Projektnummer: 01MD19012C

Gefördert durch:

Bundesministerium für Wirtschaft und Klimaschutz

aufgrund eines Beschlusses des Deutschen Bundestages

Rapide Erklärbare Künstliche Intelligenz für Industrieanlagen

AP 7: Anwendungsfälle

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Overview

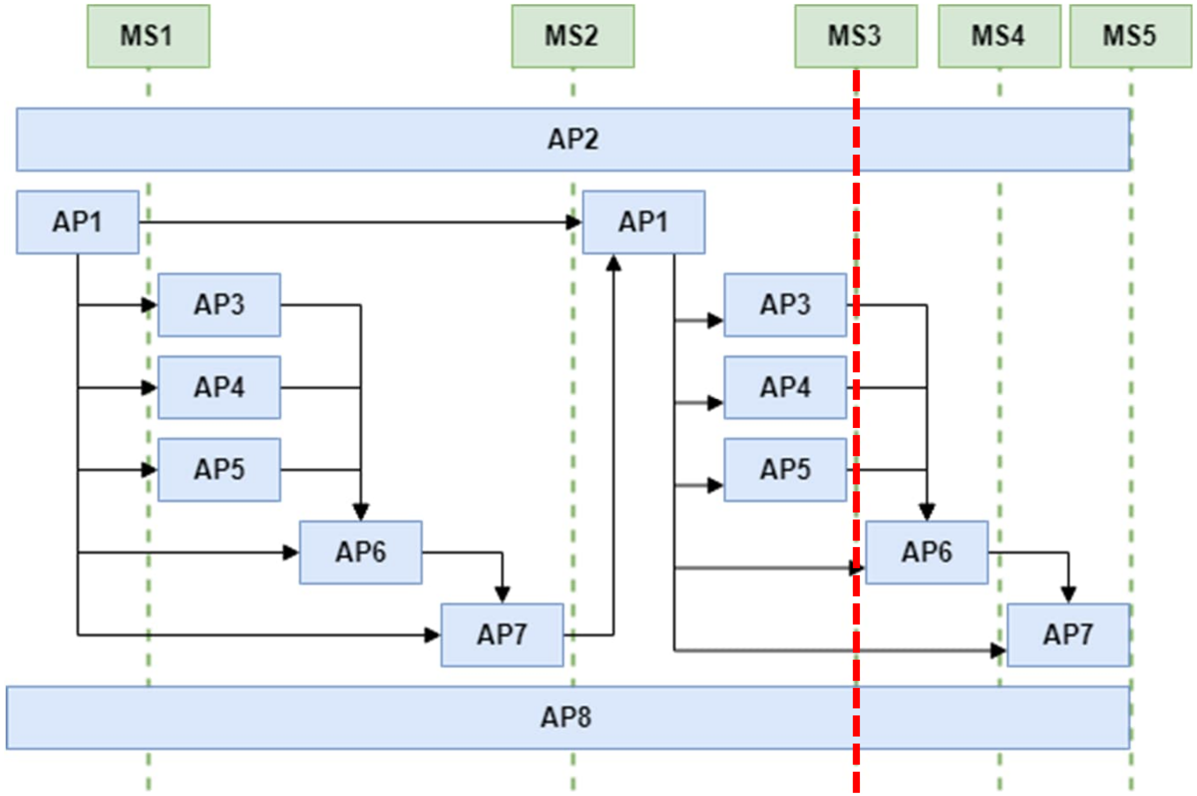
- Current State
- Use Case for Prototype 1: Skill Description Learning
- Machine Learning Evaluation
  - Quantitative Evaluation
  - Qualitative Evaluation
- Verbalization Evaluation
- Outlook

Current State

Use case development:

- Skill description learning
- Turbine package classification / turbine defect classification
- Experimental production plant
- Component selection tool
- Cybersecurity

Evaluation of first prototype on skill description learning use case



Siemens Use Case: Skill Description Learning

Motivation:

- Cyber-physical systems for more flexibility, adaptability, and transparency in production
- Skill matching assigns operations in a production process to machines
- Need skill descriptions of the machines and skill requirements of the operations
- In some cases, skill descriptions might not be available at all, e.g., in the case of a legacy module
- Defining and digitizing skill descriptions of a production module are typically done manually by a domain expert

