Towards a “cognitive enterprise”: Potentials of artificial intelligence in real applications

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Univ.-Prof. Dr. rer. nat. Sabina Jeschke
Cybernetics Lab IMA/ZLW & IfU
Faculty of Mechanical Engineering
RWTH Aachen University

& Visiting Professor at Volvo/Göteborg Sweden
Outline

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
... leading to the 4th industrial (r)evolution...

Breakthroughs - A new era of artificial intelligence

Communication technology
bandwidth and computational power

Semantic technologies
information integration

Embedded systems
miniaturization

Artificial intelligence
behavior and decision support

Google Car
2012

Watson
2011

Systems of “human-like” complexity

1st dimension: complexity level
... 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

2nd dimension: network level

- Swarm Robotics
- Team Robotics
- Smart Factory
- Car2Infra-structure
- Smart Grid
... towards a networked world

And how do these systems work?

<table>
<thead>
<tr>
<th>Communication technology</th>
<th>Embedded systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>bandwidth and computational power</td>
<td>miniaturization</td>
</tr>
</tbody>
</table>

Semantic technologies
information integration

?? Steering - Controlling ??

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

<table>
<thead>
<tr>
<th>1st industrial revolution</th>
<th>Power revolution</th>
<th>Digital revolution</th>
<th>Information revolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mechanical production systematically using the power of water and steam</td>
<td>Centralized electric power infrastructure; mass production by division of labor</td>
<td>Digital computing and communication technology, enhancing systems’ intelligence</td>
<td>Everybody and everything is networked – networked information as a “huge brain”</td>
</tr>
</tbody>
</table>

around 1750 | around 1900 | around 1970 | today |

07.06.2017
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”!
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Data-driven learning – supervised
A first example – learning from guided observations

Do you remember your childhood heroes – “The Mario Brothers” by Nintendo?

So let us write down our observations (and gather some training data)

<table>
<thead>
<tr>
<th>pos_x</th>
<th>on_ground</th>
<th>action</th>
<th>status</th>
</tr>
</thead>
<tbody>
<tr>
<td>563</td>
<td>yes</td>
<td>jump (B)</td>
<td>alive (1)</td>
</tr>
<tr>
<td>571</td>
<td>yes</td>
<td>jump (A)</td>
<td>alive (1)</td>
</tr>
<tr>
<td>580</td>
<td>yes</td>
<td>walk right</td>
<td>dead (0)</td>
</tr>
<tr>
<td>582</td>
<td>no</td>
<td>jump (A)</td>
<td>dead (0)</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

We want to learn general rules how to survive – by using data – and visualize it in a decision tree – resulting in a “classification”.

<table>
<thead>
<tr>
<th>on_ground</th>
<th>pos_x</th>
<th>action</th>
</tr>
</thead>
<tbody>
<tr>
<td>yes</td>
<td>&gt; 560 and &lt; 575</td>
<td>jump (B)</td>
</tr>
<tr>
<td>no</td>
<td>confidence (c) = 50%</td>
<td>jump (A)</td>
</tr>
</tbody>
</table>

Replicating the human evaluation
Data-driven learning – supervised
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)

07.06.2017
S. Jeschke
Can we predict the result of a HPDC (high-pressure die casting) process – by using historical data? – **YES, WE CAN!**

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**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
Data-driven learning – unsupervised

A second example – what if we do not tell “him” what’s right

What if we do not know if an observation belongs to a specific category?
Or, if an observation is good or bad?
Or, if we are ruling on bias instead of knowledge?

Let’s automatically categorize men and women. But we will not give the system ANY training material. We expect it to find patterns on the data that differ from “usual noise”.

Cleansing, preprocessing and clustering

Finding the hidden structure in data!

... neatly arranged by gender.
Quality: higher than human average

A batch of unlabeled pictures...

Unsupervised: Human factor is reduced to modeling.
(a certain “bias” usually survives – by defining the basis for proximity, or by reducing the feature vector)

Reducing the human impact
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 about chemical compositions

Searching for hidden relations in data by subgroup mining

- 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
- ...

