Towards a New Era of Artificial Intelligence:
Cognitive Machines

RWTH Research Alumni Conference
“The Fine Line Between Humans and Machines“
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I. Introduction
   - The rise of AI... and its relation to 4.0
   - Entering the scene: intelligent self-learning systems

II. The Basics: about supervised and unsupervised learning
   - ... in general
   - ... along some examples from industry
   - ... within the cluster of excellence

III. Accelerating: trial-and-error learning approaches and other fancy stuff
   - Reinforcement learning
   - Deep neural networks
   - Collaborative learning

IV. Climbing the Hill: advanced AI for a “fully” individualized production
   - The question of a creative artificial mind
   - From discrete variations to continuous variability
   - ... with AI and additive manufacturing

V. Summary and Outlook
   - Technological and societal consequences
... leading to the 4th industrial (r)evolution...

**Breakthroughs - A new era of artificial intelligence**

- **Communication technology**
  - bandwidth and computational power

- **Embedded systems**
  - miniaturization

- **Semantic technologies**
  - information integration

- **Artificial intelligence**
  - behavior and decision support

- **1st dimension: complexity level**

  - **Google Car**
    - 2012
  - **Watson**
    - 2011

  → **Systems of “human-like” complexity**
... leading to the 4th industrial (r)evolution...

**Breakthroughs - Everybody and everything is networked**

- **Communication technology**
  - bandwidth and computational power

- **Embedded systems**
  - miniaturization

- **Semantic technologies**
  - information integration

- **Artificial intelligence**
  - behavior and decision support

- **Swarm Robotics**
- **Team Robotics**
- **Smart Factory**
- **Car2Infra-structure**
- **Smart Grid**

2nd dimension: network level
In the past, technological systems have been the “image” of ourselves: we did the design, the construction, the programming. The products “behaved” accordingly – as an extension of our imagination.

For the first time ever, we are facing systems which are capable of learning – even with consciousness. Self-learning systems do not any longer stick to exactly the behavior they were designed with. We do not know exactly when and what they learn. However, to restrict the learning process to its “deterministic parts” would destroy most of their potentials.

From 4.0 to distributed brains
And how do these systems work?

Towards intelligent and (partly-) autonomous systems AND systems of systems

**1st industrial revolution**
Mechanical production systematically using the power of water and steam

**Power revolution**
Centralized electric power infrastructure; mass production by division of labor

**Digital revolution**
Digital computing and communication technology, enhancing systems’ intelligence

**Information revolution**
Everybody and everything is networked – networked information as a “huge brain”

17.10.2017
S. Jeschke
Towards machine learning
Can machines learn?

Can machines learn to predict future states? To optimize tasks themselves?...
And if so, how can they do it?
AND, MOST IMPORTANT: can it be used in production technology, and how?

→ This is what this talk is about!

How do machines learn?

A – Learning by observations and explanations
→ Data-driven learning

B – Learning by doing
→ Trial-and-error learning

I Let us take a look into easy examples of data-driven learning!

II Followed by some trial-and-error approaches...

III ... and concluded by “the mix”!
Outline

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V. Summary and Outlook
Supervised learning in high-pressure die casting

Can we predict the result of a HPDC (high-pressure die casting) process – by using historical data? – **YES, WE CAN!**

Setting: The die casting equipment in the research wing was separated from the quality check. Thus, the forms were checked with a delay in time and a considerable spatial shift. Under these conditions, „reproducibility“ of the results could not be reached...

HPDC process measurements

Historic data

Process and quality data

Prediction model

Modelling and training

Visualization of prediction

Inline and web-based (result NIO|IO with reason)
Can we predict the result of a HPDC (high-pressure die casting) process – by using historical data? – **YES, WE CAN!**

**Setting:** The die casting equipment in the research wing was separated from the quality check. Thus, the forms were checked with a delay in time and a considerable spatial shift. Under these conditions, “reproducibility“ of the results could not be reached...

Trained models can fail over time: Mechanical systems change over time, new measurement variables become available or the setup is modified. → **Extended model, integrating multiple/external data sources**

**Weather data**
Temporal correlation of weather (and circumstances)

**Acoustic measurements**
Fourier transformation & feature extraction

... in cooperation with Audi
Setting: The company was facing a certain muddle in their expert knowledge base. If all the information provided was to be true – then certain phenomena would not occur. But did.

