scch { software competence center hagenberg }

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www.scch.at

Modeling & Engineering Beyond Narrow AI

Software Center, Chalmers University

9th May 2022

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SCCH Profile

1999 founded as RTO

- initiated by Prof. Bruno Buchberger and Johannes Kepler University Linz (JKU)
- located in Hagenberg / Linz
- 110 staff / 35% PostDocs

Austrian COMET Center*

- PPP funding
- long-term partnerships with companies, universities & RTOs

Mission

- bridging academic and industrial research on AI, data & software science


Softwarepark Hagenberg 1989


Campus Hagenberg 2020

* https://www.ffg.at/en/comet-competence-centers-excellent-technologies

Overview

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- Narrow AI
- Steps Beyond
  - Transfer Learning
  - Knowlewdge Graph + ML
  - Applications

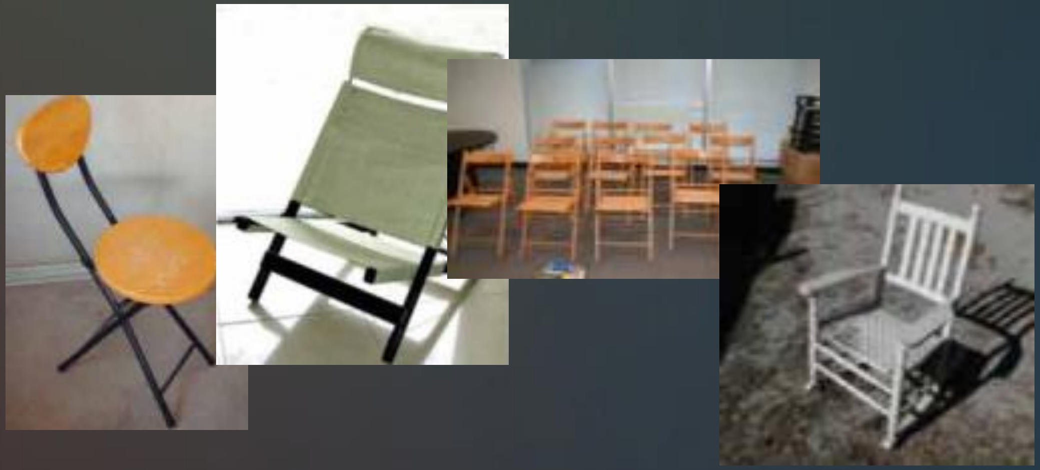
Today's AI

Breakthrough

- Large Datasets / Big Data
- Deep Learning

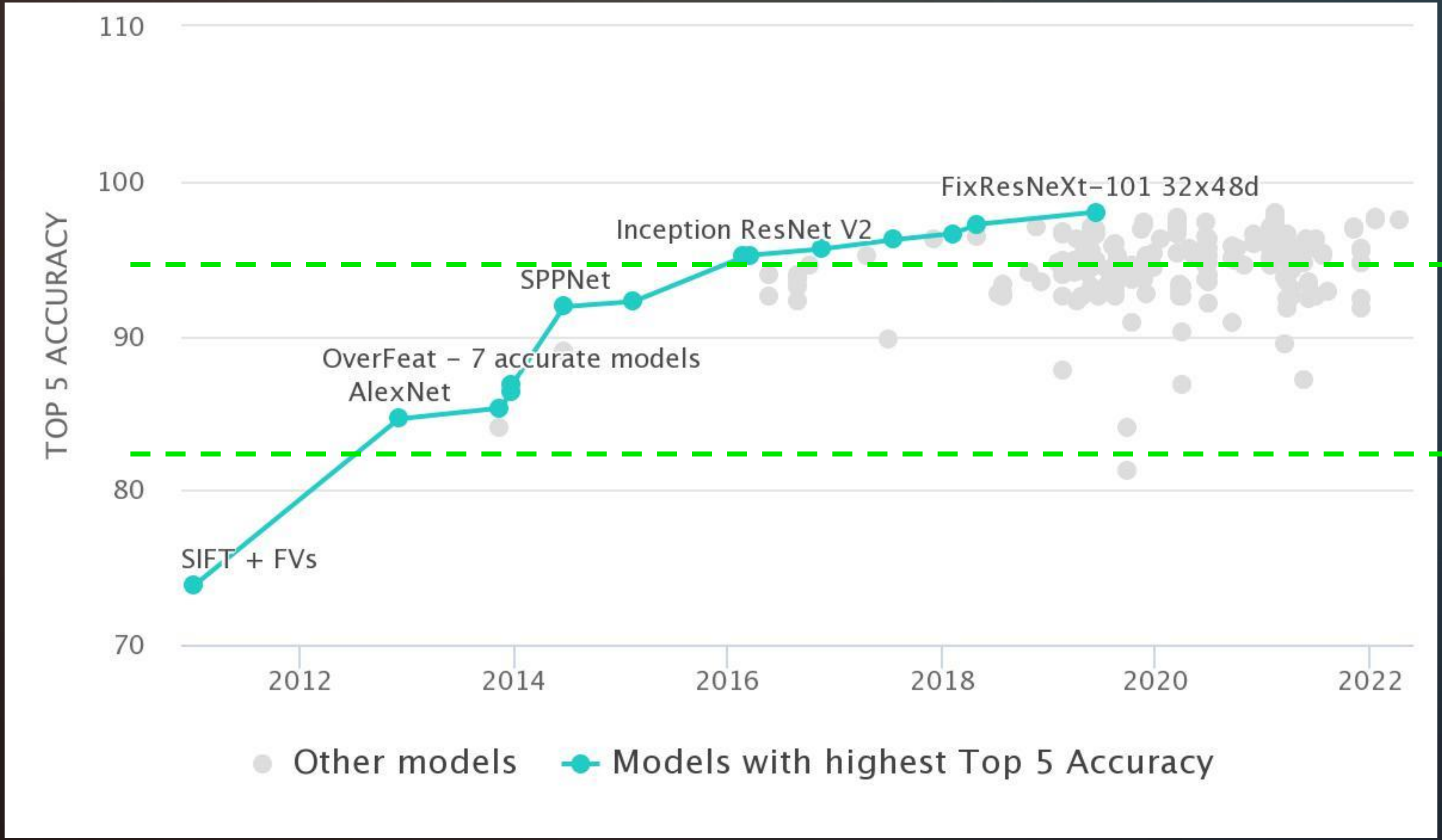
Example

- ImageNet
- 14 Mio annotated images
- over 20.000 categories



https://www.image-net.org/

ImageNet Top-5



trained humans

untrained humans

https://paperswithcode.com/sota/image-classification-on-imagenet

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Training versus Deployment

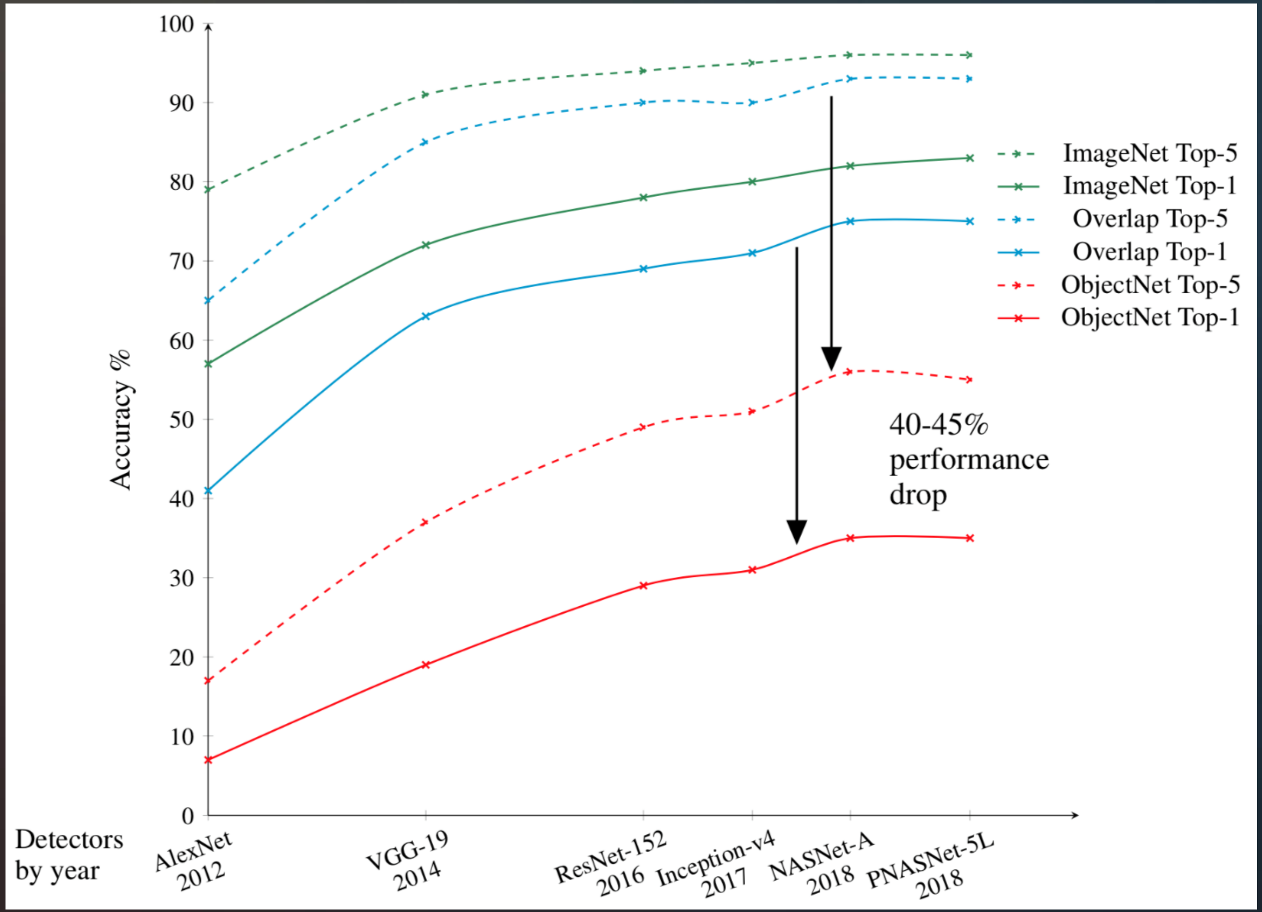
ObjectNet

like ImageNet

- only for testing
- largely centered
- unoccluded

but higher variability

- backgrounds
- viewpoints



Barbu, Andrei, et al. "Objectnet: A large-scale bias-controlled dataset for pushing the limits of object recognition models." (2019).

