



TECHNISCHE
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INSTITUTE OF
MANAGEMENT SCIENCE
Research Group of Production and
Maintenance Management

Knowledge Management 4.0

Dipl.-Ing. Theresa Madreiter

April 18, 2023

About Me

Dipl.-Ing. Theresa Madreiter



Education

- Master's degree in Mechanical Engineering - Management, TU Wien, 2020
- Ongoing: Ph.D. in Mechanical Engineering – Management, TU Wien

Areas of Research Interests

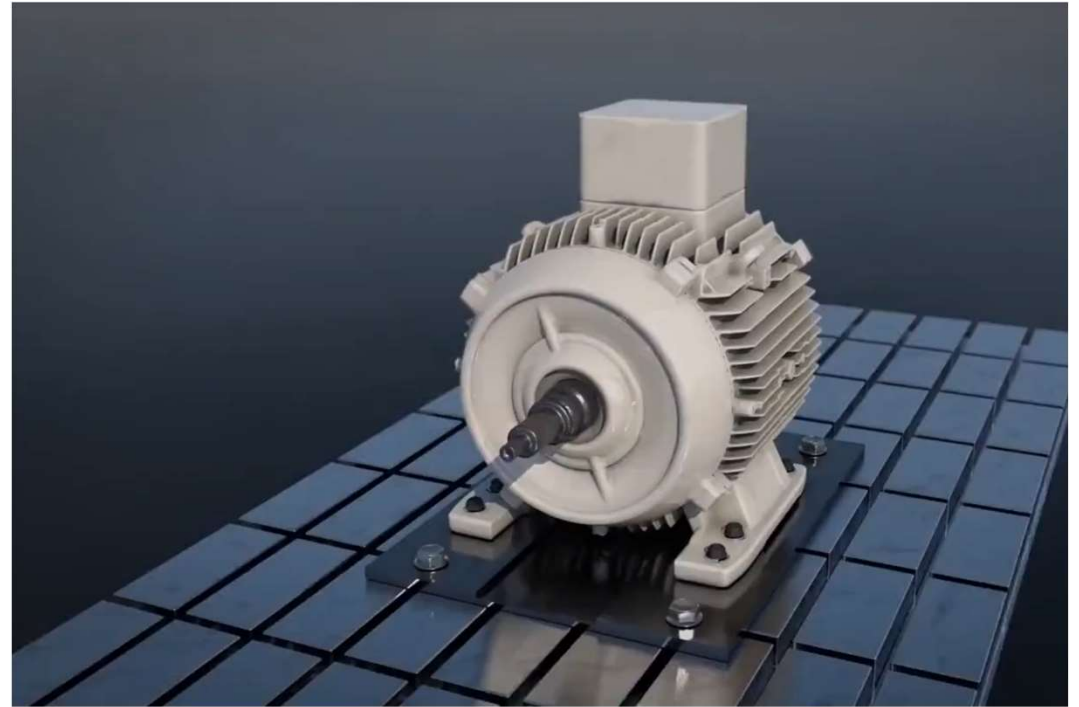
- Predictive & Prescriptive Maintenance
- Knowledge Discovery from Text
- Semantic Technology, NLP
- Predictive Data Analytics and Machine Learning