The suspicion was that some information might be outdated by now, but the specialists still believe them...

But – which one?

Data-driven learning – unsupervised learning in a somewhat “corrupt” database

Finding hidden relations in our data, we were not aware of, e.g., understanding failures or bad quality of products and processes.

Unsupervised cleaning

- Sulfur (S) > 0.04% and heat treatment  fragile structure
- Phosphorus (P) > 0.04%  reduced plasticity
- Chrome (Cr) > 16%, Molybdenum (Mo) > 13%, Nickel (Ni) > 56%  no findings
- ...

Data about chemical compositions

Searching for hidden relations in data by subgroup mining

Unsupervised cleaning in a somewhat “corrupt” database
Data-driven learning – unsupervised

Unsupervised learning for laser cutting processes

Can we use unsupervised learning to identify a group of desired process results in a highly complex process - **YES, WE CAN!**

**Part of B1** - by the cluster of excellence (since about 1/2016)

**Sheet Metal Cutting (at NLD):**

- challenge: reaching a maximum assurance of the cut quality
- reliable process simulations are available (QuCut, developed at NLD)
- thus, a large amount of training data can be generated

- Automating the cutting process along parameters coming from
  - five optics design parameters (beam quality, astigmatism, focal position, beam radius in x and y directions (elliptical laser))
  - and eight process criteria (roughness values at different depths)

[all pictures/movies: NLD, W. Schulz, 2016]
Data-driven learning – unsupervised
... using k-means clustering

Can we use unsupervised learning to identifying a group of desired process results in a highly complex process - YES, WE CAN!

Part of B1 - by the cluster of excellence (since about 1/2016)

k-means clustering groups n observations into k clusters.
Using k-means clustering on simulation data allows to...

- analyze multidimensional relationships between process criteria
- discover hidden structures in experimental results
- gain knowledge about the structure in the data

Results of cluster analysis:
- Identification of desired simulation runs (i.e. blue cluster)
- Further analytics reveals process parameters that lead to desired results

... transferred into parallel coordinates (reduced to the 8-dim. roughness space)
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Learning by doing – reinforcement learning

The next step: Using rewards to learn actions

Remember Mario: What if the machine could learn, how to solve a level? Why not use a some kind of intelligent trial-and-error?

Neuroevolution of augmenting topologies (NEAT) [Stanley, 2002]

- **Genetic algorithms on top of neural networks**
- At each **state** the system decides what **action** to do
- Actions are **rewarded** if Mario does not die in return
- Level progress by **evolving** neural networks

Reinforcement learning (R-learning)

- is inspired by behaviorist psychology – maximizing the expected return by applying a sequence of actions at a current state.
- Central part of cybernetics from its start (e.g., Minsky 1954)

Human factor is “very small”!

Now, Human factors are:
- reduced to very general, formal specifications of the neural network...
- However, human still influences the underlying representation model
Learning by doing – reinforcement learning

Application areas of reinforcement learning

Obviously: Super-Mario can easily be extended towards intralogistics scenarios...

... and more general, R-learning plays an important role in a variety of learning applications important for (individualized) production, e.g.:
  ▪ Gaining motorized skills: replacing traditional teach-in approaches
  ▪ Multiagent or distributed reinforcement learning: important as production is an assembly of a multitude of different players

⇒ Coupling to embodiment theory

⇒ Usually coupled to simulation environments to avoid “nonsense solutions”

... for learning and executing complete assembly tasks

... for learning and optimization of motions

⇒ Coupling to simulation environments to avoid “nonsense solutions”

... as “pro-training” for human-machine interaction

[Intelligent Autonomous Systems, 2015]

[UC Berkeley, 2015]
Deep learning combined with reinforcement learning

Robotinos

Mobile transportation robots from flexible routing

Competitions robocup:
2014: Winner of the World Cup
2015: Winner of the World Cup
2016: Winner of the World Cup
2017: Winner of the World Cup

Model of cooperative learning:
- Totally decentralized
- Strong cooperation
- No “hard coded components”
- Intense information sharing
- Cooperative decision making
- Re-planning during tasks
Deep learning combined with reinforcement learning

The age of deep learning (deep neural networks)

“Today, computers are beginning to be able to generate human-like insights into data.... Underlying ... is the application of large artificial neural networks to machine learning, often referred to as deep learning.”

