

Pattern Recognition and Machine Learning

Part 1: Introduction and Motivation

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Contents

Introduction

- Speech and audio signal paths in a car
- □ Basics on pattern recognition
- □ Contents of the lecture
- □ Boundary conditions of the lecture (exercises, exam, etc.)
- □ Notation used in the lecture
- □ Literature
- □ Automotive examples (with some "medical touch")

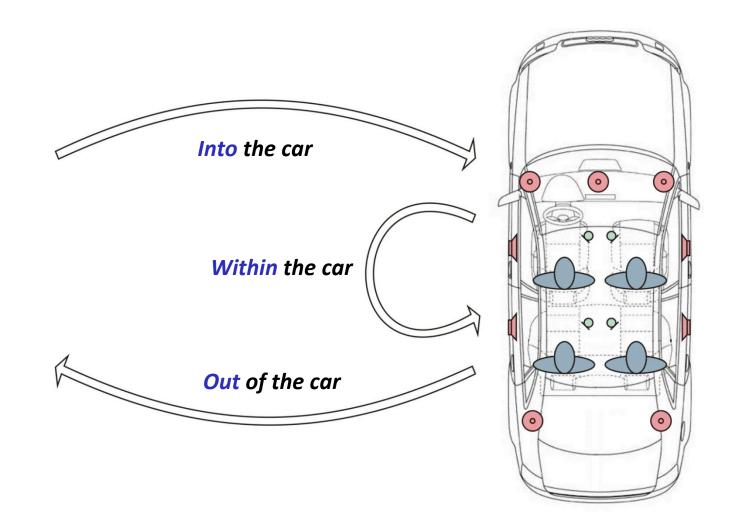






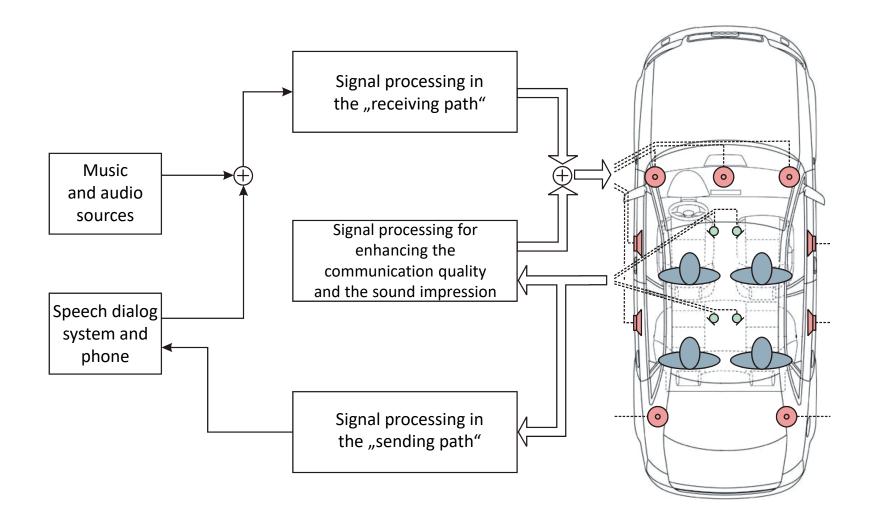
CAU

Speech and Audio Signal Paths in a Car

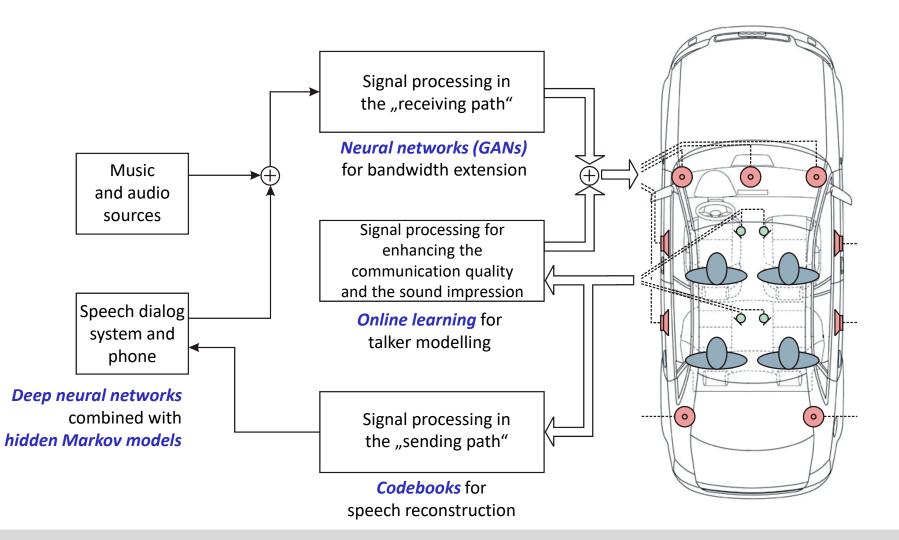




Speech and Audio Signal Paths in a Car



Speech and Audio Signal Paths in a Car





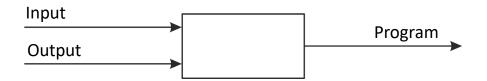
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Some Basics on the Ingredients of Pattern Recognition