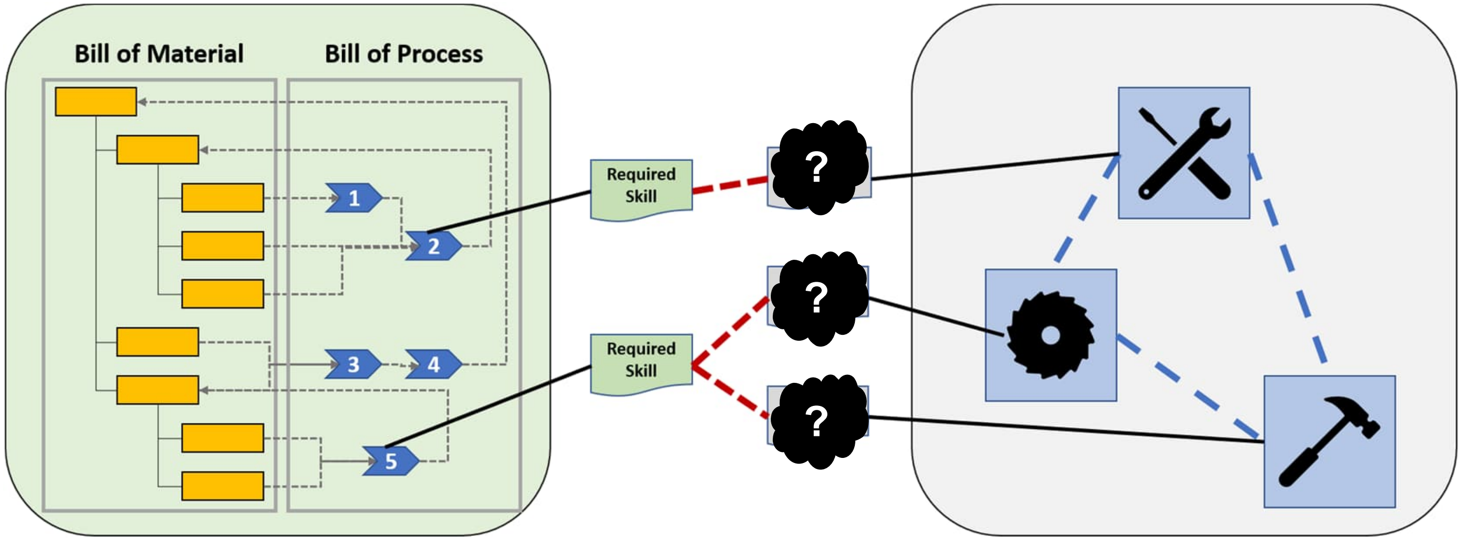
➢ Equip machines with explicit digitized skill descriptions, detailing their capabilities

Automatic skill description learning would minimize the labor time and domain expertise needed to equip production modules with their descriptions.

Siemens Use Case: Skill Description Learning

Given:

- Production log data – instance data
- Production ontology – background data



Desired: Skill descriptions of machines

Skill Description Learning: Data

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Knowledge base – ontologies:

- Process: Ontology modeling all operations that can be carried out at the production plant
- Production: Ontology modeling the equipment of the production plant, especially the machines
- Product: Ontology modeling the building blocks of the products

Setting:

- Number of concepts: 83
- Number of individuals: 79
- Number of data properties: 18
- Number of object properties: 6
- Number of learning problems: 23

Skill Description Learning: Example

Positive examples: Operation instances of the skill “Inserting by Module 1”
(**Negative examples**: Operation instances of other skills than “Inserting by Module 1”)

Background knowledge: domain knowledge regarding operations and corresponding instances e.g., material used in instances

Desired class expression examples:

- Involves initial material roof 1 and base 2
- Has resulting material base 1 connected with roof 1
- Resulting material has orientation value 180
- Has optimization parameter value “quality“
- …

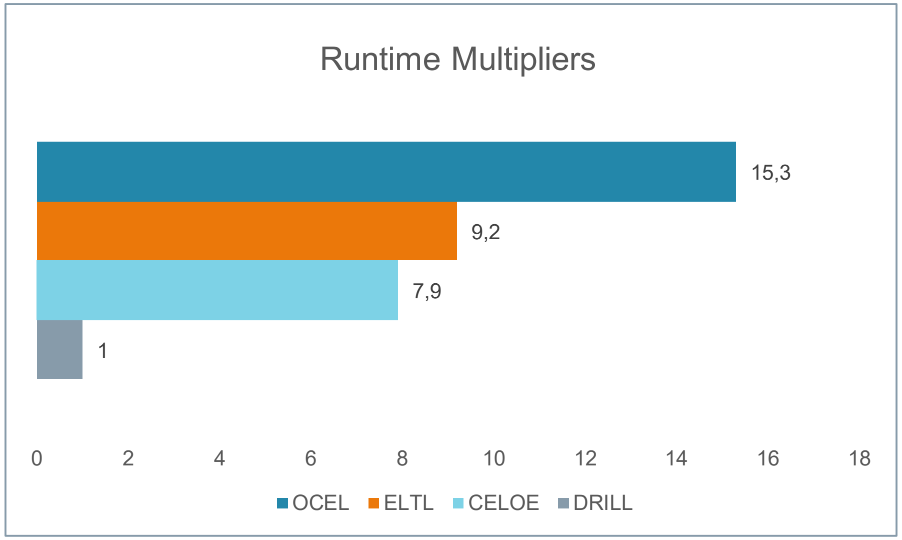
We want to arrive at a complete and precise description for the skill.