Today‘s AI is largely Narrow AI

based on

- big data at training time
- decoupled modeling and deployment cycles

restricted to

- static context
- limited to pre-defined task

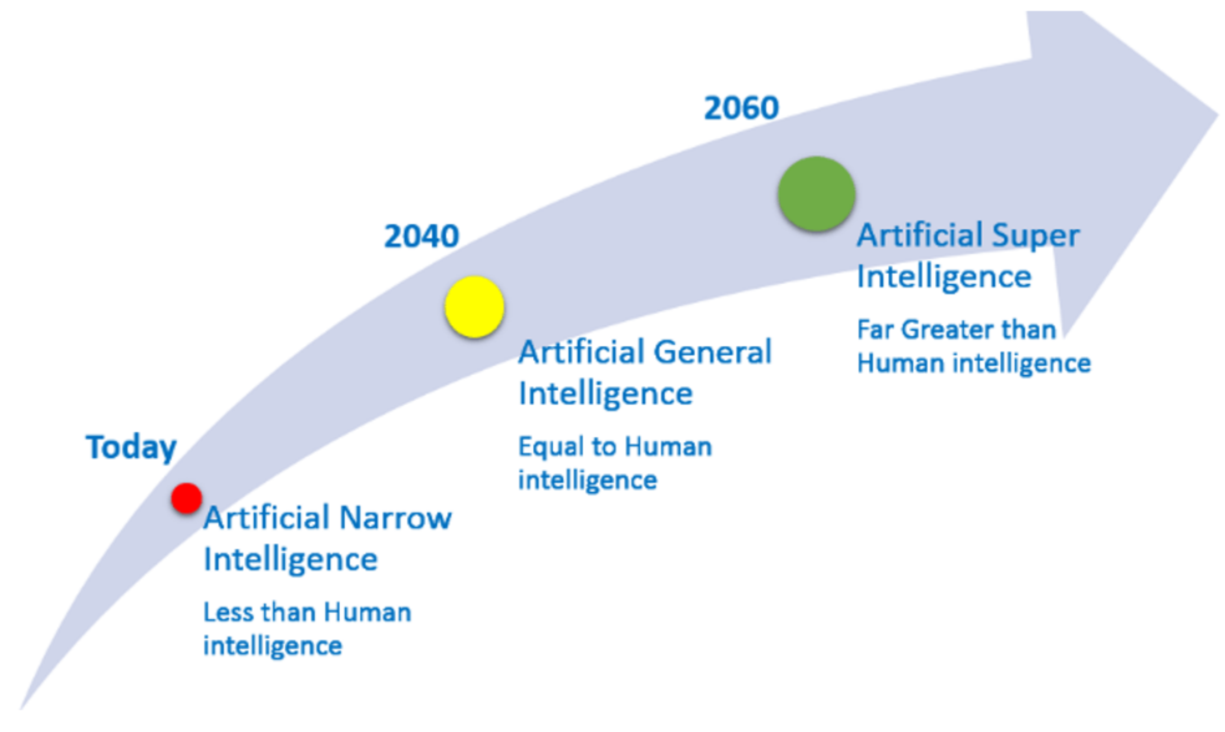


Figure 4: Future evolution of Artificial Intelligence

https://master-iesc-angers.com/artificial-intelligence-machine-learning-and-deep-learning-same-context-different-concepts/

Limiting Factors

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Limiting Factors of Today's ML-based AI

Theory Gap (Statistical Learning)
lack of uniqueness, lack of confidence measure
lack of control of high-dim effects

Theory-Practice Gap
narrow AI, data hungry, faliure of big data assumption, limited data, bias, limited XAI

Adoption Gap
high adaption efforts, AI expert centric, reuse in its infancy, high initial costs

Social Threats
skill gap, acceptance problems

Fischer, L.; Ehrlinger, L.; Geist, V.; Ramler, R.; Sobiezky, F.; Zellinger, W.; Brunner, D.; Kumar, M.; Moser, B.: **AI System Engineering**—Key Challenges and Lessons Learned. *Mach. Learn. Knowl. Extr.* **2021**, *3*, 56-83.

Approach

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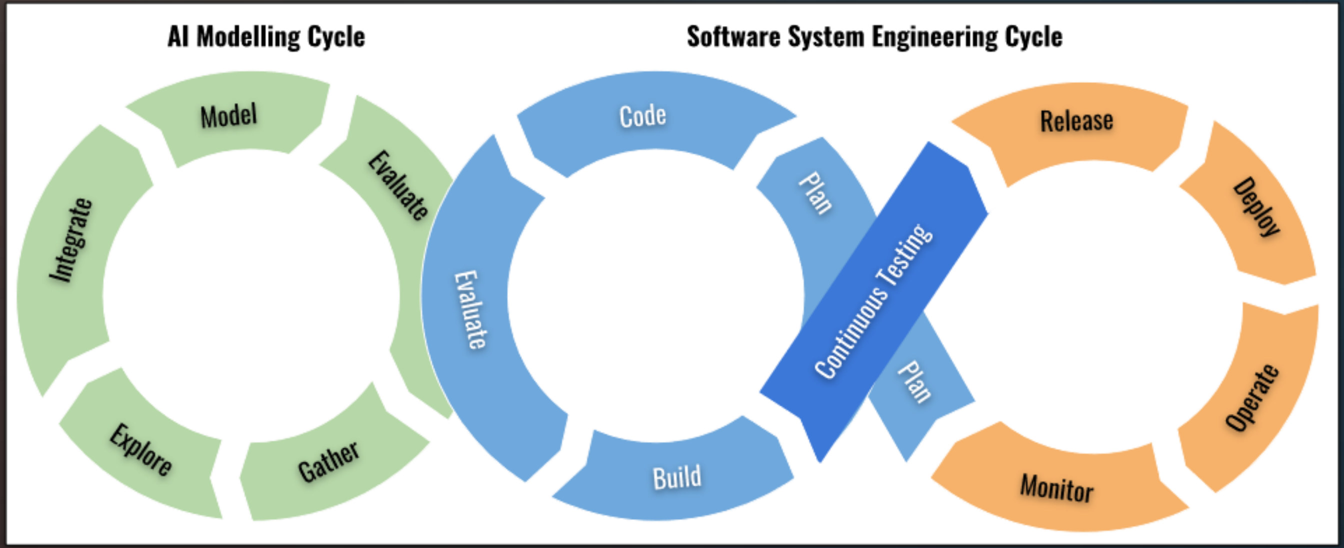
Modeling / Engineering