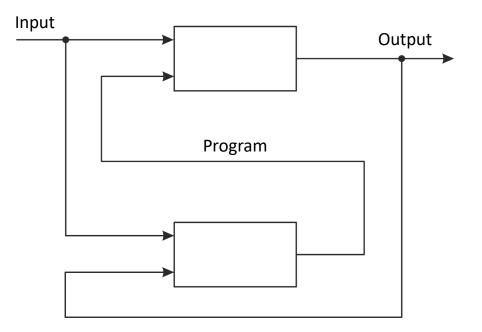
Basic signal processing:



Machine learning / pattern recognition:

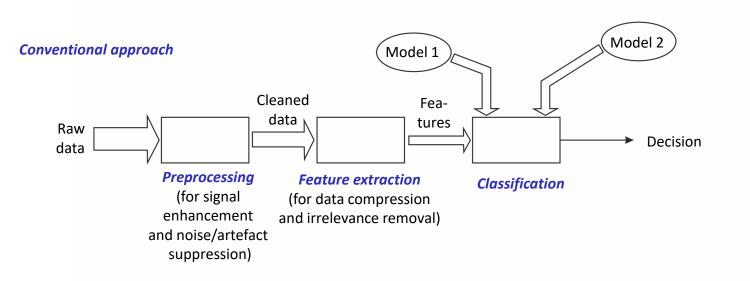


"Fully installed" systems:





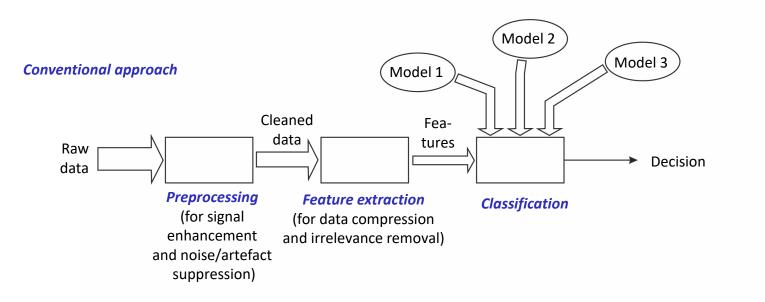
Some Basics on the Ingredients of Pattern Recognition – Conventional versus "End to End"





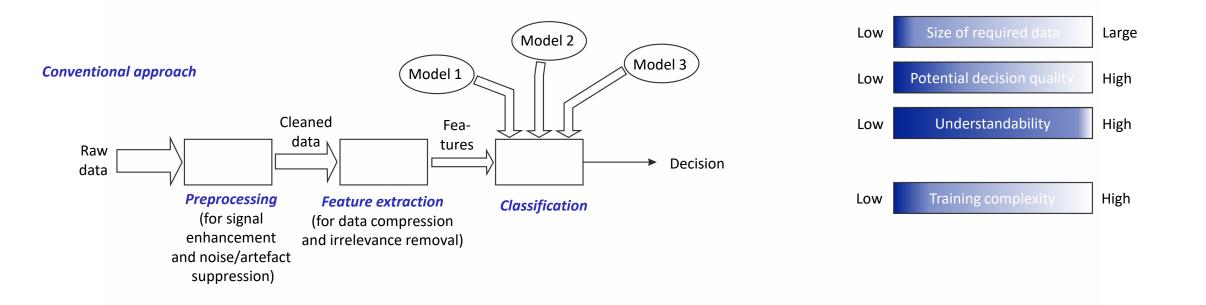
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Some Basics on the Ingredients of Pattern Recognition – Conventional versus "End to End"