Unsupervised cleaning

Finding hidden relations in our data, we were not aware of, e.g., understanding failures or bad quality of products and processes 2015
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)

**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 learning... using k-means clustering

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)

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

2nd paper currently under review at wgp
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V. Summary and Outlook
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)

- 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:
- 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

... for learning and optimization of motions

[Intelligent Autonomous Systems, 2015]

usually coupled to simulation environments to avoid “nonsense solutions”

... for learning and executing complete assembly tasks

With phase estimation

Without phase estimation

The speed of the robot movement is the same in both cases

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

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>
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<tbody>
<tr>
<td>Faces</td>
<td>Search</td>
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<tr>
<td>Self-Driving Vehicles</td>
<td>CRM</td>
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</table>

<table>
<thead>
<tr>
<th>Sound</th>
<th>Time Series</th>
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<tr>
<td>Voice search</td>
<td>Health data</td>
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<tr>
<td>Music generation</td>
<td>Sensors</td>
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<tr>
<td>translation</td>
<td>Finance</td>
</tr>
</tbody>
</table>

Central part of “cognitive computing”

Deep Learning: Why for NLP?

One Model rules them all?

DL approaches have been successfully applied to:

- Automatic summarization
- Machine translation
- Natural language generation
- Speech processing
- Sentiment analysis
- Parsing
- Information retrieval (IR)

- Conference resolution
- Morphological segmentation
- Word sense disambiguation
- Part-of-speech tagging
- Optical character recognition (OCR)
- Word segmentation
- Speech recognition
- Information retrieval (IR)

- Discourse analysis
- Named entity recognition (NER)
- Sentence boundary disambiguation
- Question answering
- Natural language understanding

- Topic segmentation and recognition
- Speech segmentation
- Information extraction (IE)

Anomaly detection with H2O Deep Learning

The good

The bad

The ugly

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)

Handwriting recognition

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

Deep learning combined with reinforcement learning is used for improving flexible motion patterns for robots. The CENSE PROJECT, by the cluster of excellence, focuses on this application.

**Q-Learning** (special case of R-Learning)

Communication via web service connection

Simulation environment

Environment model

Deep neural network

Next step: Improving topology towards CNN (convolutional neural network)
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The creative artificial mind
Where the Story Goes: AlphaGo

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.

Bringing it all together!

- Training set
  30 million moves recorded from games played by humans experts

- Creating deep neural networks
  12 network layers with millions of neuron-like connections

- Predicting the human move
  (57% of time)

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)

Achieving one of the grand challenges of AI
The creative artificial mind
Playing with diversity!

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
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=lDtmy6YorG4 (10/2016)

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

Microsoft Visual Storytelling (SIS): machines becoming creative

“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]

- **DII (descriptions for images in isolation):** Traditional storytelling software
- **SIS (stories for images in sequence):** new approach towards storytelling, including
  - Based on SIND – Sequential Image Narrative Dataset: 81,743 unique photos in 20,211 sequences, aligned to both descriptive (caption) and story language.
  - [Margaret Mitchell / Microsoft, 04/2016, together with colleagues from Facebook]

<table>
<thead>
<tr>
<th>DII</th>
<th>SIS</th>
</tr>
</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>
</tr>
<tr>
<td>Adult male wearing sunglasses lying down on black pavement.</td>
<td>[M] got exhausted by the heat.</td>
</tr>
<tr>
<td>The sun is setting over the ocean and mountains.</td>
<td>Sky illuminated with a brilliance of gold and orange hues.</td>
</tr>
</tbody>
</table>

Visual-Storytelling by **Microsoft** based on deep neural networks (convolutional neural networks)
The creative artificial mind

Google DeepDream: machines becoming creative

“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)

Van Gogh’s Starry Night interpreted by Google DeepDream based on deep neural networks

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]
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Summary and Outlook
Along the production & supply chain...