- enhance loss function
- enhance by linked data
- model adaptation during/after deployment



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Approach 1: Coping with Data Shift

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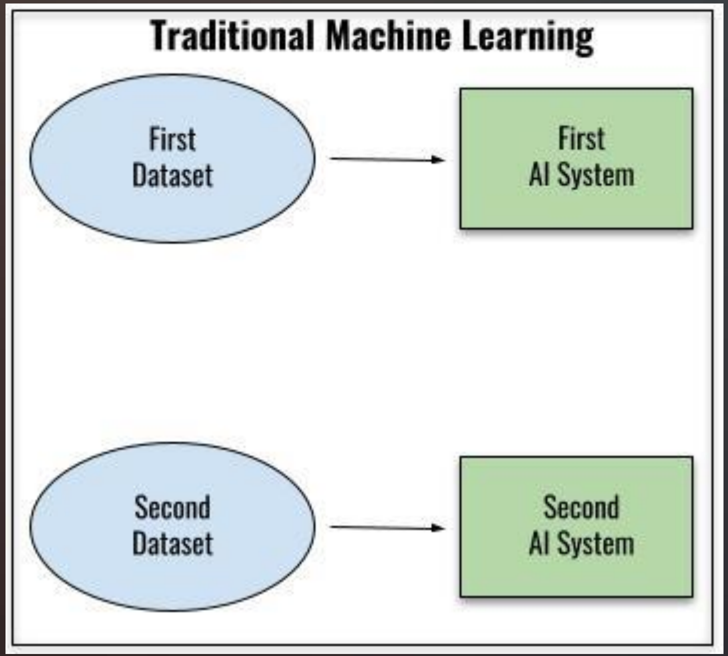
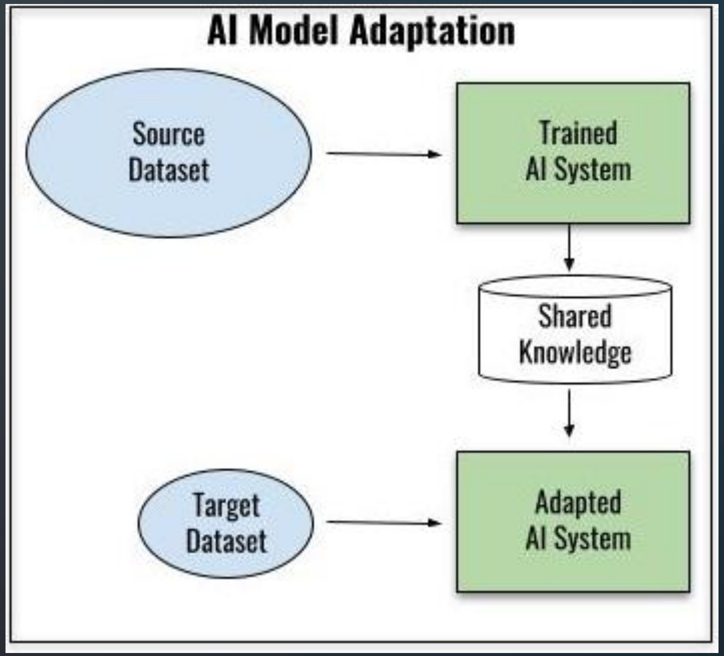
Transfer Learning

- Domain adaptation
- Source domain
- Target domain





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Math Approach

Enhance Loss Function

– enforce similar NN representation

Problem

– hyperparameter ?

distance, e.g. based on moments

$$\min_{g\in\mathcal{G},\phi\in\Phi} \widehat{\varepsilon}_S(g\circ\phi) + \alpha \cdot d(\phi(\mathbf{x}),\phi(\mathbf{x}'))$$

classifier

error in source domain

NN representation

W. Zellinger, N. Shepeleva, M.-C. Dinu, H. Eghbal-zadeh, **H.D. Nguyen**, **B. Nessler**, **S. Pereverzyev**, **B. A. Moser**. "The balancing principle for parameter choice in distance-regularized domain adaptation." Advances in Neural Information Processing Systems 34 (NeurIPS 2021)

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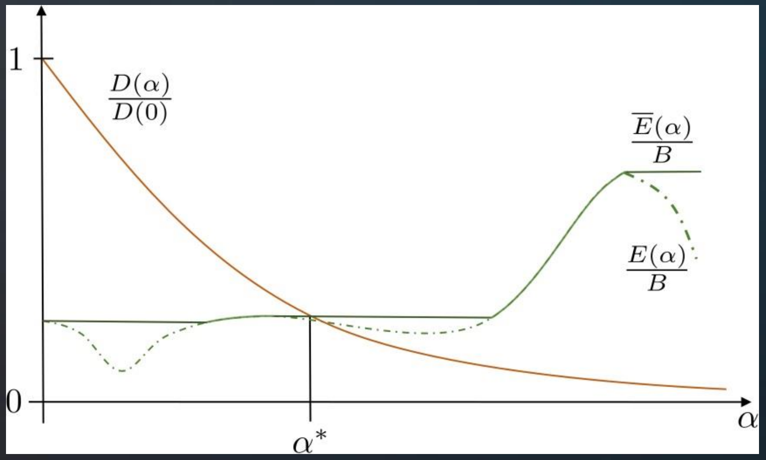
Approach - NeurIPS 2021