Siemens Use Case: Skill Description Learning

- Creation of ontology for the use case
- Adaptation of ontology for the methodology
- Application of DRILL
- Evaluation of machine learning results and discussion (with UPB)
- Application of verbalization component
- Evaluation of verbalization results and discussion (with ULEI)

DRILL Experiments Results: Quantitative

	F-measure (mean)	F-measure (std)	Accuracy (mean)	Accuracy (std)
DRILL	**1**	0.02	**1**	0
CELOE	**1**	0	**1**	0
OCEL	-0.01	0	0.96	0.21
ELTL	0.91	0.24	0.97	0.11
	NumClassTested (mean)	NumClassTested (std)	Runtime (mean)	Runtime (std)
DRILL	285.83	846.34	**0.39**	0.59
CELOE	223.70	521.92	3.07	0.23
OCEL	7520.48	3154.19	5.98	0.04
ELTL	-1	0	3.57	1.14



- The mean and standard deviation are calculated using all 23 learning problems
- DRILL and CELOE both have perfect F-measure and accuracy

DRILL Experiments Results: Qualitative

Expected Outcome	DRILL	CELOE	OCEL	ELTL
hasPositionParam_0 ⊓ hasOptimizationParamQuality ⊓ hasOrientationParam_0 ⊓ hasPunchingText_ ⊓ involvesInitialMaterialBase2	**hasPositionParam_0 ⊓ involvesInitialMaterialBase2**	ChargingByEmptyModule1	ChargingByEmpty Module1	ChargingByEmpty Module1
hasOptimizationParamQuality ⊓ hasOrientationParam_0 ⊓ hasPunchingText_ ⊓ involvesInitialMaterialPlate1 ⊓ ((hasPositionParam_4 ⊓ involvesInitialMaterialBase2) ⊔ hasPositionParam_0))	**involvesInitialMaterialBase2 ⊓ involvesInitialMaterialPlate1**	involvesInitialMaterialPlate1 ⊓ (PunchingByIndustrialRobot1 ⊔ (InsertingByIndustrialRobot1 ⊓ involvesInitialMaterialBase2))	null	hasPunchingText_ ⊓ involvesInitialMaterial Plate1

- For DRILL, we can include an “exclude concept” functionality to avoid trivial concepts. This functionality improves the qualitative results while there is a quantitative results trade-off.
- For CELOE, 18 out of 23 target expressions are highly trivial; same for OCEL, with another two null results. For ELTL, at least 16 out of 23 predictions are equally trivial, while for DRILL, there are no obviously trivial results.

Verbalization Results: Examples

DRILL Class Expression:

(hasPositionParam_0 ⊓ involvesInitialMaterialBase2)

Verbalization:

Every charging by empty module 1 has position parameter 0 whose an involves initial material base 2.

DRILL Class Expression:

(hasPositionParam_1 ⊓ hasPunchingText_)

Verbalization:

Every inserting by assembly module 2 is a has position parameter 1 whose a has no punching text.

DRILL Class Expression:

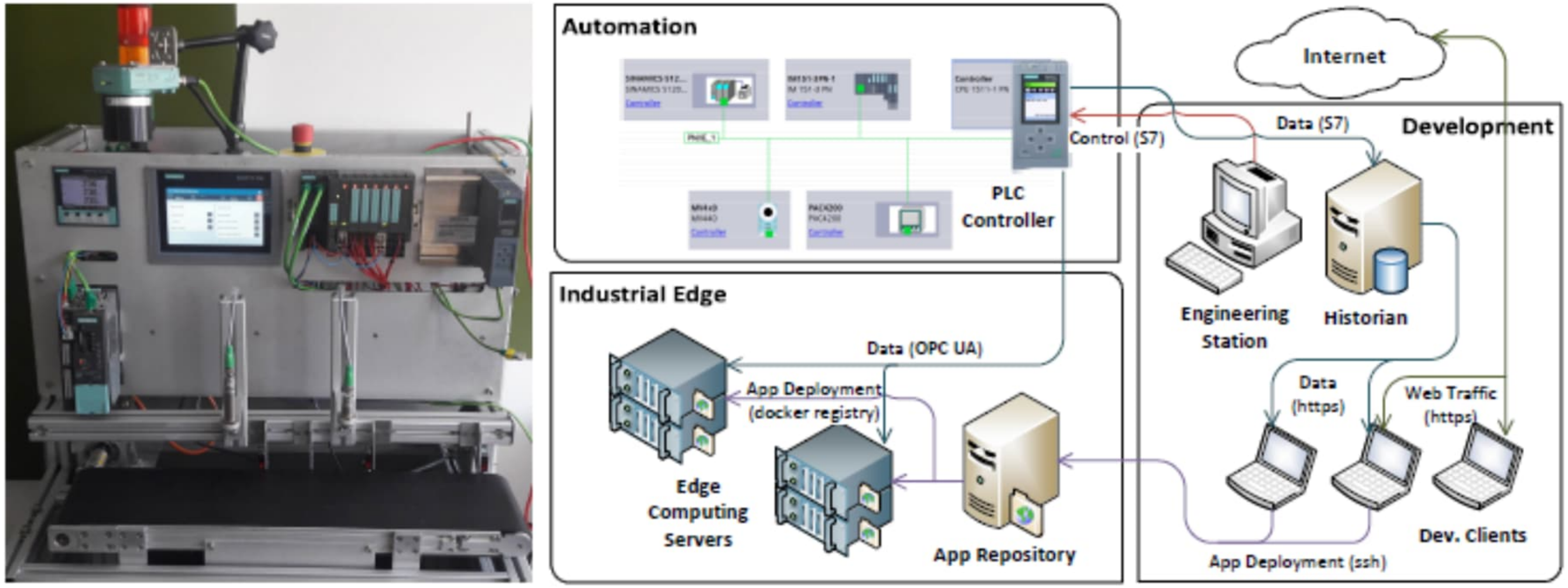
(hasPositionParam_4 ⊓ (involvesInitialMaterialBase2 ⊓ (involvesInitialMaterialBlock4 ⊔ involvesInitialMaterialPlate1)))

Verbalization:

Every industrial robot 1 is a has position parameter 4 whose an involves initial material base 2 whose an involves initial material block 4 or an involves initial material plate 1.

Outlook

➢ Use case for prototpye 2: intrusion detection in cybersecurity



Demonstrator System for Cybersecurity Use Case

Selected Publications

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- "Ontology-based Skill Description Learning for Flexible Production Systems", Himmelhuber, A., Grimm, S., Runkler, T., Zillner, S., ETFA 2020, Vienna
- "Skill Description Learning: Wissen über Maschinen rekonstruieren", Pressemeldung, see https://raki-projekt.de/news/2020-26-05-Skill-Description-Learning
- "Neural Multi-Hop Reasoning With Logical Rules on Biomedical Knowledge Graphs", Liu, Y., Hildebrandt, M., Joblin, M., Ringsquandl, M., Raissouni, R., Tresp, V., ESWC 2021
- " A New Concept for Explaining Graph Neural Networks ", Himmelhuber, A., Grimm, S., Zillner, S., Ringsquandl, M., Joblin, M. and Runkler, T., International Workshop on Neural-Symbolic Learning and Reasoning 2021
- "Combining Sub-symbolic and Symbolic Methods for Explainability ", Himmelhuber, A., Grimm, S., Zillner, S., Joblin, M., Ringsquandl, M. and Runkler, T., International Joint Conference on Rules and Reasoning 2021
- "TLogic: Temporal Logical Rules for Explainable Link Forecasting on Temporal Knowledge Graphs", Liu, Y., Ma, Y., Hildebrandt, M., Joblin, M., Tresp, V., AAAI 2022

Besten Dank für die Aufmerksamkeit!

