Artificial Intelligence in the Internet of Production

Rethink! SPMS 2017
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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

**Embedded systems**
- miniaturization

**Semantic technologies**
- information integration

**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

Car2Infrastructure

Smart Grid
... towards a networked world

And how do these systems work?

Communication technology
bandwidth and computational power

Embedded systems
miniaturization

Semantic technologies
information integration

?? Steering - Controlling ??

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

around 1750

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

around 1900

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

around 1970

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

today

Information revolution
Everybody and everything is networked – networked information as a “huge brain”
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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V. Summary and Outlook
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>
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<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”.

on_ground

<table>
<thead>
<tr>
<th>pos_x</th>
<th>&gt; 560 and &lt; 575</th>
<th>action</th>
</tr>
</thead>
<tbody>
<tr>
<td>yes</td>
<td>jump (B)</td>
<td></td>
</tr>
<tr>
<td>no</td>
<td>confidence (c) = 50%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>c = 75%</td>
<td></td>
</tr>
</tbody>
</table>

jump (B)

jump (A)

supervision

c = 100%

c = 75%
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 spacial shift. Under these conditions, "reproductibility" 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
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“.

A batch of unlabeled pictures...

Cleansing, preprocessing and clustering

Finding the hidden structure in data!

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

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

**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?

- Sulfur (S) > 0.04% and heat treatment \(\rightarrow\) fragile structure
- Phosphorus (P) > 0.04% \(\rightarrow\) reduced plasticity
- Chrome (Cr) > 16%, Molybdenum (Mo) > 13%, Nickel (Ni) > 56% \(\rightarrow\) no findings
- ...
Unsupervised learning for laser cutting processes

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
... 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

2nd paper currently under review at wgp
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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)

Now, Human factor is “very small”!

- 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]

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

→ Usually coupled to simulation environments to avoid “nonsense solutions”
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.”

[Cognitive Labs, 2016]

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”
→ ...

[Minh, 2015]

Human factor practically zero.

[nature, 2015]
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...

Images
- Faces
- Self-Driving Vehicles

Text
- Search
- CRM

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)

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

Handwriting recognition

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

Communication via web service connection

Q-Learning (special case of R-Learning)

Deep neural network

Deep learning to replace teach-in programming

Communication via web service connection

Q-Learning (special case of R-Learning)

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=lDtmy6YorG4 (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 original module

The new module – design-process supported by AI
The creative artificial mind

Playing with diversity – allowing for alternative mental models!

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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
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)
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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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

Development & planning

In production

Flexible task management

Creative adaptive machine regulation

After sales & maintenance

Cobot workplace design and workplaces

Creative learning from previous designs

Al-supported machine ramp Up

Real and model-based world combined: Integrated planning

Flexible task management

Creative adaptive machine regulation

Driven by AI-Human

Driven by Autonomous AI
Summary and Outlook
From intelligent islands to cognitive enterprises

- **Actors**
  - Steering of actions

- **Actuators**
  - Data transfer

- **Cognition**
  - Decision making
  - Data analysis
  - Data structuring
  - Data aggregation

- **Brain**
  - Data transfer

- **Perception**
  - Data capturing

- **Sensors**

26.09.2017
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.

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Thank you!

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Studies of Physics, Mathematics, Computer Sciences, TU Berlin

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Fellowship „Studienstiftung des Deutschen Volkes“

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Project leadership, TU Berlin, Institute for Mathematics

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Set-up and leadership of the Multimedia-Center at the TU Berlin

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