Tikhonov-regularized inverse problem	Distance-regularized domain adaptation
$f_\alpha \in \arg\min_{f\in\mathcal{H}} \lVert \widehat{V} f - \widehat{g} \rVert_{\mathcal{K}}^2 + \alpha \lVert f \rVert_{\mathcal{H}}^2$	$g_\alpha \circ \phi_\alpha \in \arg\min_{g\in\mathcal{G},\phi\in\Phi} \widehat{\varepsilon}_S(g\circ\phi) + \alpha\, d(\phi(\mathbf{x}), \phi(\mathbf{x}'))$
$\lVert f_\alpha - f_{\mathcal{H}} \rVert_{\mathcal{H}} \le S(\alpha) + A(\alpha)$	$\varepsilon_T(g_\alpha \circ \phi_\alpha) \le D(\alpha) + E(\alpha)$
decreasing sampling error $S(\alpha)$	decreasing domain distance $D(\alpha)$
increasing approximation error $A(\alpha)$	bounded learning errors $E(\alpha)$
$A(\alpha)$ not estimable	$E(\alpha)$ not estimable
balance $A(\alpha^*) = S(\alpha^*)$	balance $\frac{D(\alpha^*)}{D(0)} = \frac{\overline{E}(\alpha^*)}{B}$

Results

- optimality criterium
- deterministic algorithm
- first approach for disjoint domains
- works even for unsupervised data
- no labels in source
- no transmission of data; only moments



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Industrial Application

Sensor-Measurement Calibration

- Melamine production
- Handling different process lines

Problem

- Prediction of degree of polymerization from NIR sprectroscopy sensor
- Modeling concentration given absorbance
- Sample size is often small (i.e. N < 100)

Fotocredit:
AMI Agrolinz Melamine Intern.

Ramin Nikzad-Langerodi, Werner Zellinger, Susanne Saminger-PLatz, Bernhard Moser, "Domain adaptation for regression under Beer–Lambert's law." Knowlege-Based Systems, Vol 210, 106447, Dec 2020

Usefulness of Transfer Learning

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Scope of Applicability

- Tackle limited data and small lot-size problems
- Compensate for data shift („reality gap“)
- Model calibration in non-stationary environments