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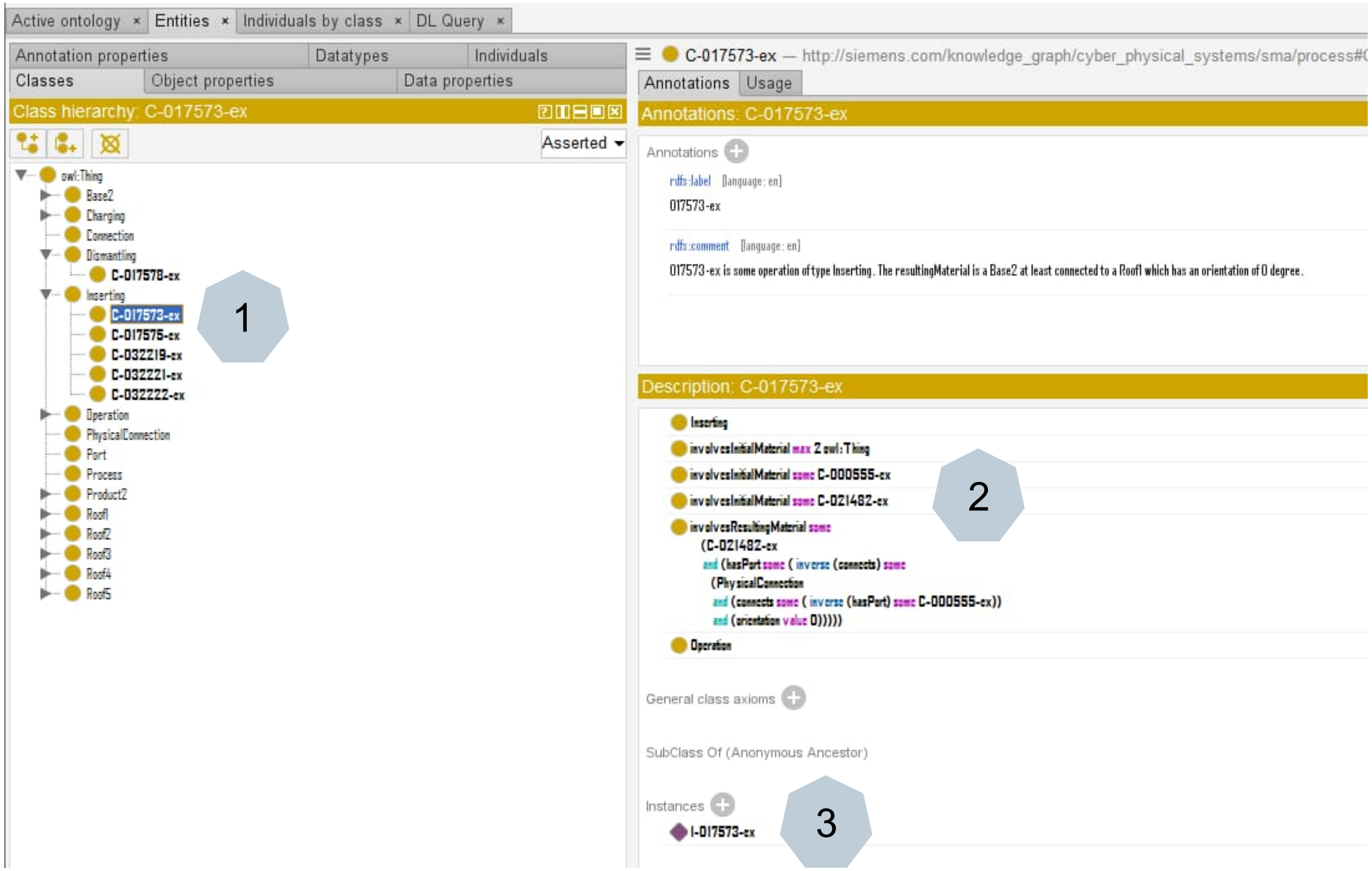
Skill Description Learning: Ontology



1. Operation of the skill “Inserting by Module 1”
2. Background knowledge regarding the operation, e.g., material involved
3. Instance of the operation

DRILL Experiments Results: Quantitative

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	F-measure (mean)	F-measure (std)	Accuracy (mean)	Accuracy (std)	NumClassTested (mean)	NumClassTested (std)	Runtime (mean)	Runtime (std)
DRILL	0.77	0.23	0.96	0.04	6326.04	5293.18	3.21	1.96
CELOE	1	0	1	0	223.7	521.92	3.87	0.35
OCEL	-0.01	0	0.91	0.28	7192.78	3024.48	6.76	0.26
ELTL	0.91	0.24	0.97	0.11	-1	0	4.32	1.13

- The mean and standard deviation are calculated using all 23 learning problems.
- DRILL has lower F-measure than the DL-Learner algorithms, while the accuracy performance is comparable. This could be due to the fact that DRILL excludes certain concepts in the class expressions, which makes the learning more difficult, while the DL-Learner algorithms could provide trivial solutions with better performance.
- DRILL tests a significantly higher number of classes than CELOE (around 30 times more) and slightly fewer classes than OCEL.
- DRILL only needs around the same time as CELOE and half the runtime as OCEL, showing the scalability of the approach.