Deep Q-Networks (also "deep reinforcement learning", Q refers to the mathematical action-prediction-function behind the scenes....):
Learning directly from high-dimensional sensory input

➔ AI starts to develop strategies to beat the game
➔ Signs of “body consciousness”
➔ ...

Human factor practically zero.
Deep learning combined with reinforcement learning

Application areas of deep neural networks

... a variety of practical applications
High potential for improving production technology – in particular in highly-dynamic, continuous and flexible applications

Deep Learning is machine perception for...

<table>
<thead>
<tr>
<th>Images</th>
<th>Text</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Faces</td>
<td>• Search</td>
</tr>
<tr>
<td>• Self-Driving</td>
<td>• CRM</td>
</tr>
<tr>
<td>Vehicles</td>
<td></td>
</tr>
</tbody>
</table>

Sound

- Voice search
- Music generation
- Translation

Time Series

- Health data
- Sensors
- Finance

Central part of “cognitive computing”

Deep Learning: Why for NLP?

One Model rules them all?
DL approaches have been successfully applied to:

- Automatic summarization
- Conference resolution
- Discourse analysis
- Machine translation
- Morphological segmentation
- Named entity recognition (NER)
- Natural language generation
- Word sense disambiguation
- Relationship extraction
- Speech processing
- Part-of-speech tagging
- Sentence boundary disambiguation
- Sentiment analysis
- Optical character recognition (OCR)
- Question answering
- Parsing
- Word segmentation
- Natural language understanding
- Information retrieval (IR)
- Speech recognition
- Topic segmentation and recognition
- Speech segmentation
- Information extraction (IE)

Handwriting recognition

In production: e.g. for anomaly recognition in quality checks, even if all products are individualized and thus different

Face/picture/object recognition

In production: e.g. for automated guided vehicles (AGV) as a basis for highly dynamic paths in a factory for individualized products

Natural language processing

In production: e.g. for automated translation of descriptions, users guides, or for human-machine interaction (worker with robot)
Deep learning combined with reinforcement learning

Deep learning to deal with variations

Can we make a robot really understand its task and perform movements that solve this task adapting to dynamic and variable circumstances of the real world?

Setting: An industrial robot with a very elastic joint is to grab objects from a distinct location a and pitch them into a hole at location b. Here, the shapes of the objects possess a certain variation – like „real bananas“. Traditional programming is inflexible – slightest variations leads to failure of the task.

Can we make the robot learn to grab and put different kind of objects?

Pretraining

- to reduce the amount of experience needed to train visuomotor policies
- Enhance security for robot and environment as it limits the motion to a certain “frame”

Neural network of 7 (4) layers

- (3 convolutional layers for vision, skipped here)
- 1 expected position layer that converts pixel-wise features to feature points
- 3 fully connected layers to produce the torques.

Deep learning combined with reinforcement learning

Deep learning to replace teach-in programming

Can we use deep learning to improve flexible motion patterns for robots – all towards lot size 1? – **YES, WE CAN!**

**The CENSE PROJECT** – by the cluster of excellence (since 5/2016)

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Q-Learning (special case of R-Learning)

Communication via web service connection

Simulation environment

Deep neural network

Feature vectors

Environment state

Environment model

REST API

Simulation environment

Input Layer

Hidden Layer I

Hidden Layer II

Output Layer

Aktionen

hooh

runter

links

rechts

vor

zurück

Rotation im UZS

Rotation um UZS

Next step:

Improving topology towards CNN (convolutional neural network)
The distributed brain
The “Kindergarten for robots” by Google

Alternative w/o simulations: Transferring human/biological learning processes into all areas – combined with the power of cooperation, “collective learning”

A new approach:
object manipulation by “trial-and-error”

- approach is goal-centric (not insight-oriented! – as in biological systems)
- two components:
  1. a grasp success predictor, which determines the success potential for a given motion (by a CNN)
  2. a continuous servoing mechanism, that uses a CNN to continuously update the robot’s motor commands (feedback loop)
- trained using a dataset of over 800,000 grasps
- collected using a cluster of 14 similar (but not identical !!) robotic manipulators