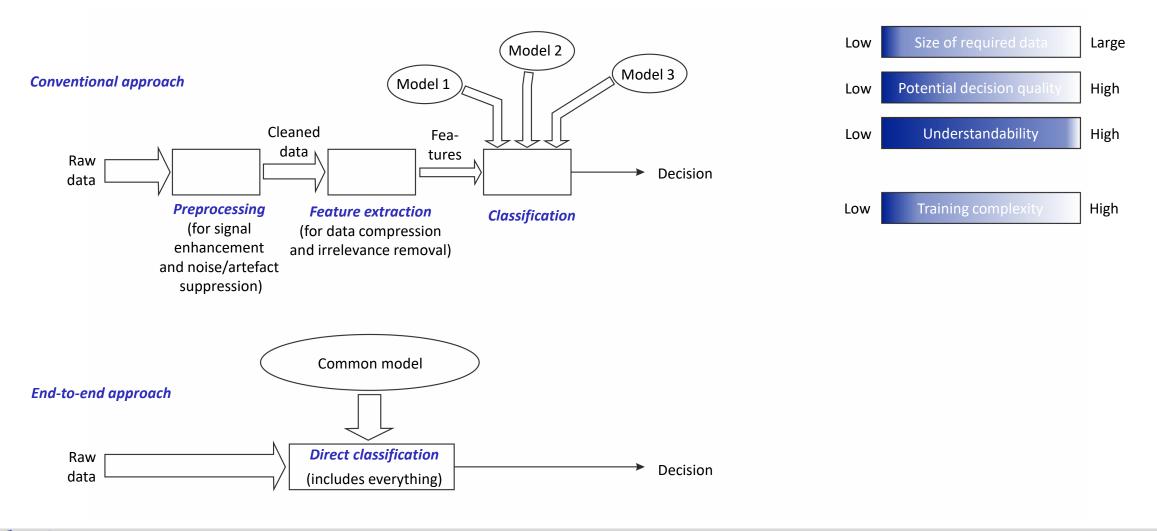
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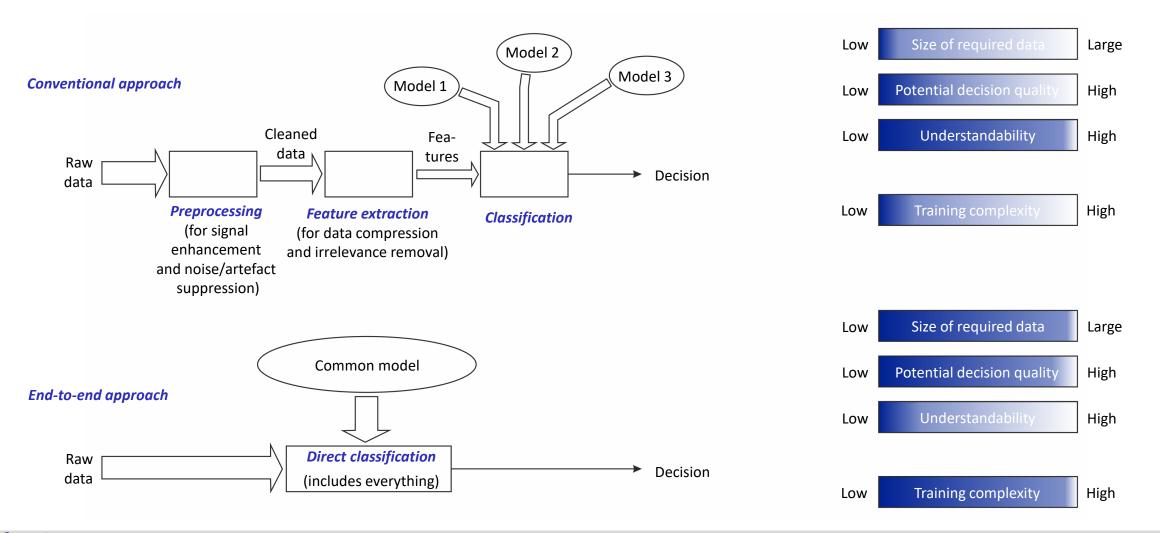
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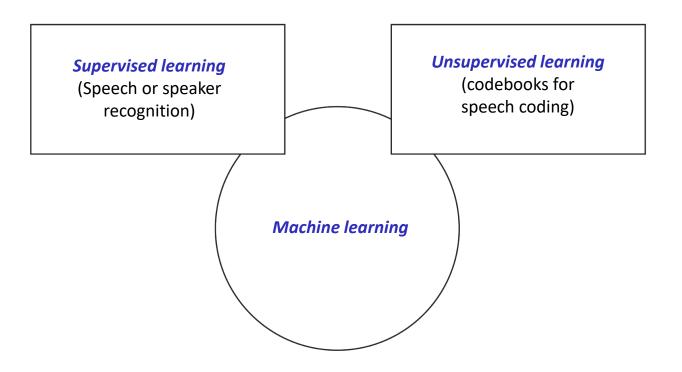
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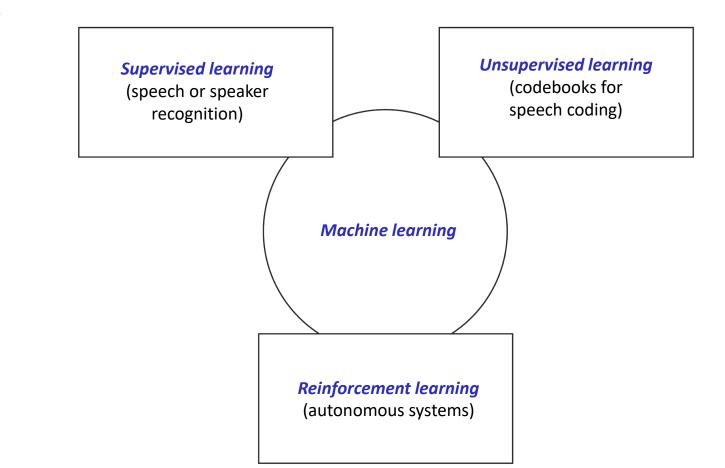
The Different Types of Machine Learning