- Creative learning from previous designs
- Al-supported machine ramp Up
- Real and model-based world combined: Integrated planning
- Transparent Live Cycle
- Predictive and prescriptive
- Flexible task management
- Creative adaptive machine regulation
- Cobot workplace design and workplaces

Driven by Al-Human
Driven by Autonomous AI
Summary and Outlook

From intelligent islands to cognitive enterprises

- Steering of actions
- Data transfer
- Decision making
- Data analysis
- Data structuring
- Data aggregation
- Data capturing

Aachen University
07.06.2017
S. Jeschke
Summary
Lot size 1 at justifiable costs

Artificial Intelligence
- ... integrating virtual and augmented environments for training and learning
- ... forms the basis of safe execution of AI-driven trial-and-error models

Augmented Reality
- ... allowing for automatically managing highly complex “building block models”
- ... finally, allowing for continuous variations of existing models

Additive Manufacturing
- ... allowing to produce all types of components (even totally new ones)
- ... on the fly and without ordering, storage processes etc.

Leading to a “full melt” of PRODUCTION and LOGISTICS

Enhancing the PRODUCTS’ flexibility
Enhancing the MANUFACTURINGs’ flexibility
Thank you!

www.ima-zlw-ifu.rwth-aachen.de
Prof. Dr. rer. nat. Sabina Jeschke

1968 Born in Kungälv/Sweden
1994 NASA Ames Research Center, Moffett Field, CA/USA
10/1994 Fellowship „Studienstiftung des Deutschen Volkes“
1997 Diploma Physics
1997 – 2000 Research Fellow, TU Berlin, Institute for Mathematics
2000 – 2001 Lecturer, Georgia Institute of Technology, GA/USA
2001 – 2004 Project leadership, TU Berlin, Institute for Mathematics
04/2004 Ph.D. (Dr. rer. nat.), TU Berlin, in the field of Computer Sciences
2004 Set-up and leadership of the Multimedia-Center at the TU Berlin
2005 – 2007 Juniorprofessor „New Media in Mathematics & Sciences“ & Director of the Multimedia-center MuLF, TU Berlin
2007 – 2009 Univ.-Professor, Institute for IT Service Technologies (IITS) & Director of the Computer Center (RUS), Department of Electrical Engineering, University of Stuttgart
since 06/2009 Univ.-Professor, Head of the Cybernetics Lab IMA/ZLW & IfU, Department of Mechanical Engineering, RWTH Aachen University
2011 – 2016 Vice Dean of the Department of Mechanical Engineering, RWTH Aachen University
since 03/2012 Chairwoman VDI Aachen
since 05/2015 Supervisory Board of Körber AG, Hamburg
Can we use supervised learning to improve very flexible production processes towards lot size 1? – **YES, WE CAN!**

**The BRAIN PROJECT** - by the cluster of excellence (since 9/2016)

Data-driven learning – supervised learning in individualized production (1)

**Hot Rolling /metals (at ibf):**

- Coils or slabs depend highly on the costumer
- So far, the rolling schedule is driven by experience rather than by automated design
- Process simulations of mill trains are “physically incomplete”, real experiments are expensive
- Automating the rolling schedule along parameters as the number of millings, pressure applied, and temperature

**Two Models were evaluated for the supervised learning task.**
- A White Box Model combining many different decision trees (Random Forest).
- A Black Box Model, an artificial neural network (Multi-Layer-Perceptron).

<table>
<thead>
<tr>
<th>Results</th>
<th>RF (normalized data)</th>
<th>MLP (raw data)</th>
<th>MLP (normalized data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy ((R^2)-Score)</td>
<td>97,33 %</td>
<td>88,41 %</td>
<td>96,17 %</td>
</tr>
<tr>
<td>Mean-Absolute-Error</td>
<td>0,024 a.u.</td>
<td>11,04 μm</td>
<td>0,030 a.u.</td>
</tr>
<tr>
<td>Training Time</td>
<td>5,68 sec.</td>
<td>1,73 sec.</td>
<td>1,42 sec.</td>
</tr>
</tbody>
</table>

**Trade off between speed & transparency**

“Best” trade so far: MLP
Can we use supervised learning to improve very flexible production processes towards lot size 1? – **YES, WE CAN!**

**The BRAIN PROJECT** - by the cluster of excellence (since 9/2016)

---

**Injection Moulding / synthetics (at IKV):**
- For lot size 1, real experiments are expensive
- Current simulations in the field help to optimize the results but do not feedback with the process
- At IKV, a large amount of training data is available
- High quality process simulations available
- Automating the moulding process along parameters coming from geometry, weight, etc.