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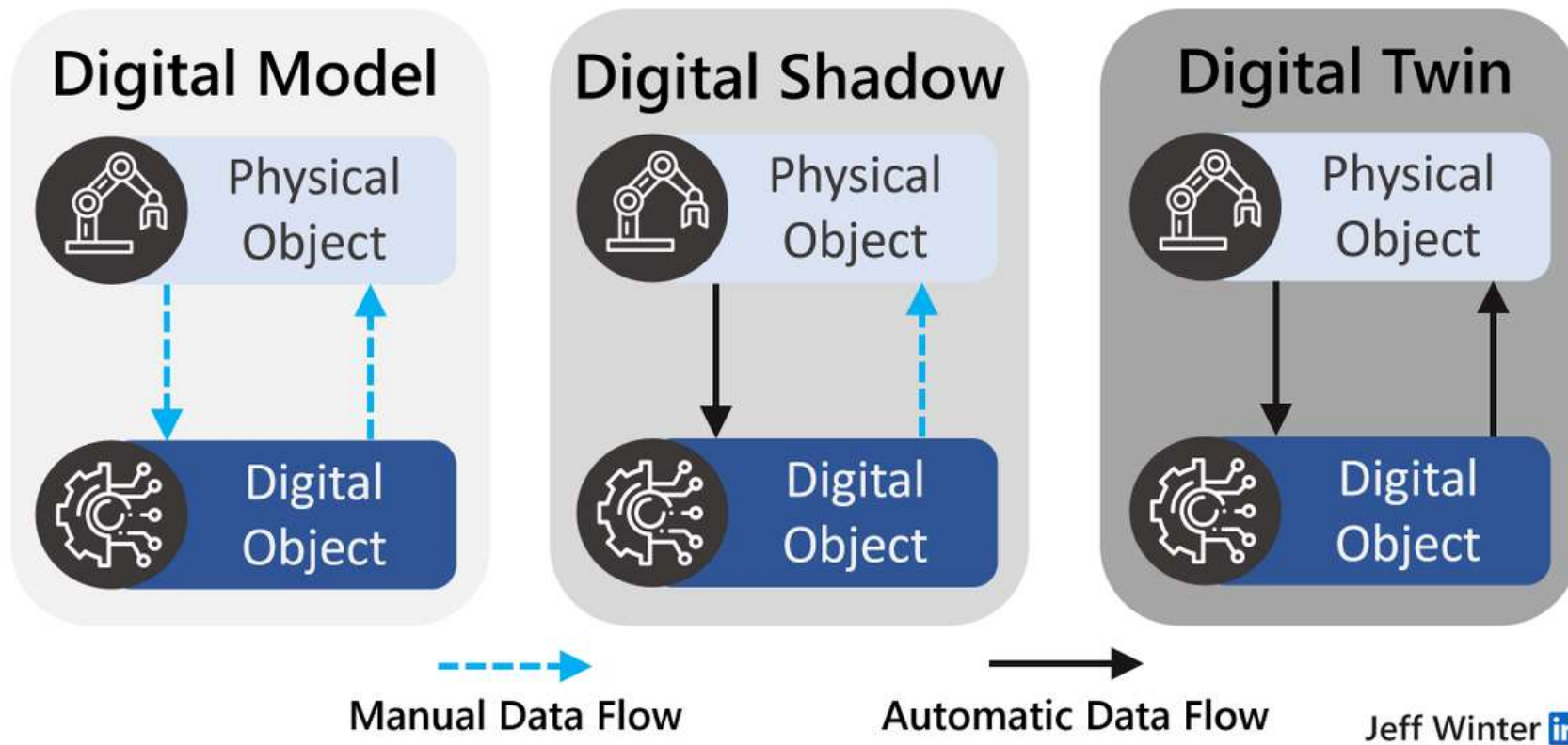
LAST WEEK...



WHAT IS A DIGITAL TWIN?