AI Engineering

- Reuse of pre-trained models
- Data efficiency
- Distributed architectures

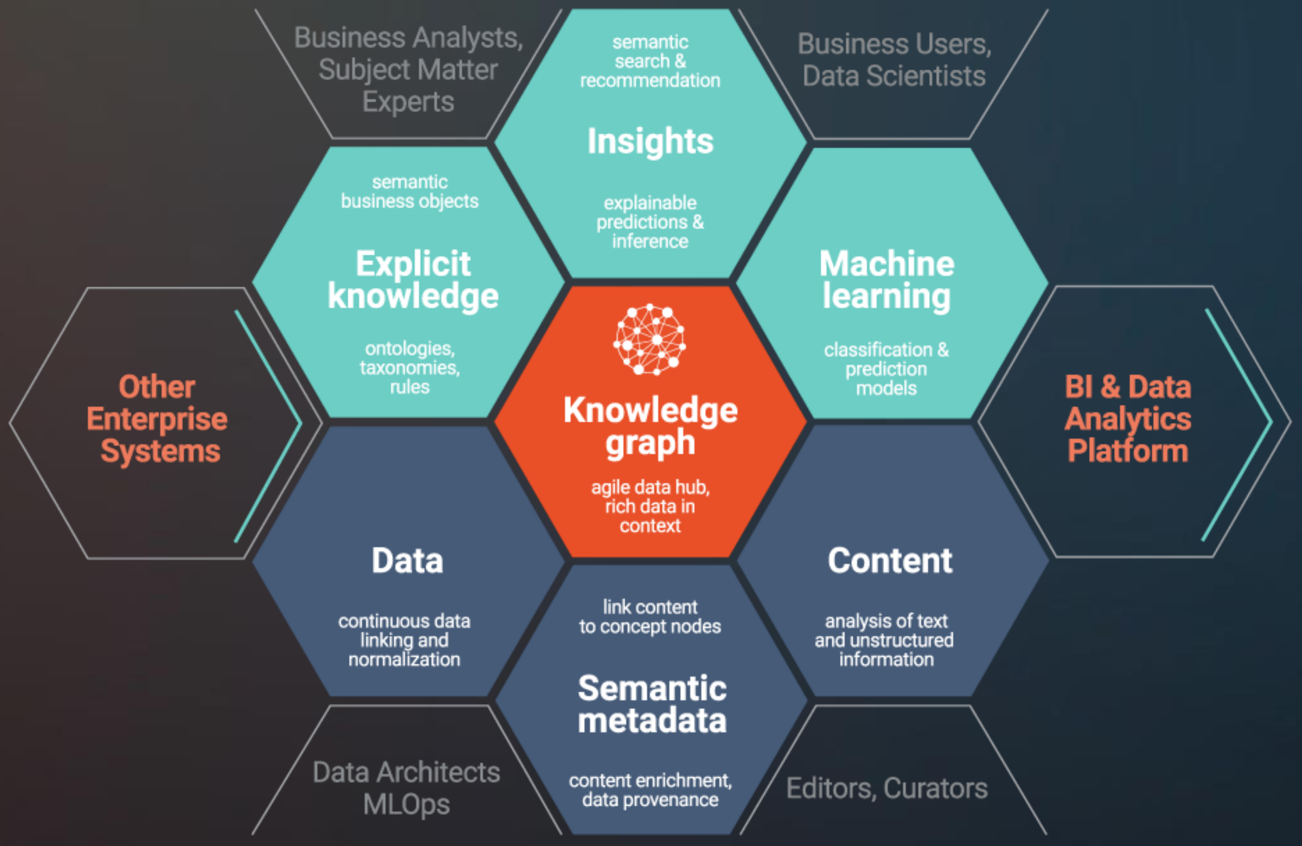
Approach 2: Linked Data

Contextualization

- Knowledge Graph (KG)
- Processes, policies etc
- Human in the Loop, Teaming

Relational ML

- ML on linked data
- KG Updating
- Recommendations



https://www.ontotext.com/knowledgehub/

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Approach 2: KG + ML

Central Challenge

- Keep KG consistent and up-to-date
- within short cycles

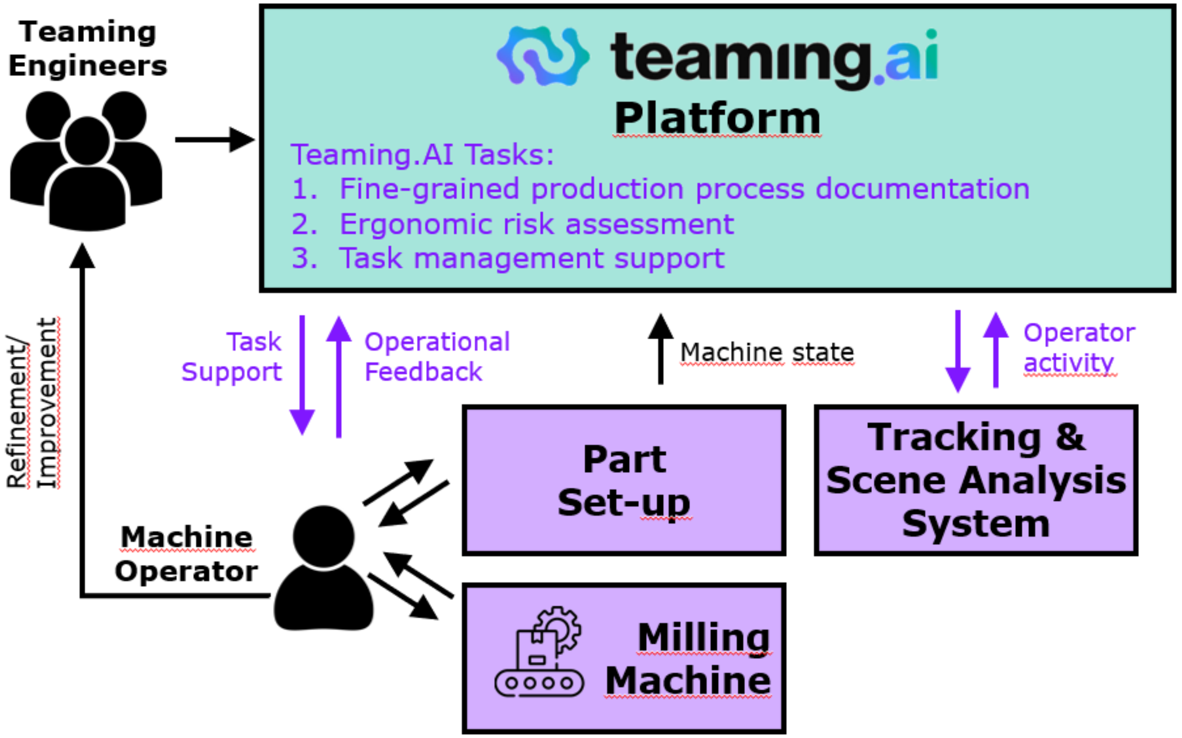
Application

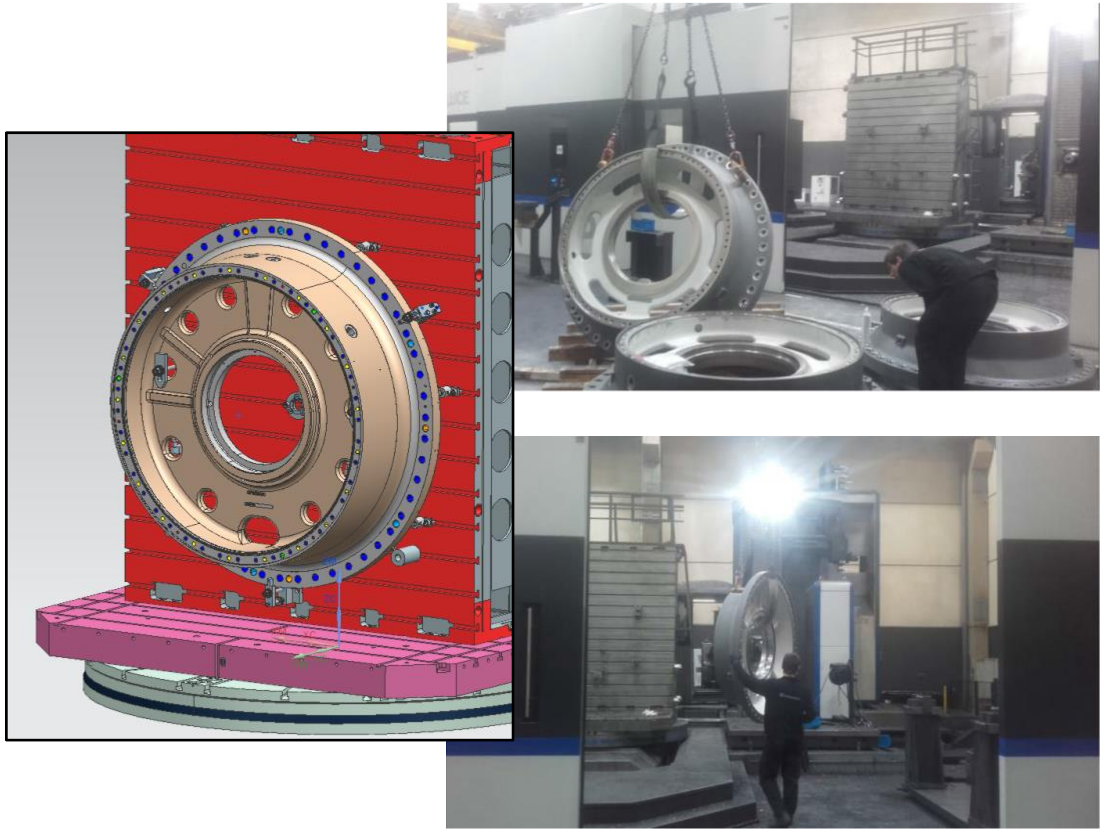
- Human AI Teaming

Use Case: Ergonomic Risk Prevention