---

**Are current ML methods able to predict process parameters based on simulation data combined with few experimental data?**

→ Algorithm comparison for different tasks

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>$R^2$ Width</th>
<th>$R^2$ Length</th>
<th>$R^2$ Mass</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polynominal</td>
<td>0.631</td>
<td>0.819</td>
<td>0.147</td>
</tr>
<tr>
<td>Ridge Polynominal</td>
<td><strong>0.817</strong></td>
<td><strong>0.827</strong></td>
<td><strong>0.317</strong></td>
</tr>
<tr>
<td>K-nearest Neighbors</td>
<td>0.398</td>
<td>0.442</td>
<td>0.463</td>
</tr>
<tr>
<td>Support Vector</td>
<td>0.781</td>
<td>0.134</td>
<td>0.280</td>
</tr>
<tr>
<td>Multilayer Perceptron</td>
<td>-301.821</td>
<td>-12.239</td>
<td>-0.018</td>
</tr>
</tbody>
</table>

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**Mixed training data leads to better models**
Learning by doing
Hot rolling - revisited

What if...
... we let the AI model rule our rolling schedule
→ Finding hidden correlation between process parameters

- Physical modelling of interdependencies between process targets too complex → not all side effects are covered
- Interdependencies between process targets can be interpolated using a Reinforcement Learning Agent
- Training based on previous classified rolling schedules for single parameters

What if…
… we let the AI model rule our rolling schedule
→ Finding hidden correlation between process parameters

- Possible rolling schedules
- Reward functions based on process window
- Reliable schedules
- Non reliable schedules
Deep learning combined with reinforcement learning

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

“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]

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)
The creative artificial mind

The “AlphaGo” for Mechanical Engineering

Imagine: AI as regulating loop in production
- What if the production follows a non-deterministic cycle (e.g. in health: implants)?
- AI as addition to classic deterministic control approaches: Handle non-deterministic complex adaptive behavior

Learning in the data world
- Human Input
- Data Models

Oberserving and learning in the real world
- Sensors
- Actuators
- Human Input

Regulating Loop
- Human Iteration
- Machines

Based on Supervised
Based on Reinforcement

07.06.2017
S. Jeschke
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)

Robot playing the „wire loop game“ (at IMA & WZL):

- challenge: guiding a metal loop along a twisted wire (geometry unknown) without touching the loop to the wire
- reliable simulations are available, which allows for first training in VR before experimenting in the real world

- Automating the motion path along different wires
- Getting rid of the teach-in programming as it is not flexible enough for individualized production
- Transfer to the process of production and assembly
  - Planning of welding lanes
  - Applying of glue beads
  - Assembly of limp components
Summary
The “new AI”: Cognitive Computing

“Cognitive computing (CC) makes a **new class of problems computable**. It addresses complex situations that are **characterized by ambiguity and uncertainty**; in other words it handles human kinds of problems. ...To do this, systems often need to weigh conflicting evidence and suggest **an answer that is “best” rather than “right”**.

Cognitive computing systems **make context computable**.

“Cognitive computing systems [are] a category of technologies that uses natural language processing and machine learning to **enable people and machines to interact more naturally** [...]. These systems will learn and interact to **provide expert assistance** to scientists, engineers, lawyers, and other professionals **in a fraction of the time it used to take**.”

“Cognitive computing is the **simulation of human thought processes** in a computerized model.... involves **self-learning systems** that use **data mining**, **pattern recognition** and **natural language processing** to mimic the way the human brain works.”

Intuitive intelligent interaction with humans...

