram visualization for speech. It shows multiple horizontal lines of energy, indicating different phonetic components. The x-axis represents time and the y-axis represents frequency.

1

2

3

4

Examples and case studies: TEA

- Distance between zero crossings: distinct behaviour of oscillation at start and end

whistling



speech



Examples and case studies: TEA

- Distinct ratio: $\frac{\text{zero crossings}}{\text{direction changes}}$

whistling

```
Raw - Avg: 163.7 ; Abs Avg: 2368.5 ; ratio: 1.857 ; sd: 1.04  
Spec - avg: 8.1 ; sd: 2055.67 ; avg dis: 315.9 ; sd dis: 102655.69  
Prof - avg: 7954.4 ; sd: 2.15 ;
```

speech

```
Raw - Avg: 170.5 ; Abs Avg: 471.0 ; ratio: 12.190 ; sd: 566179.8  
Spec - avg: 12.5 ; sd: 4447.67 ; avg dis: 115.4 ; sd dis: 13669.85  
Prof - avg: 1411.2 ; sd: 1673821.1 ;
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Examples and case studies: TEA

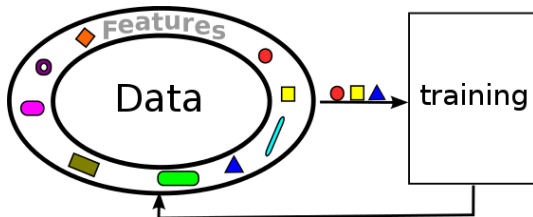
- Significant change in standard deviation of chunks

whistling

```
Raw - Avg: 163.7 ; Abs Avg: 2368.5 ; ratio: 1.857 ; sd: 1.04  
Spec - avg: 8.1 ; sd: 2058.18 ; avg dis: 315.8 ; sd dis: 102655.69  
Prof - avg: 7954.4 ; sd: 2.15 ;
```

speech