In production:
- Gaining confidence in tasks where simulations environments are not available (so far, or ever)
- E.g., handling of limp material could be trained that way, thus allowing for new automation in the final assembly in car manufacturing

object manipulation “up to today”
- robotic manipulation: relies heavily on advance planning and analysis; with relatively simple feedback, such as trajectory following (results often slow and unstable, non-adaptive)

“Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection” (grasping e.g. sponges)
[Levine et.al., Google, 02/2016]
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Go originated in China more than 2,500 years ago. Confucius wrote about it. As simple as the rules are, Go is a game of profound complexity. This complexity is what makes Go hard for computers to play, and an irresistible challenge to AI researchers. [adapted from Hassabis, 2016]

The problem: \(2.57 \times 10^{210}\) possible positions – that is more than the number of atoms in the universe, and more than a googol times \(10^{100}\) larger than chess.

\[\text{Training set} \]

30 million moves recorded from games played by human experts

\[\text{Creating deep neural networks} \]

12 network layers with millions of neuron-like connections

\[\text{Predicting the human move} \] (57% of time)

By 19/10/2017, AlphaGo Zero has been introduced. Human factor practically zero.

Learning non-human strategies

AlphaGo designed by Google DeepMind, played against itself in thousands of games and evolved its neural networks; Monte Carlo tree search

March 2016:

Beating Lee Se-dol (World Champion)

AlphaGo won 4 games to 1. (5 years before time)

![Image: 'Our goal is to beat the best human players not just mimic them' Google Deep Mind]
What if ... we would use AI not only for “boring and lengthy routing work” – but as an entity to inspire us, come up with its own ideas ...  
- Enriching our perspectives through foreign intelligence types, in line with the diversity philosophy, but in its original intention, namely in terms of “variety of mental models”?

**Siemens “Product Design and Manufacture”** -  
https://www.youtube.com/watch?v=IDtmy6YorG4 (10/2016)

**Setting:**
the elevator bell crank is to be new-designed. Relevant parameters are weight (!!), strength, stress path, energy efficiency...

**Hidden agenda:**
Innovation. Overcoming the “human bias” and “NIH” syndrome
The creative artificial mind
Playing with diversity – allowing for alternative mental models!

What if ... we would use AI not only for “boring and lengthy routing work” – but as an entity to inspire us, come up with its own ideas ...

- Enriching our perspectives through foreign intelligence types, in line with the diversity philosophy, but in its original intention, namely in terms of “variety of mental models”?

Siemens “Product Design and Manufacture” - https://www.youtube.com/watch?v=IDtmy6YorG4 (10/2016)

Result (selective...):
- Much less residual stress
- 20% lighter
- Much more organic design

Cognitive Computing:
using biological models

The original module

The new module – design-process supported by AI
“Creativity is a phenomenon whereby something new ... is formed. The created item may be intangible (such as an idea, a scientific theory, a musical composition or a joke) or a physical object (such as an invention, a literary work or a painting).”

[adapted from Wikipedia, last visited 5/3/2016]

### The creative artificial mind

**Microsoft Visual Storytelling (SIS): machines becoming creative**

<table>
<thead>
<tr>
<th><strong>DII (descriptions for images in isolation):</strong></th>
<th><strong>SIS (stories for images in sequence):</strong></th>
</tr>
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<tbody>
<tr>
<td>Traditional storytelling software</td>
<td>new approach towards storytelling, including</td>
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<td>Based on SIND – Sequential Image Narrative Dataset: 81,743 unique photos in 20,211 sequences, aligned to both descriptive (caption) and story language.</td>
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<td>[Margaret Mitchell / Microsoft, 04/2016, together with colleagues from Facebook]</td>
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<th><strong>Visual-Storytelling by Microsoft based on deep neural networks (convolutional neural networks)</strong></th>
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</thead>
<tbody>
<tr>
<td>A group of people that are sitting next to each other.</td>
<td>Having a good time bonding and talking.</td>
<td>The sun is setting over the ocean and mountains.</td>
</tr>
<tr>
<td>Adult male wearing sunglasses lying down on black pavement.</td>
<td>[M] got exhausted by the heat.</td>
<td>Sky illuminated with a brilliance of gold and orange hues.</td>
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Visual-Storytelling by Microsoft based on deep neural networks (convolutional neural networks)
“Creativity is a phenomenon whereby something new ... is formed. The created item may be intangible (such as an idea, a scientific theory, a musical composition or a joke) or a physical object (such as an invention, a literary work or a painting).”