Goal: To assess the ergonomic risk and to predict which sequences of actions are ergonomically favorable.

GOIMEK





KG Architecture

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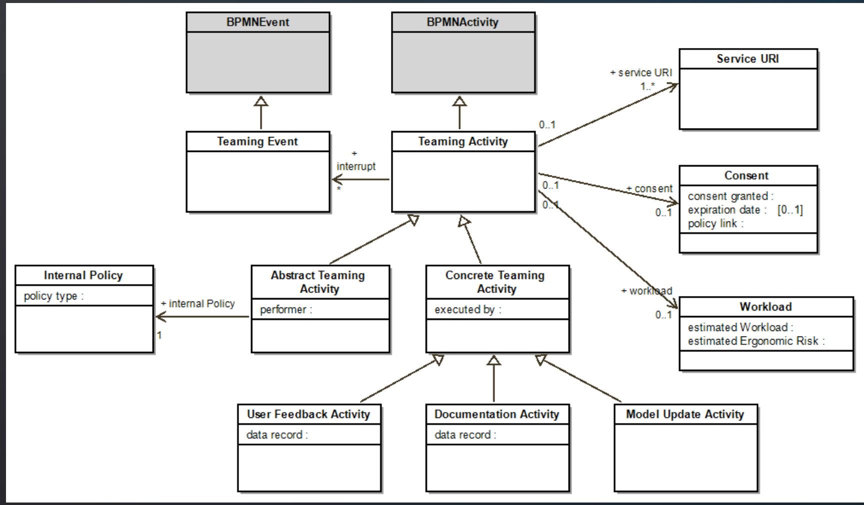
Modular Approach

- layers for events / activities / policies
- use concept of abstract activities from CREMA project

Reference Architecture Industry 4.0

- decomposes complex I4.0 manufacturing systems into loosely coupled layers
- cross-industry model



Cloud-based Rapid Elastic MAnufacturing
www.crema-project.eu

KG Processing

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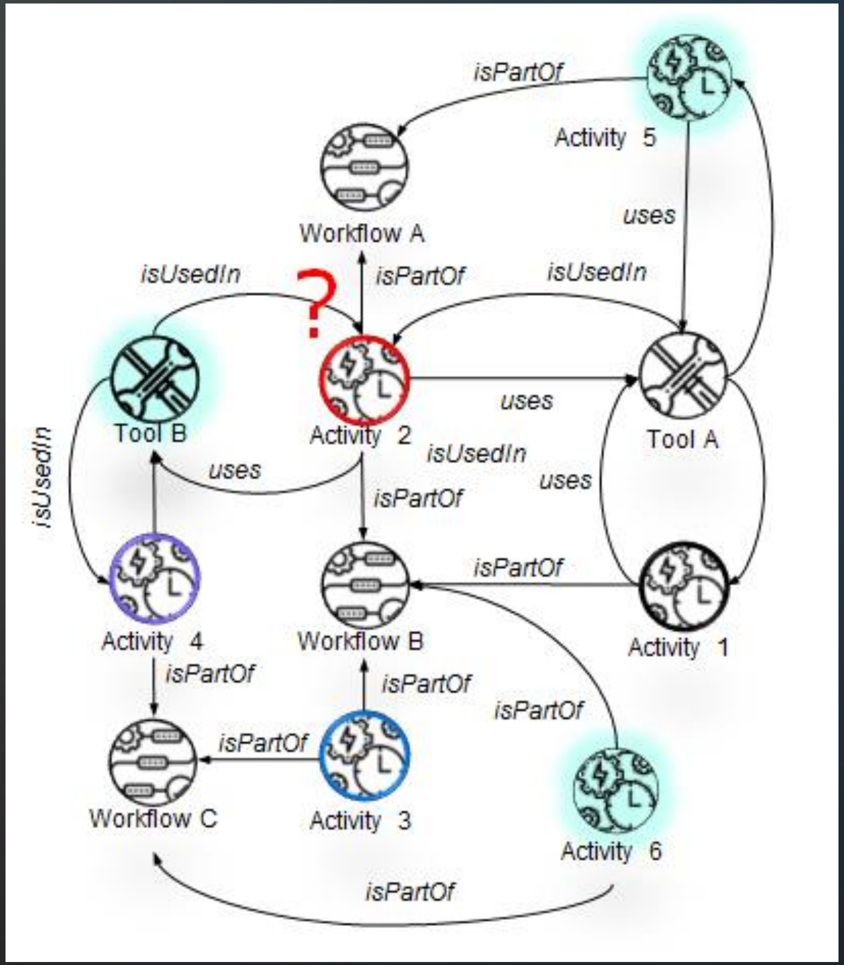
Maintain KG