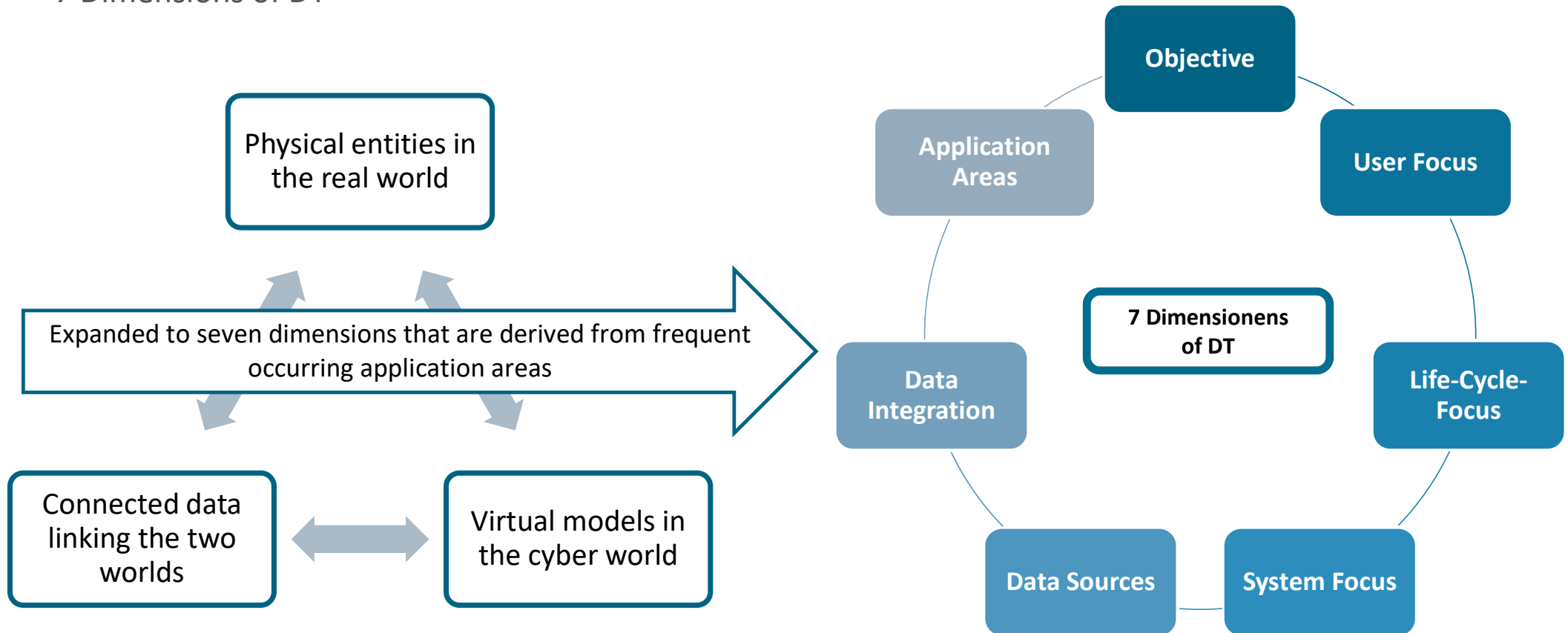
What is a Digital Shadow vs. Digital Model vs. Digital Twin?

