Introduction to Industrial Transfer Learning
Motivation

**Challenges for machine learning in manufacturing**

- Dynamic processes → high training effort
- Insufficient data → representative and reliable data required
**Industrial Transfer Learning**

**Challenges for Machine Learning in Production**

- One key requirement of successful ML: representative and reliable data basis
- Main data sources in production have advantages and disadvantages regarding costs and data quantity

### Running Production
- High quantity
- Little variation
- Highly optimized

### Test Environment
- Small quantity
- High variation
- High costs

### Simulation (Experiments)
- Simplification
- High variation
- Low costs

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**How to learn from different domains?**
Industrial Transfer Learning

Challenges for Machine Learning in Production

Process variations lead to high learning effort for AI
e.g. new product, other material, tool change, new machine

Product A
New Data & Training

Product B
New Data & Training

Product C
New Data & Training

How to overcome process variations?
Industrial Transfer Learning

Transfer Learning – An Emerging Paradigm

What is Transfer Learning?

Traditional ML: learning a problem from scratch

Transfer Learning: use of existing knowledge

Result: faster learning process with less target data

“Transfer learning will be the next driver of ML success.”
Andrew Ng, NIPS 2016 keynote

### Use Cases of Deep Transfer Learning

<table>
<thead>
<tr>
<th><strong>Self-Driving Cars</strong></th>
<th><strong>Robotics</strong></th>
<th><strong>Music Classification</strong></th>
<th><strong>Computer Vision</strong></th>
<th><strong>Natural Language Processing</strong></th>
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<tbody>
<tr>
<td>Use of simulation environment to train artificial intelligence</td>
<td>Pretraining in simulation for grasping and manipulation</td>
<td>Use of large datasets for classifying music genre</td>
<td>Transfer of pattern recognition (e.g. edges, objects) to new images</td>
<td>Use of pretrained language models for specific NLP tasks</td>
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Industrial Transfer Learning

Industrial Transfer Learning – A Definition

In the field of production, **industrial transfer learning** refers to **machine learning methods** and techniques that make use of **source data** from different production **process domains** or **process variations** with the goal to create **robust, accurate and data efficient models** for a certain **target task**.

![Diagram showing the process domain and process variation]

- **Process domain**:
  - Real Machine
  - Pre-production
  - Expert Knowledge
  - Simulation

- **Process variation**:
  - Product
  - Material
  - Tool
  - Machine
Industrial Applications

Simulation to Reality Transfer for Predictive Quality
Simulation to Reality Transfer for Predictive Quality

Predictive Quality in Injection Molding

- Supporting process designers in the **initial set-up** of a machine by **predicting quality criteria** from **machine parameters**

- Increasing data efficiency by **transfer learning from simulation to real world**

- Conducting design of **experiments** on **real machine** and **simulation** with six parameters

- Cavity Temperature
- Cooling Time
- Melt Temperature
- Quality (part weight)
- Injection Time
- Holding pressure level
- Holding pressure time

Plate Specimen
Simulation to Reality Transfer for Predictive Quality

Bridging the Reality Gap

**Transfer Learning**
- Pretraining in simulation (Cadmould 3D-F)
- Finetuning of the network

**Model Training**
- Neural network with two hidden layers with 40 neurons
- Activation function: tanh
Successful Transfer

Use of simulation data improves prediction models for real process

Improvement in accuracy by factor of 3
Reduction of learning effort (iterations) by 80%

Reduction of Training Effort

<table>
<thead>
<tr>
<th>Transfer</th>
<th>Baseline</th>
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Number of Training Iterations

Increasing Data Efficiency

<table>
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<tr>
<th>Performance</th>
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<tbody>
<tr>
<td>Without Transfer</td>
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<tr>
<td>Transfer</td>
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</table>

Number of Real Experiments
Continuous improvement of model by new simulated experiments

- AI bridges the gap between simulation and real manufacturing process
- Use for automated design in production line
- In case of uncertain predictions:
  - Automatic triggering of new experiments in simulation
  - Transfer of newly gained knowledge to real process
Industrial Applications

Continual Learning of a Predictive Quality Model
Predicting quality criteria from machine parameters by means of a neural network

Production of a new product variants
Changes in geometry and process behavior
➢ Predictions no longer work
➢ Requires training of a new prediction model

Difference of quality for different products

- Cavity Temperature
- Cooling Time
- Melt Temperature
- Injection Time
- Holding pressure level
- Holding pressure time

Quality (Deformation)
Use of Previous Knowledge for Transfer

Continual Learning of Predictive Quality Model

Learning without forgetting

Amount of data decreases
Learning capability increases

Product 1

Transfer

Product 2

Transfer

Product 3

Transfer

Product 4

Transfer
Continual Learning of Predictive Quality Model

Incremental Learning without Forgetting

- Finetuning
- Retuning

Learning without forgetting

Process specific, product specific

Product 1
Product 2
Product 3
Continual Learning of Predictive Quality Model

**Improving Efficiency and Learning**

**Improved Performance**
- Continual learning approach keeps up performance
- Traditional approach becomes worse with every product

**Improved Data Efficiency**
- Number of required training data is reduced for every product
- Prediction model can generalize better to new parts

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![Graph showing performance and training data for products](image)

- **Performance**
  - Continual Learning
  - Learning from Scratch

- **# Training Data**
  - Continual Learning
  - Learning from Scratch

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18  Industrial Transfer Learning
Chair of Technologies and Management of Digital Transformation, University of Wuppertal
Industrial Applications

Sim2Real Transfer for Reinforcement Learning in Robotics
Reinforcement Learning

Automated Trial-and-Error by Learning AI Model

- AI agent learns by means of interactions with its environment
  - Agent observes state
  - Agent chooses action
  - Environment issues reward

- Actor-critic architecture
  - Critic: learns the action-value function
  - Actor: specifies the current policy

- Deep Deterministic Policy Gradient (DDPG).
  - Used for a number of continuous control tasks in simulated environments
Use of DDPG in the Real World

- The wire loop game as an easy-to-control sandbox scenario.
  - **State**: camera images, **Action**: three degrees of freedom (forward, sideways, rotation), **Reward**: contact between fork and wire

High training effort on real industrial robot!
**Sim2Real Transfer for Reinforcement Learning in Robotics**

**Transfer Learning with Domain Randomization**

- Training in real robotic environment is time consuming and costly
- Solution: transfer learning from simulation to the real world
- Creating robust AI by randomizations in simulation

**Randomizations:** Camera position and rotation, color, texture, noise
**Sim2Real Transfer for Reinforcement Learning in Robotics**

**Results**

- Improving performance: number of errors in real environment is drastically reduced
- Cost savings: reduction of real iterations with robot for training by 70%

**Higher Reliability**

With transfer: attention of agent lies on correct areas in image (red area)

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<tr>
<th>Input Image</th>
<th>Without Transfer</th>
<th>Transfer Learning</th>
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<tr>
<td><img src="image1.png" alt="Image 1" /></td>
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