- detect incompleteness / inconsistencies
- predict corrections
- fast updates by light-weight KG (H. Paulheim)



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Architecture

Event Stream Brocker

– simple vs. complex events

Dynamic KG

– single integrated data store

– digital semantic shadow

– short update cycles

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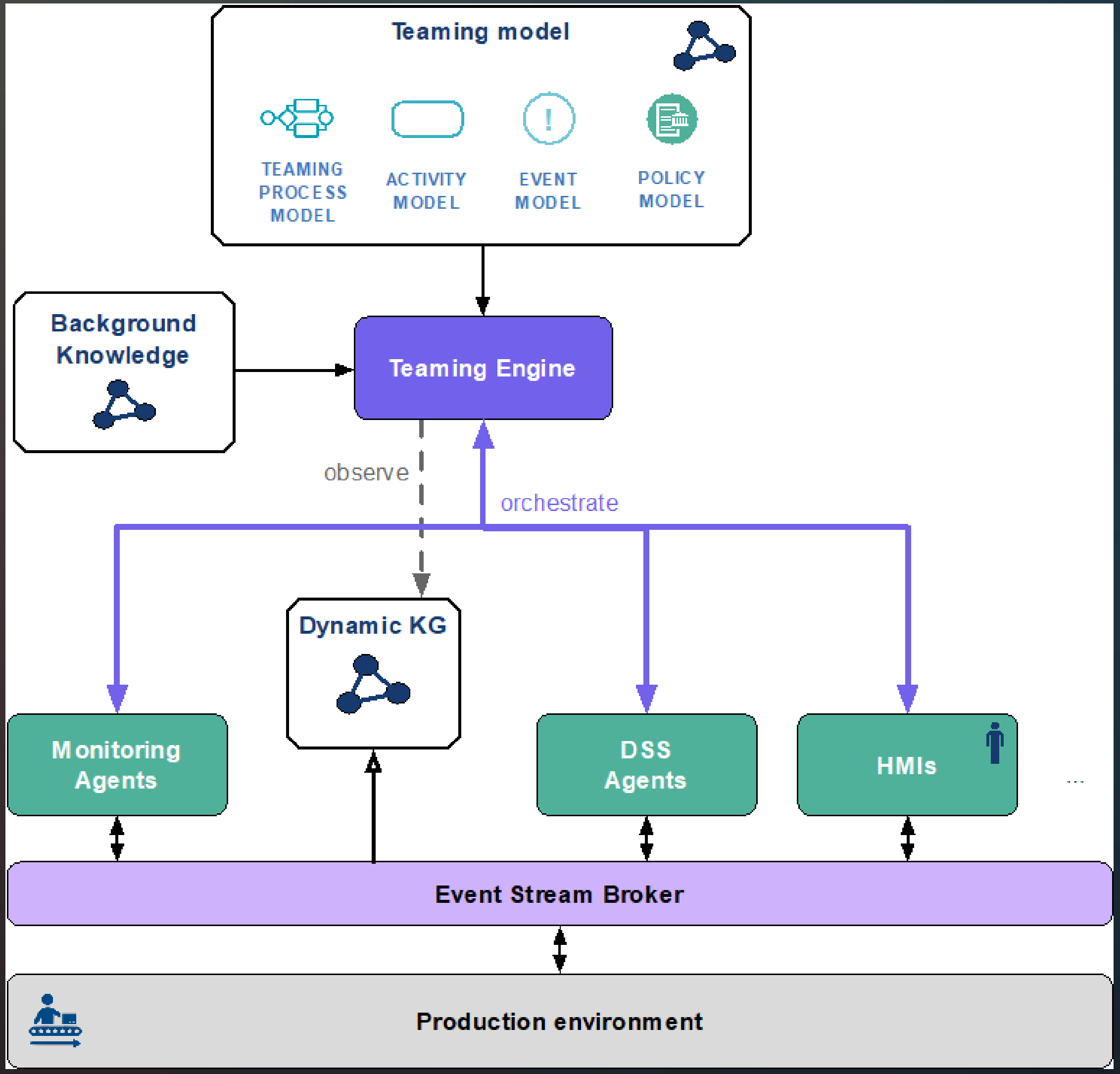
- P. Haindl et al: Towards a Reference Software Architecture for Human-AI Teaming in Smart Manufacturing, ICSE-NIER 2022



Applying KG to Software Engineering

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Project AK-Graph (G. Buchgeher/SCCH)

– encode architecture knowledge (standards)

– provide design guidance, e.g. support security by design for industrial automation systems

– automated architecture evaluation

Challenge

– extraction of tacit knowledge

– rule learning

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