Supervised versus unsupervised learning:





The Different Types of Machine Learning



Supervised/unsupervised learning versus Reinforcement learning:



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Contents of the Lecture (Entire Term)

Preprocessing for improving the "noise robustness"

Single-channel noise suppression and cost functions
 Beamforming

Data compression

Feature extraction

Pattern recognition

Codebooks

- Gaussian mixture models (GMMs)
- Neural networks (NNs)
- Hidden Markov models (HMMs)
- □ Explainable artificial intelligence (explainable AI)

Exercise



TensorFlow

(Programing environment and example data bases available via the our website)





Boundary Conditions of the Lecture

ECTS points

5 credit points

□ Oral examination

□ about 45 minutes per student

After the term

□ Talks (part of the exercise)

□ About 10 minutes talk plus 5 minutes discussion

□ Topics are available from now on

Lecture slides

□ In the internet via *dss-kiel.de*



Notation – Part 1

Scalars: x(n)□ Signals: Coefficient index □ Impulse responses (time-variant): $h_i(n)$ $y(n) = \sum_{i=0}^{N-1} x(n-i) h_i(n)$ Example for a (real) convolution: Vectors: $\boldsymbol{x}(n) = \begin{bmatrix} x(n), x(n-1), \dots, x(n-N+1) \end{bmatrix}^{\mathrm{T}}$ Signal vectors: \Box Impulse response vectors (time-variant): $h(n) = \left[h_0(n), h_1(n), \dots, h_{N-1}(n)\right]^T$ \Box Example for a real convolution: $y(n) = \mathbf{x}^{T}(n) \mathbf{h}(n) = \mathbf{h}^{T}(n) \mathbf{x}(n)$ $\mathbf{A}(n) = \begin{bmatrix} a_{00}(n) & a_{01}(n) & \dots & a_{0N}(n) \\ a_{10}(n) & a_{11}(n) & \dots & a_{1N}(n) \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$ **Matrices:**

Boldface and uppercase
$$a_{M0}(n) = a_{M1}(n) \dots a_{MN}(n)$$



Notation – Part 2

Random variables and processes:

□ Notation: $x(n), x_1(n), x_2(n)$ No differences between deterministic signals and random processes – different writing styles: $x(\eta, n), x(\omega, n), X(n)$

D Probability density function: $f_x(x,n), f_{x_1x_2}(x_1,x_2,n_1,n_2)$

□ Stationary random processes:
$$f_x(x, n) = f_x(x, n+n_0) = f_x(x)$$

 $f_{x_1x_2}(x_1, x_2, n_1, n_2) = f_{x_1x_2}(x_2, x_2, n_1+n_0, n_2+n_0)$
 $= f_{x_1x_2}(x_1, x_2, n_2-n_1)$

□ Expected values of stationary random processes:

$$E\{x(n)\} = \int_{x=-\infty}^{\infty} x f_x(x) dx = m_x^{(1)} = m_x$$

$$E\{x^2(n)\} = \int_{x=-\infty}^{\infty} x^2 f_x(x) dx = m_x^{(2)}, \quad E\{g(x(n))\} = \int_{x=-\infty}^{\infty} g(x) f_x(x) dx$$



Notation – Part 3

Auto and cross correlation for real, stationary random processes:

□ Auto-correlation function:

$$\mathbf{E}\Big\{x(n)\,x(n+l)\Big\} = s_{xx}(l)$$

□ Cross-correlation function:

$$\mathbf{E}\Big\{x(n)\,y(n+l)\Big\} = s_{xy}(l)$$

□ (Auto) power spectral density:

$$S_{xx}(\Omega) = \sum_{l=-\infty}^{\infty} \mathbf{E}\left\{x(n) x(n+l)\right\} e^{-j\Omega l} = \sum_{l=-\infty}^{\infty} s_{xx}(l) e^{-j\Omega l}$$

□ (Cross) power spectral density:

$$S_{xy}(\Omega) = \sum_{l=-\infty}^{\infty} \mathbf{E}\left\{x(n)\,y(n+l)\right\} e^{-j\Omega l} = \sum_{l=-\infty}^{\infty} s_{xy}(l)\,e^{-j\Omega l}$$





Notation – Part 4

Stationary white noise:

Auto-correlation function:

$$s_{xx}(l)\Big|_{\text{white noise}} = \begin{cases} \sigma_x^2, & \text{if } l = 0, \\ 0, & \text{else.} \end{cases}$$

□ Auto power spectral density:

$$S_{xx}(\Omega)\Big|_{\text{white noise}} = \sigma_x^2$$





Application Examples



Just a few examples for pattern recognition and machine learning from our automotive branch:

- □ Hands-free telephony (cleaning) and dialog systems (recognition)
- □ Siren detection (detection)
- Bandwidth extension (estimation)
- □ Prediction of steering movements (recognition/prediction)



Application Examples

A few words before we start:

- Pure research projects have to be high-risk ones to get funding.
- In the following you will see some of the current projects of the DSS group. Some of them are low-risk ones (e.g. Master thesis), some stem out of a high risk class.
- Partly pattern recognition and machine learning is in the focus, partly also new sensor concepts.
- It can not always be guaranteed that the project goals will / can be reached.





Application Examples – Hands-free Telephony and Speech Dialog Systems

Problem:

- Speech recordings in a car are superposed with several distortions:
 - Echo components (remote partner, dialog system output)
 - Background noise
 - Embedded speech recognition

- Apply adaptive filters to cancel and/or suppress distortions.
- Details will be explained in the next two weeks.
- Further details are in taught in the lecture "Adaptive Filters".



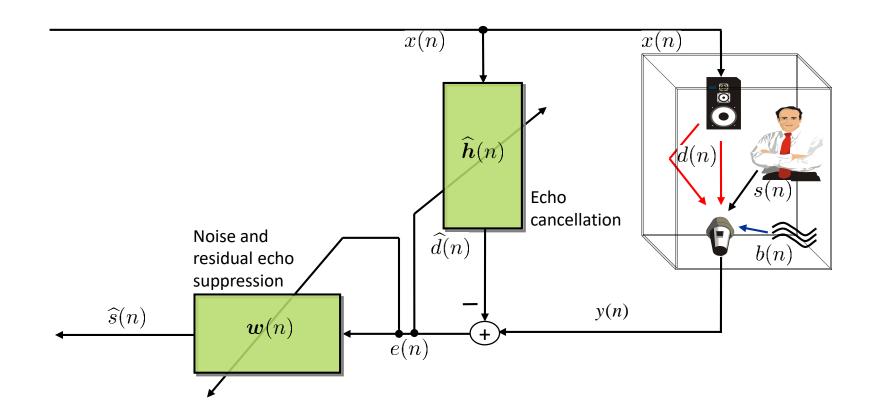




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Application Examples – Hands-free Telephony and Speech Dialog Systems

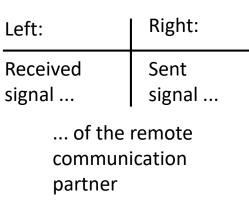
Hands-free telephony – a basic system:

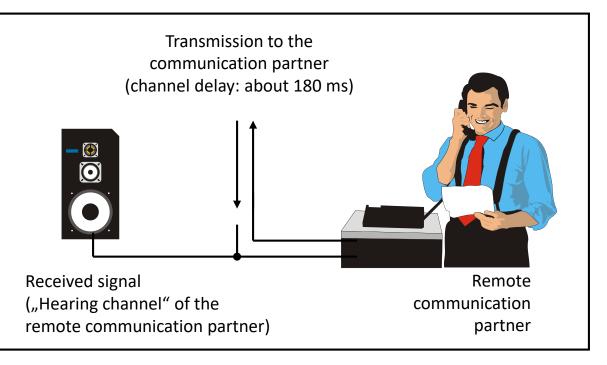




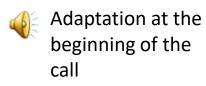
Application Examples – Hands-free Telephony and Speech Dialog Systems