```
Raw - Avg: 170.5 ; Abs Avg: 471.0 ; ratio: 12.190 ; sd: 566179.8  
Spec - avg: 12.5 ; sd: 4448.60 ; avg dis: 115.4 ; sd dis: 13669.85  
Prof - avg: 1411.2 ; sd: 1673821.1 ;
```



Continued next week ...

Outline

Introduction

Toolchain

Projects

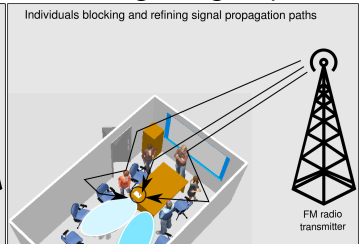
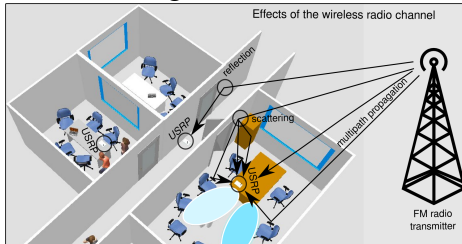
Conclusion

RF-based activity recognition

During propagation, radio signals experience a multitude of effects due to the environment

Can we learn about the environment from the signal evolution observed at a receiver?

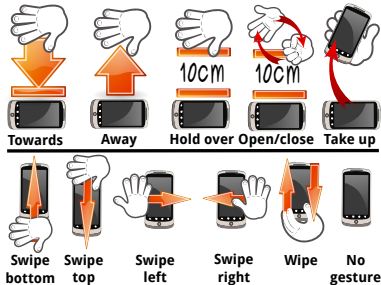
- Multi-path propagation
- Scattering
- Reflection
- Blocking of signal paths



RF-based activity recognition

Sensewaves Video

RF-based activity recognition



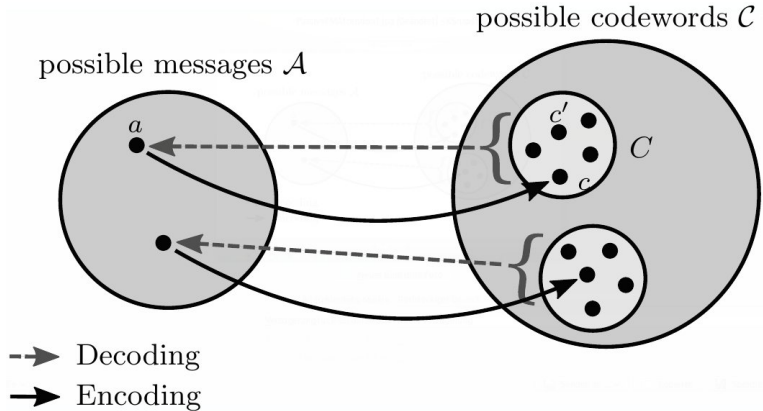
	Classification							
	Aw	Ho	To	No	Op	Sr	St	recall
Aw	.7	.02			.06	.09	.13	.70
Ho	.03	.28	.22	.05	.2	.16	.06	.28
To		.09	.76	.07	.06		.02	.76
No		.05	.06	.73	.14	.01	.01	.73
Op	.01	.15	.1	.14	.49	.04	.07	.49
Sr	.02	.01		.01	.06	.83	.07	.83
St	.12	.03	.01		.05	.14	.65	.65
prec	.795	.444	.661	.730	.462	.654	.644	

		Classification				
		Away	Towards	No gesture	S. top	recall
round truth	Away	.83			.17	.83
	Towards		.88	.09	.03	.88
	No gesture	.01	.05	.92	.02	.92
	S. top	.14	.02	.02	.82	.82
precision		.847	.926	.893	.788	

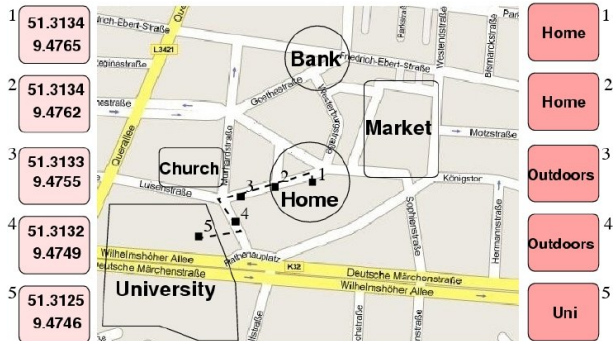
Context-based security



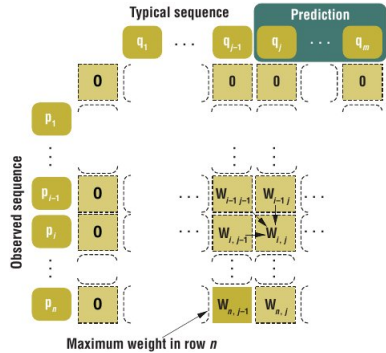
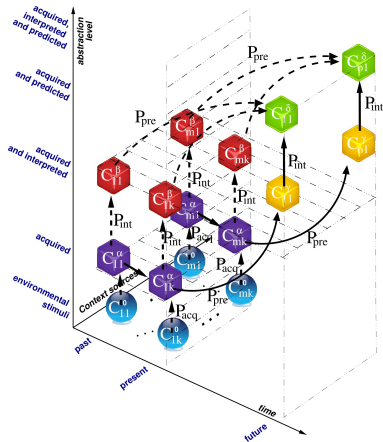
Context-based security



Context prediction



Context prediction



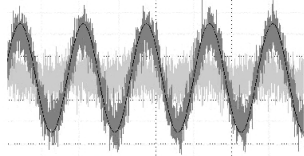
Collaborative transmission

Phase 4:

Feedback is broadcast to the network

Phase 3:

Receiver estimates the phase synchronisation level of the received sum signal

**Phase 2:**

Source nodes transmit to the destination as a distributed beamformer

**Phase 1:**

Source nodes adjust their carrier phase offset and frequency randomly



Collaborative transmission / IoT



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Questions?

Stephan Sigg

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Literature

- C.M. Bishop: Pattern recognition and machine learning, Springer, 2007.
- R.O. Duda, P.E. Hart, D.G. Stork: Pattern Classification, Wiley, 2001.