Relationship Between the Physical World & Digital World

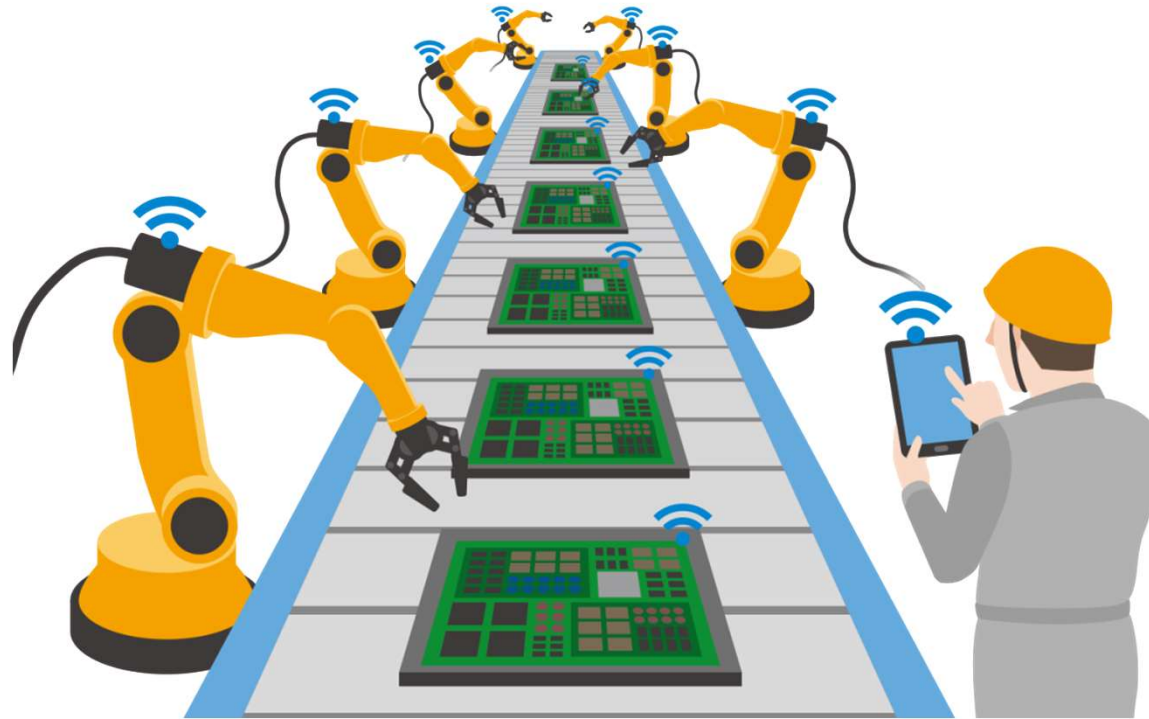


Digital Twin (DT) in Manufacturing and Maintenance

7 Dimensions of DT



Hochhalter, J., Leser, W. P., Newman, J. A., Gupta, V. K., Yamakov, V., Cornell, S. R., et al. (2014). Coupling DamageSensing Particles to the Digital Twin Concept