Stereo signals (16 kHz):

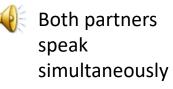




Initial filter convergence:



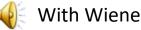
Double talk:



Enclosure dislocations:

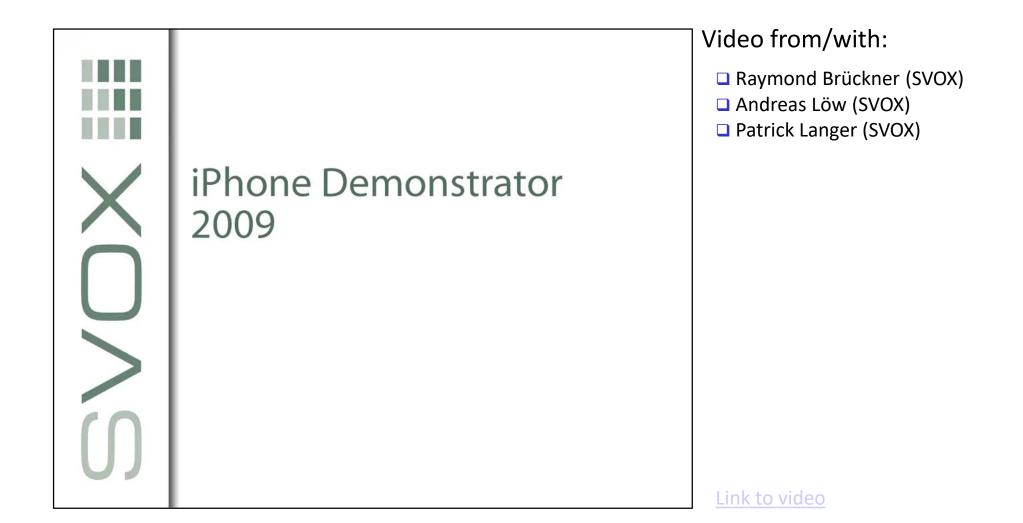


Without Wiener filter



With Wiener filter

Application Examples – Hands-free Telephony and Speech Dialog Systems





Application Examples – Detection of Sirens and other "Outside Events"

Problem:

The sound of sirens is sometimes hard to hear in a car (due to good damping of passenger compartments or due to loud music) and it's hard to estimate the direction of the source.

- □ Pattern recognition on the basis of microphone signals.
- Usually not much better as a human listener.







Application Examples – Detection of Sirens and other "Outside Events"

Problem:

The sound of sirens is sometimes hard to hear in a car (due to good damping of passenger compartments or due to loud music) and it's hard to estimate the direction of the source.

- □ Pattern recognition on the basis of microphone signals.
- Usually not much better as a human listener.
- New sensors (outside microphones, in cooperation with a small company in Revensdorf called "mechakustik")
 - □ Extremely high demands concerning robustness.
 - Large potential to be better than a human listener.







Problem:

- Current connections have a limited bandwidth (telephone speech quality).
- New standards such as HD voice are better, but the are still limited (in terms of bandwidth and speech quality in general).

- Estimation of the missing frequency components by means of pattern recognition and adding those on the receiver side.
- □ Usage of new network types (GAN approaches).

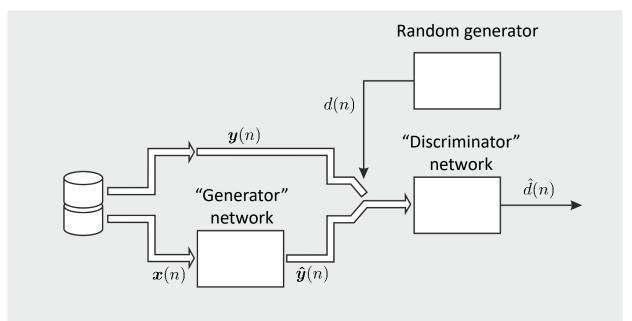






Basic approach:

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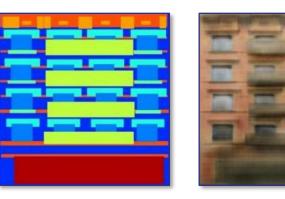




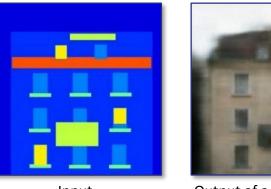


Basic approach:

- Example for a so-called GAN approach:
 - Reconstruction of houses on the basis of rectangles
 - Conventional approach in the second column.