Copying human thought processes
Summary

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
From the history of autonomous vehicles

2009: Truck robot platoons – **distributed intelligence**

The KONVOI project (several institutes from RWTH & industry partners)

- 2005-2009
- automated / partly autonomous transportation e.g. by electronically coupling trucks to convoys
- several successful tests with trucks: Chauffeur, KONVOI, SARTRE (EU), Energy-ITS (Japan), ...

- Adv. driver assistance system for trucks
- short distances between vehicles of approx. 10m at a velocity of 80 km/h
- Energy-ITS: 4m ! (2013)

- KONVOI:
  - Car2infrastructure components!
  - Model of multi agent systems

expected improvements: beyond safety, reduction of fuel consumption and gained road space
Organization forms on demand – individualized by client – initialized by product

- Heterogeneous player modeled as multi agent concept
- Models from biology and social sciences
- Based on autopoiesis & embodiment theory

Product agitates as “super-agent”:
- Plans production and transportation steps
- Requests services from agents
- Negotiates with other products for agent-resources

Konvoi 2005-2009, RWTH with partners
(partly) autonomous driving via convoys

Projects at IMA/ZLW & IfU

Changes already „under construction“

With decentralized models towards lot size 1

© Daniel Ewert 2013

With decentralized models towards lot size 1
Lend the robots a face
Into Service Robotics: The next step – the “Oscars”

Transform mobile robotic experiences into the field of service robotics

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
New forms of human machine interaction

About the role of emotion in human-machine-interaction

Plato (ca. 400 BC)
“Human behavior flows from three main sources: desire, emotion, and knowledge.”

However, it took a while before emotions were considered important in computer science.

Rosalind Picard (since 1997; MIT)
“Computers that will interact naturally and intelligently with humans need the ability to at least recognize and express affect.”

Picard coined the term “affective computing”

KISMET - MIT (1990-2000; Cynthia Breazeal)
- Analysis and simulation of human-like emotions
- Research on interaction between robots and humans
- Part of the “organic development”
Did you ever **yell** at your GPS, e.g. when it told you the equivalent of **“drive through that river ahead!”**? 😊

Well, WE do constantly. And so the story went on like this:

**Motivation and goal:** Transform the GPS into an intelligent co-driver, i.e. get it to adapt to your emotions!

**Solution:** A machine-learning based system architecture. Did it work? Often! Was it fun? Hell, yeah! 😊

**Ingredients in a nutshell**

- Primary source of emotion: driver speech
- Machine-learning algorithm: Support Vector Machine (SVM)
- Training database: talk show based corpus (lots of yelling)
- Test-bed: a driving simulator
- Test persons: old and young
Changes already „under construction“

Towards human-robot cooperation: hybrid teams

New “body concepts” for robots:
- New types of “sensible” robots, mainly “lightweight”

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

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

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

Towards hybrid teams and in-the-box production

INDUSTRIE (KLASSISCH)

INDUSTRIE 4.0

PhD Ying Wang, RWTH, IMA/ZLW & IfU, 2016

© F.Welter Aachen
Some even more “out of space” concepts

The new driver

„My colleague the robot...“

Again more: 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.

Again more: 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.
Some even more “out of space” concepts

The third dimension

“The megacities of the future

At a certain point, due to purely mathematical reasons, extended 3-dimensional building structures can not longer be served by purely 2-dimensional (street) networks.

“In 2030, 70% of all humans will live in cities. Already then, about 10% will live in megacities (i.e., more than 10 Mio people). Escalating…”

[Freestyle translation, source PWC studies]

Source: National Geographic Magazine

Source: Cargo sous terrain, CH
Some even more “out of space” concepts

The new construction

„Digital warehouses are replacing physical spare parts storages“

[freestyle translation, source Logistik magazine]

„3D printing is on its way to leave the somewhat ‘restricted’ areas of spare part business, tool making etc. and is about to become a serious challenger for all traditional manufacturing models“.