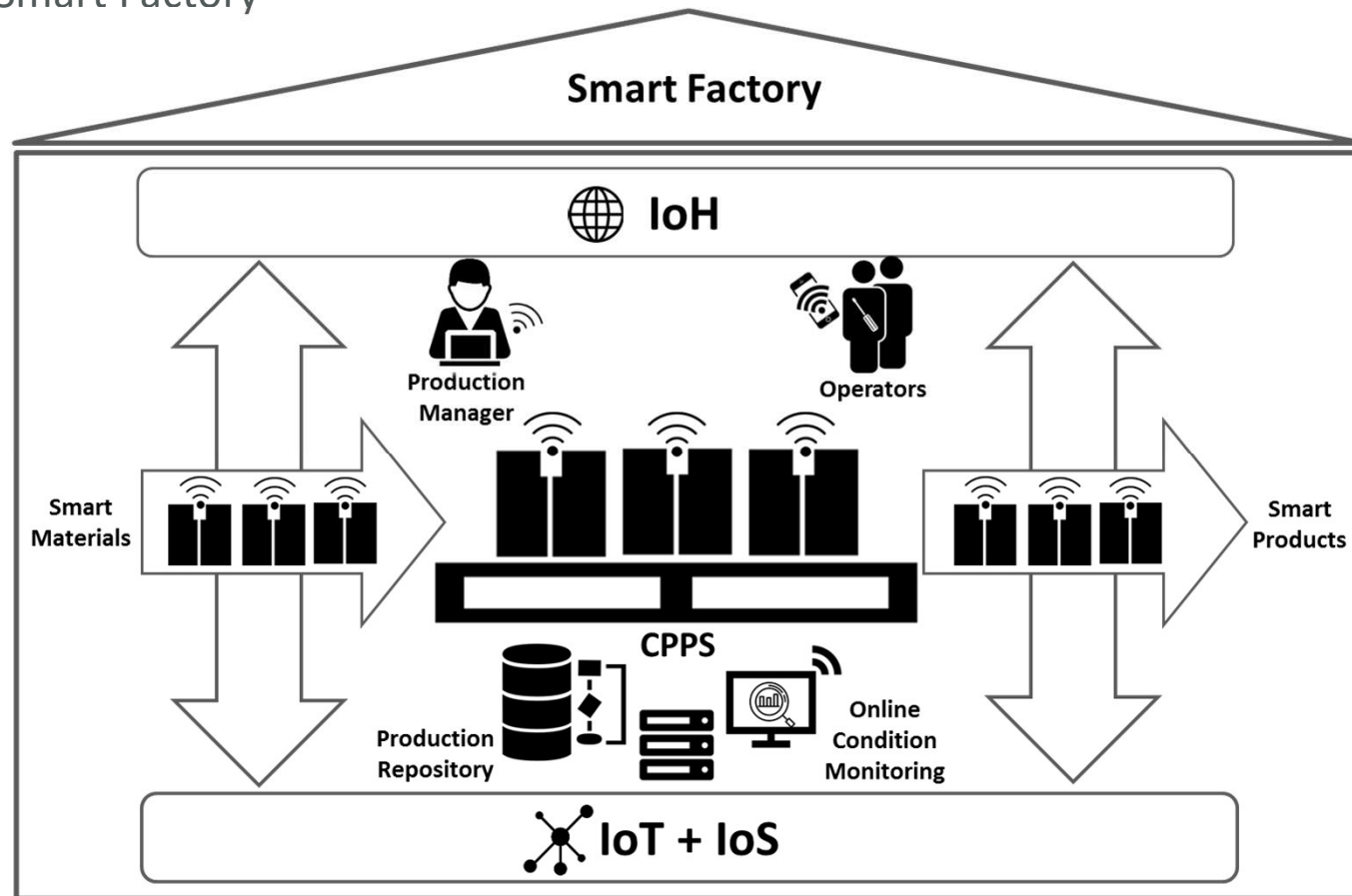


WHAT IS A SMART FACTORY?

Source of picture: <https://www.baslerweb.com/en/vision-campus/markets-and-applications/image-processing-industry-4-0/>

Cyber Physical Production Systems (CPPS) – Abstract Architecture

Utilizing CPS in a Smart Factory



IoT= Internet of Things
IoH=Internet of Human
IoS= Internet of Software

Source: F. Ansari, P. Hold, W. Sihn, Human-Centered Cyber Physical Production System: How Does Industry 4.0 impact on Decision-Making Tasks? IEEE TEMSOCN,



WHAT IS INDUSTRIAL AI?