Source: P. Isola, J.-Y. Zhu, T. Zhou, A. A. Efros: *Image-to-Image Translation with Conditional Adversarial Networks*, CoRR, vol. abs/1611.07004, 2016.



Input



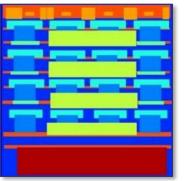
Dutput of a conventionally trained network





Basic approach:

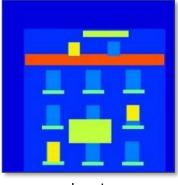
- Example for a so-called GAN approach:
 - Reconstruction of houses on the basis of rectangles
 - Conventional approach in the second column.
 - GAN approach in the third column.











Input



Output of a conventionally trained network



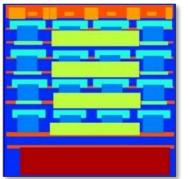
Output of a conditional GAN approach





Basic approach:

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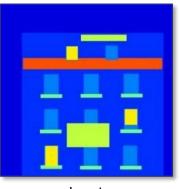




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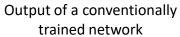






Input







Output of a conditional GAN approach



Original





Audio examples:

□ *Narrowband* connection (still the most often used connection):

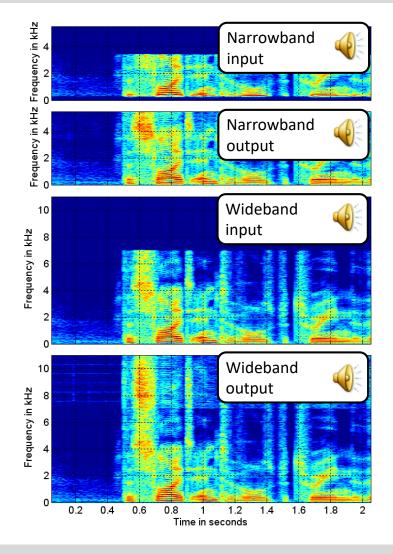
□ Bandwidth of about 3.4 to 3.8 kHz

Extension to 5.5 to 8 kHz

□ *Wideband* connection (HD voice, available today):

Bandwidth of about 7 kHz

□ Extension to 11 kHz







Application Examples – Prediction of Steering Movements

Problem:

- Contactless measurement of brain, heart, and muscle activities.
- Here first only a prediction of steering movements while driving a car.







Application Examples – Prediction of Steering Movements

Problem:

- Contactless measurement of brain, heart, and muscle activities.
- Here first only a prediction of steering movements while driving a car.

Solution:

□ Recording of brain signals (and pattern recognition).





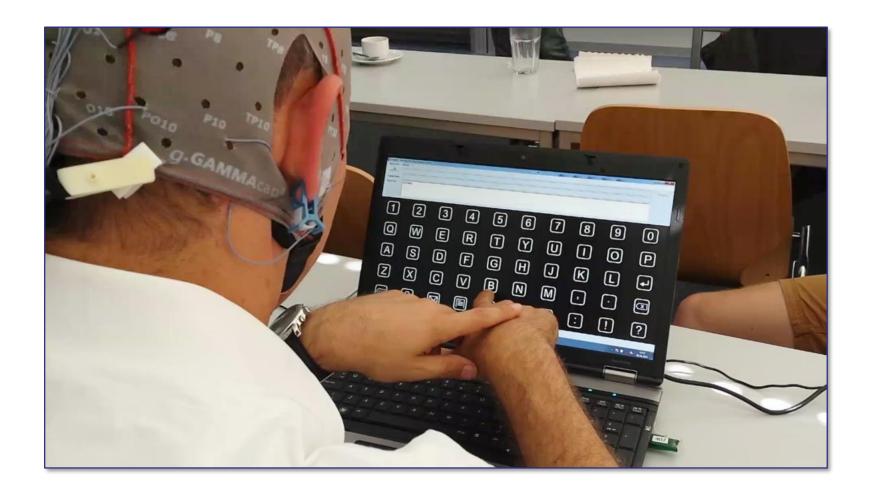


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Application Examples – Detection of Sirens and other "Outside Events"

Basic idea:

Usage of brain-computer interfaces (BCIs).