[adapted from Wikipedia, last visited 5/3/2016]

“Do Androids Dream of Electric Sheep?”
(science fiction novel by American writer Philip K. Dick, published in 1968)

Computational creativity (artificial creativity) ... is a multidisciplinary endeavor that is located at the intersection of the fields of artificial intelligence, cognitive psychology, philosophy, and the arts.

[adapted from Wikipedia, last visited 5/3/2016]

„Can machines be creative?“ by Iamus, a computer clustercomposing classical music by genetic algorithms, concert for Turings 100th birthday

[youtube]

Van Gogh’s Starry Night interpreted by Google DeepDream based on deep neural networks
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The bio-inspired brain
AI entering the physical world – the Internet of Things takes shape

Application in the “virtual space”

- Game engines
- Desktop applications
- Internet (as an information space)

Real world applications

- Agriculture robots
- Production robots
- Medical devices
- Smart dust
- Autonomous cars

Un-embodied agents

Embodied agents

The more the virtual and the real world interwove each other, the more the need for HPC in robotics.

17.10.2017
S. Jeschke
New challenges for HPC

**General purpose vs. specialized architectures**

- In traditional machine learning, "general purpose computers" are considered.
- These computers have no strong similarities of biological brain structures.
- Even if they work less effective than biological brains (so far), they have a enormous energy consumption.

- In the “brain projects”, specialized computer architectures are developed, driven by biological paradigms.
- These architectures are more efficient for certain tasks, but do not follow the “general purpose idea” any longer.
- Hardware and software become strongly coupled. Thus, experimental changes become more complicated.

"You don’t need to be a bird to fly.”
... however, it’s ok to be a bird to fly!

machine learning

neuromorphic computing

17.10.2017
S. Jeschke
New challenges for HPC

Examples for neuromorphic chips

**Intel, sensor image processing architecture**

- **Spinningaker**: Spiking Neural Network Architecture
- Spiking: includes time and temporal coding
- **novel computer architecture**
- goal: to use 1 mio. ARM processors (currently 0.5 mio) in a massively parallel computing platform based on spiking neural networks
- “One Million Chips Mimic One Percent Of The Brain”
- By Steve Furber, Univ. of Manchester, one of the world’s best microprocessor designers

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**SpiNNaker, component of the Human Brain Project**

- Intel Reveals Spin-based Neuromorphic Chip Design with up to 300 times lower energy consumption
- Involves the combined use of spintronics and memristors (memory resistors, not constant but depend on the history of current). In a cross-bar switch lattice, lateral spin valves act as neurons, and memristors act as synapses.

New challenges for HPC
Super Computer for Artificial Intelligence

AI Bridging Cloud Infrastructure ABCI:
- Specialized on AI applications, in particular deep learning (DL)
- Strategic goal: pushing forward Artificial Intelligence and Machine Learning, accelerating the deployment of AI into real businesses and society

Facts and figures:
- Where: Japan Tokyo
- Who: ITRI & AIST
- Costs: $173 million
- When: 1Q 2018 (Plan)
- Storage: 20 PB
- Energy: < 3 MW Power; < 1.1 Avg. PUE
- Petaflops: 130; for comparison (as by 20/06/17):
  - China Sunway: 93
  - US Titan: 17.3
  - Germany Hornet: 5.6

Speciality of Design:
- focused on low precision floating rather than Linpack performance
- GPU NVIVIA based – higher degree of parallel computing (with reduced precision)

Neural networks do not very much depend on high precision – the algorithm is not „fragile“
New “body concepts” for robots
- New types of “sensible” robots, mainly “lightweight”

Real-time capability:
- New fast sensors allow avoiding accidents in close cooperation

New intelligence models:
- New AI for “context understanding”

Audi’s collaborative robots in Ingolstadt, the “Cobots” pick up components and pass them to workers (02/2015)

Towards hybrid teams and in-the-box production
In a few years, automated driving might outcompete human drivers. **Security issues**, the demographic change, and the decreasing attractiveness of the job may add to a fast change.
Robot applications with distributed structures

Into Service Robotics: The next step – the “Oscars”

Transform mobile robotic experiences into the field of service robotics

Performing service robot tasks
- Distribute brochures and serving drinks
- Path planning, room exploration, ...