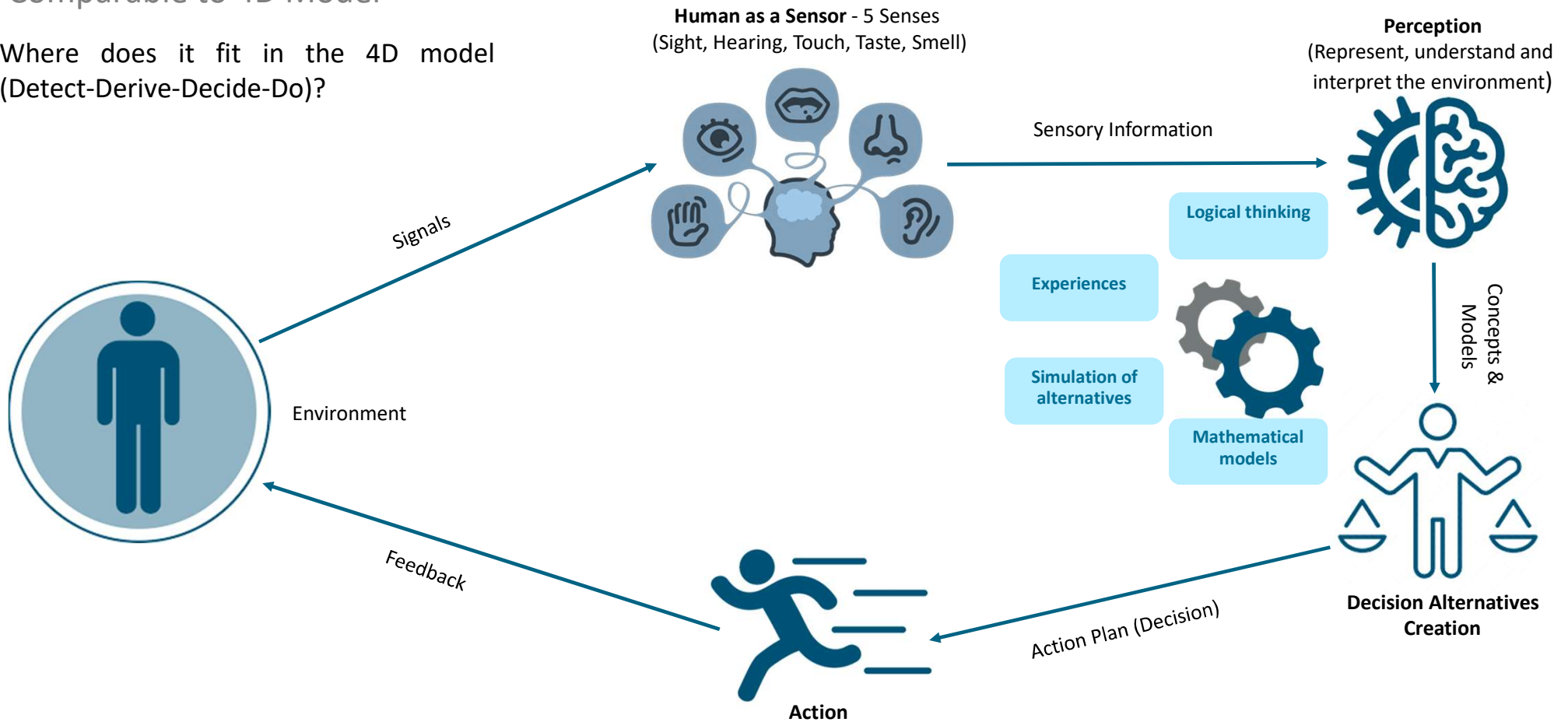
INTRODUCTION TO INDUSTRIAL AI

– AI, MACHINE LEARNING, DEEP LEARNING

Human Decision-Making Process

Comparable to 4D Model

Where does it fit in the 4D model
(Detect-Derive-Decide-Do)?



Human Intelligence

Definitions

- The ability to comprehend; to understand and profit from experience (Oxford Dictionary)



What is Cognitive Science and Cognitive Computing?

Cognitive Science (CS)

Multi- & Interdisciplinary

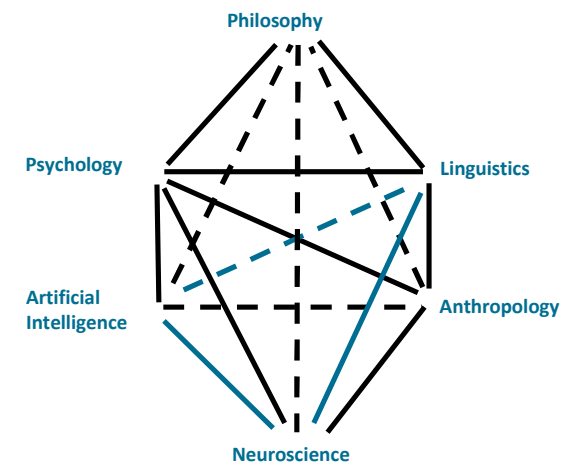
- CS aims to understand how human brain (as a complex system) works.
- Cognitive abilities like perception, thinking, learning, motoric and speech are being examined and modelled.
- To understand this system only slightly at all – it's necessary to illuminate it from all sides.
- According to Stanford Encyclopedia of Philosophy, CS is the interdisciplinary study of mind and intelligence, embracing
 - Philosophy
 - Psychology
 - Artificial intelligence
 - Neurosciences
 - Linguistics
 - Anthropology (Origins and social relationships of human beings)
 - (Other disciplines such Education, physiology, etc.)

Sources:

G. A. Miller, The cognitive revolution: a historical perspective, *Trends in cognitive sciences* 7.3 (2003): 141-144.

Cognitive Science, Stanford Encyclopedia of Philosophy, 2014, <https://plato.stanford.edu/entries/cognitive-science/>