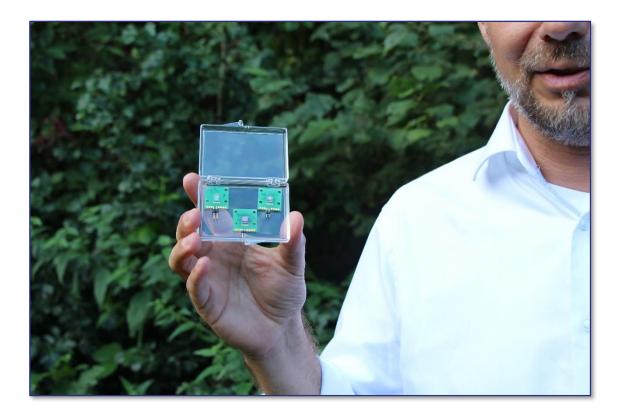


Application Examples – Prediction of Steering Movements

Problem:

- Contactless measurement of brain, heart, and muscle activities.
- Here first only a prediction of steering movements while driving a car.

- □ Recording of brain signals (and pattern recognition) ...
- □ ... not electrically, but magnetically.

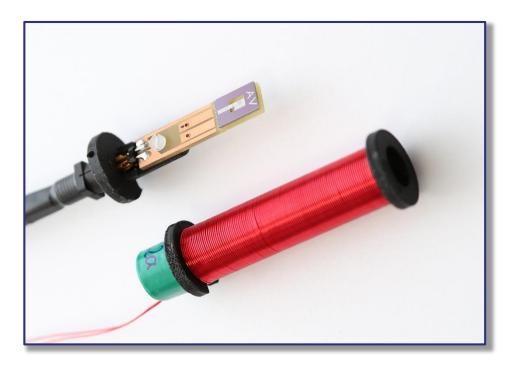


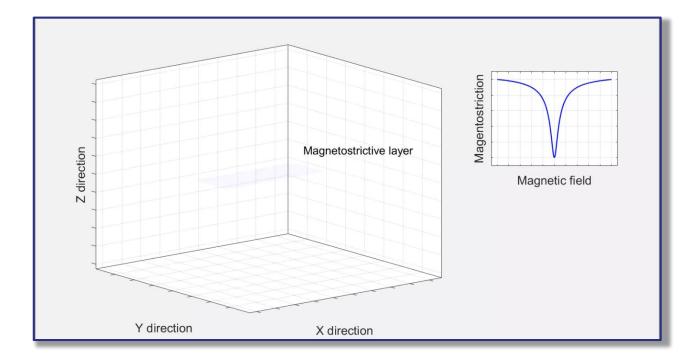




Application Examples – Prediction of Steering Movements

Magnetoelectric sensors:





□ Sensors e.g. in cantilever structure (or as SAW sensors)

- □ Magnetostrictive layer (FeCoSiB)
- □ Piezo layer (AIN)

□ Basic principle of cantilever-based magnetoelectric sensors

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Application Examples – Prediction of Steering Movements

Magnetoelectric sensors:

- □ Collaborative research center 1261 at our university.
- Extremely sensitive magnetic sensors, that allow for unshielded and non-cooled magnetic sensor systems.
- □ For medical purposes a limit of detection in the fT regime are required, currently we achieve only pT.
- However, alternative sensor systems are available already right now.

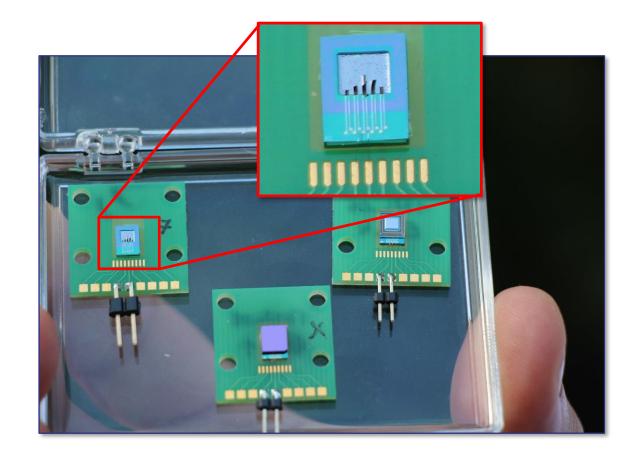


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Application Examples – Prediction of Steering Movements

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- Extremely sensitive magnetic sensors, that allow for unshielded and non-cooled magnetic sensor systems.
- □ For medical purposes a limit of detection in the fT regime are required, currently we achieve only pT.
- However, alternative sensor systems are available already right now.
- In cooperation with the ISIT in Itzehoe (also part of the CRC 1261), very small magnetic sensors can be produced.





Summary and Outlook



Summary:

- □ Speech and audio signal paths in a car
- Basics on pattern recognition
- Contents of the lecture
- Boundary conditions of the lecture (exercises, exam, etc.)
- Notation used in the lecture
- Literature
- □ Automotive examples (with some "medical touch")

Next part:

□ Cost functions and noise suppression