1. Investigating “new” human machine interfaces and interaction schemes
   - Simple, intuitive
   - Schematic eyes following you
   - “natural eyes behavior”: randomly looking around, showing interest by blinking, looking bored, ...

2. Investigating the “Uncanny Valley”: when features look almost, but not exactly, like natural beings, it causes a response of revulsion among the observers (Mori 1970)

3. Investigating diversity specific reactions (gender, age, culture) to artificial systems and in particular robots

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Robot applications with distributed structures

From embodiment ... to humanoids

Embodiment theory: „intelligence needs a body“

The existence of a body (incl. sensors and actuators) are basic prerequisites to build experience and finally the development of intelligence.

The Bongard robot – learning through embodiment [Bongard, 2006; Lipson, 2007]

Embodiment theory: „different bodies = different intelligences“

... leading to humanoids / humanoid components

### Prof. Dr. rer. nat. Sabina Jeschke

<table>
<thead>
<tr>
<th>Year</th>
<th>Event</th>
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<tbody>
<tr>
<td>1968</td>
<td>Born in <strong>Kungälv/Sweden</strong></td>
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<tr>
<td>1991 – 1997</td>
<td>Studies of <strong>Physics, Mathematics, Computer Sciences</strong>, TU <strong>Berlin</strong></td>
</tr>
<tr>
<td>1994</td>
<td><strong>NASA</strong> Ames Research Center, Moffett Field, <strong>CA/USA</strong></td>
</tr>
<tr>
<td>10/1994</td>
<td>Fellowship „Studienstiftung des Deutschen Volkes“</td>
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<tr>
<td>1997</td>
<td>Diploma Physics</td>
</tr>
<tr>
<td>1997 – 2000</td>
<td>Research Fellow, TU Berlin, Institute for <strong>Mathematics</strong></td>
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<tr>
<td>2000 – 2001</td>
<td>Lecturer, Georgia Institute of Technology, <strong>GA/USA</strong></td>
</tr>
<tr>
<td>2001 – 2004</td>
<td>Project leadership, TU Berlin, Institute for Mathematics</td>
</tr>
<tr>
<td>04/2004</td>
<td><strong>Ph.D.</strong> (Dr. rer. nat.), TU Berlin, in the field of <strong>Computer Sciences</strong></td>
</tr>
<tr>
<td>2004</td>
<td>Set-up and leadership of the Multimedia-Center at the TU Berlin</td>
</tr>
<tr>
<td>2005 – 2007</td>
<td>Juniorprofessor „New Media in Mathematics &amp; Sciences“ &amp; Director of the <strong>Multimedia</strong>-center MuLF, TU Berlin</td>
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<tr>
<td>2007 – 2009</td>
<td>Univ.-Professor, Institute for IT Service Technologies (IITS) &amp; Director of the Computer Center (RUS), Department of <strong>Electrical Engineering</strong>, University of <strong>Stuttgart</strong></td>
</tr>
<tr>
<td>since 06/2009</td>
<td>Univ.-Professor, Head of the Cybernetics Lab IMA/ZLW &amp; IfU, Department of <strong>Mechanical Engineering</strong>, RWTH <strong>Aachen</strong> University</td>
</tr>
<tr>
<td>2011 – 2016</td>
<td><strong>Vice Dean</strong> of the Department of <strong>Mechanical Engineering</strong>, RWTH <strong>Aachen</strong> University</td>
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<tr>
<td>since 03/2012</td>
<td>Chairwoman VDI Aachen</td>
</tr>
<tr>
<td>since 05/2015</td>
<td>Supervisory Board of <strong>Körber AG</strong>, Hamburg</td>
</tr>
<tr>
<td>SoSe 2017</td>
<td><strong>Visiting Professor at Volvo Cars</strong>, Göteborg/Sweden</td>
</tr>
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17.10.2017
S. Jeschke