[source Prof. Erman Tekkaya, TU Dortmund]

| Water carbonators reaching high sales figures |
| 3D printing of house (source Univ. of Southern California 2013) |
| 3D print of pasta – Barilla (tests since 2015) |

On-demand production

Harbor Rotterdam – 3D printer farm for metal printing (after piloting, now roll-out in 2016)

“plastics instead of parcels?” - UPS moving from logistics to 3D printing (tests since 2013)
5.0 – a revolution of a distributed artificial intelligence

Society 4.0 – „sandwiched“ between 4.0 and other revolutions

4th Industrial Revolution

4.0 – an era of “new” cooperations

1. In science: interdisciplinary perspectives
2. In organizations: strong participation of all groups
3. In society: strong integration of the plural perspectives resulting from the heterogenous demands

Work 4.0 – everything under change

1. Not restricted to specific jobs or fields
2. New service models demand for new competences
3. The creativity of technology

Innovation 4.0 – a question of culture

1. The vendor change
2. Difference between evolutionary and revolutionary innovations
3. The new Innovators
4. Globalization has its additional effects on speed and plurality

Digital natives entering the scene
1. The “fall” of the expert
2. Shared economy
3. The “as a service” paradigm
4. Meeting demographic and migration challenges
The creative artificial mind

From discrete to continuous variance

From the paradigm „Individualization by building blocks“...
- Consumers chose from predefined options
- Processes are separately planned and realised for each option

2017

Customer specifying car to individual needs; at home; incl. „continuous features“
+ 20 cm, drivers seat area

Delivery of individualized car

... Towards the paradigm „Individualization by continuous models“
- Consumers taylor their individual (non-prodefined) product
- Processes are carried out in real-time, within a model

2030
The creative artificial mind

**Industry 4.0 does not only change the “routine” jobs**

The typical assumption...

... that job changes in 4.0 are mainly addressing blue collar jobs and/or routine jobs does not hold true.

From „blue collar – low qualified“ to „white collar – middle class“...

but probably, this is just a transition phenomenon

**High qualified jobs**

... as e.g. health professionals face already the taking over through AI in certain fields by Watson, Google Flu, etc.

**Social robots**

... will become capable of taking over even complex tasks with personal presence as in health or home care

**Decentralized platforms**

... with automated consensus models (e.g. blockchain) take over complex administrative tasks e.g. in judiciaries

**Virtual and augmented environments**

... allowing for new international players, even in tasks requiring humans and presence

**Autonomous systems**

... as autonomous cars and more advanced production technology will change the blue collar – low qualified as well

**White collar jobs**

... are under massive change due to the enhancement in AI, here the impact often hits “middle class jobs”
Innovations in 4.0
The vendor change around „cars“

Characteristics of Industrial Revolutions: The vendor change

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”

Latest version of Google’s self driving car (Huffington Post, 28.5.2014)

Sony announced autonomous car in 2015, based on their experience in visual sensors

Google: First autonomic car with street license, 2012

Apple Inc.

Ford 021C concept car 2012, designed by Newson now at Apple (1999)

Tesla X 2015, other Teslas since 2006; Forbes: “most innovative enterprise”

Car specialists? – No.
- Connectivity & data specialists.
- Energy & sensor specialists.

Around 1750

Around 1900

Around 1970

Today
Innovations in 4.0

The vendor change around „cars“

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An autonomous car is more like a computer on wheels than a car which includes one or many computers.

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Advantage of decentralized control structures

Intralogistics goes mobile: The Festo Logistics League

Mobile transportation robots from flexible routing

Competencies:
- localization & navigation
- computer vision
- adaptive planning
- multi agent strategies
- sensory & hardware

Competitions robocup:
- 2012: 0 points in World Cup
- 2013: 4th in World Cup
- 2014: Winner of the GermanOpen
- **2014: Winner of the World Cup**
- **2015: Winner of the World Cup**
- **2016: Winner of the World Cup**

Critical factors for success:
- Totally decentralized
- No ”hard coded components“
- Strong cooperation
- Re-planning during tasks

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http://www.carologistics.org/