Howard Gardner's Hexagon



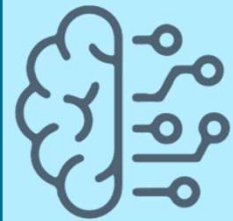
Connections among the Cognitive Science

Unbroken Lines = Strong interdisciplinary ties

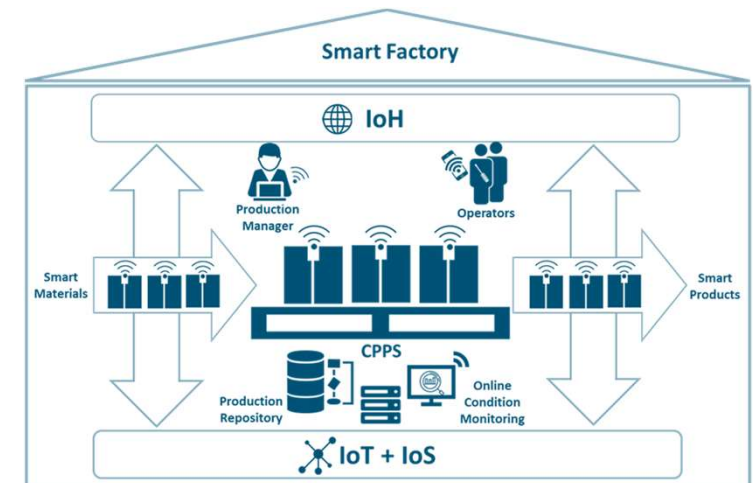
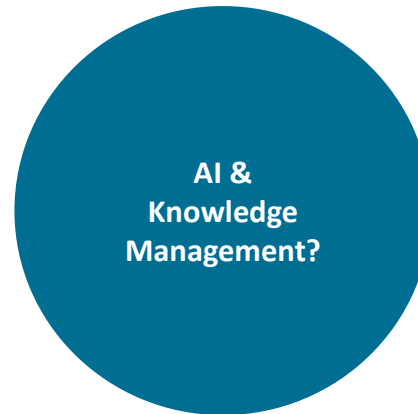
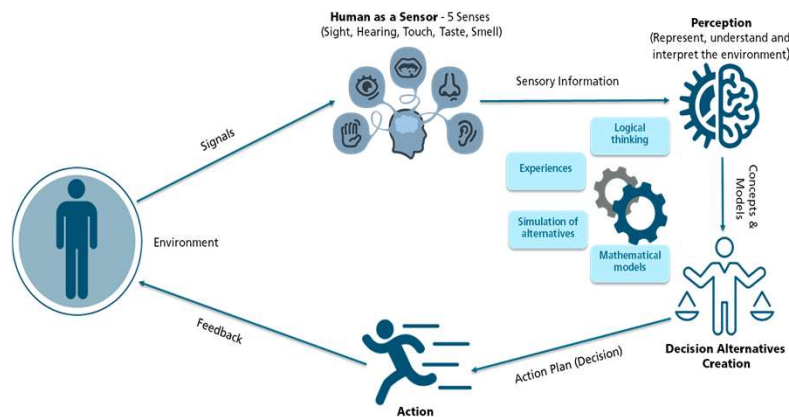
Broken Lines = Weak interdisciplinary ties

Cognitive Computing

Enabler to Imitate Human Decision-Making Models



Cognitive computing aims at handling human kinds of problems and transferring human (complex) decision-making processes to artificial models and computable algorithms.



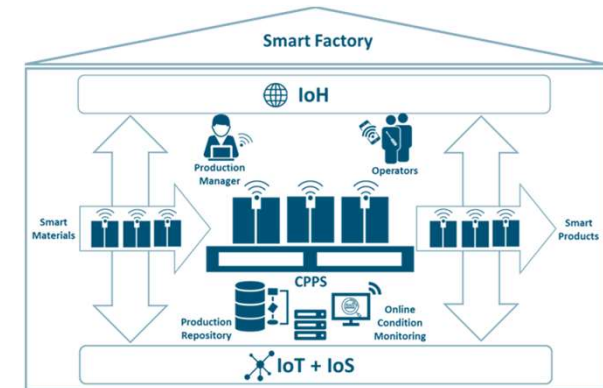
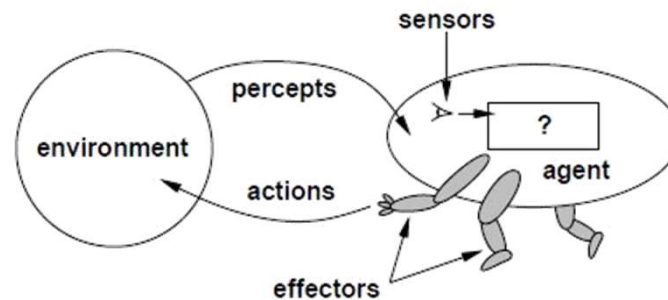
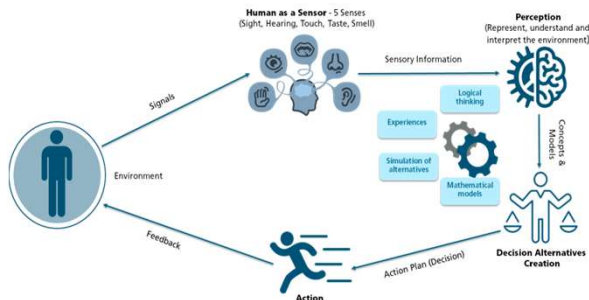
Sources:

J. E. Kelly, J.E. and S. Hamm, Smart Machines: IBM's Watson and the Era of Cognitive Computing; Columbia Business School Publishing: New York, 2013.

F. Ansari, et al., Problem Solving in the Digital World: Synoptic Formalism, Incrementalism and Heuristics, Encyclopedia of Computer Science and Technology, 2nd Edition; Laplante, P., Ed.; Taylor & Francis: New York, 2017.

What is Artificial Intelligence (AI)?

Russell & Norvig defined Four Possible Goals for AI



Processing and Reasoning	Thinking Humanly Systems that Think like humans	Thinking Rationally Systems & Agents that Think rationally.
Behavior-Based	Acting Humanly Systems that Act like humans	Acting Rationally Systems & Agents that Act rationally
	Human-Based	Ideal Rationality

Russell, S. & Norvig, P., 2009, Artificial Intelligence: A Modern Approach 3rd edition, Saddle River, NJ: Prentice Hall.

Artificial Intelligence, Stanford Encyclopedia of Philosophy, 2018, Link: <https://plato.stanford.edu/entries/artificial-intelligence/#Rel>

Artificial Intelligence (AI)

What is AI?

AI is defined as a subfield of computer science

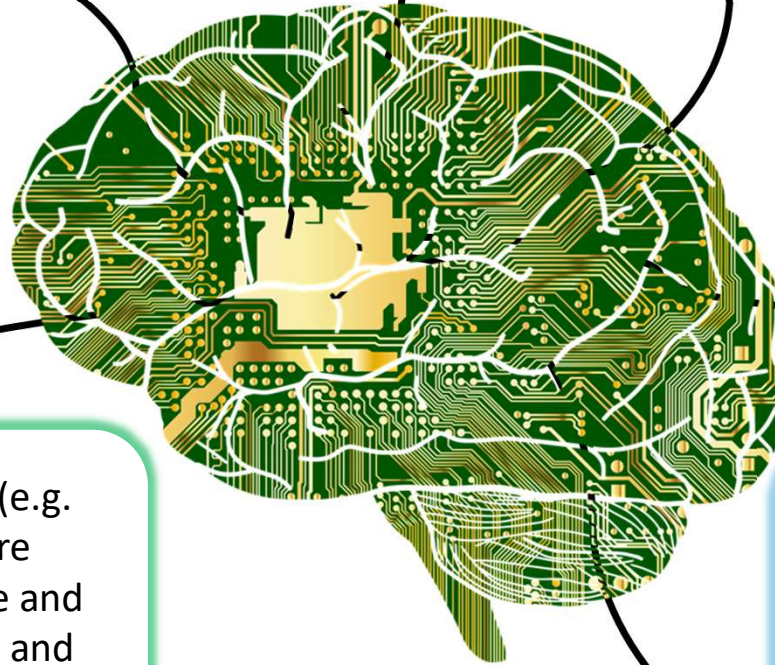
AI includes reasoning, learning and self-improvement

AI is already used in business applications (e.g. automation, data analytics, NLP)

Due to the emphasis on learning, Machine Learning is considered one of the central sub-areas of AI

Process intelligence technologies (e.g. Process Mining, Data Mining) are providing companies with accurate and comprehensive insight to monitor and improve operations in real-time

AI aims to develop data-based algorithms whose functions are typically associated with human intelligence

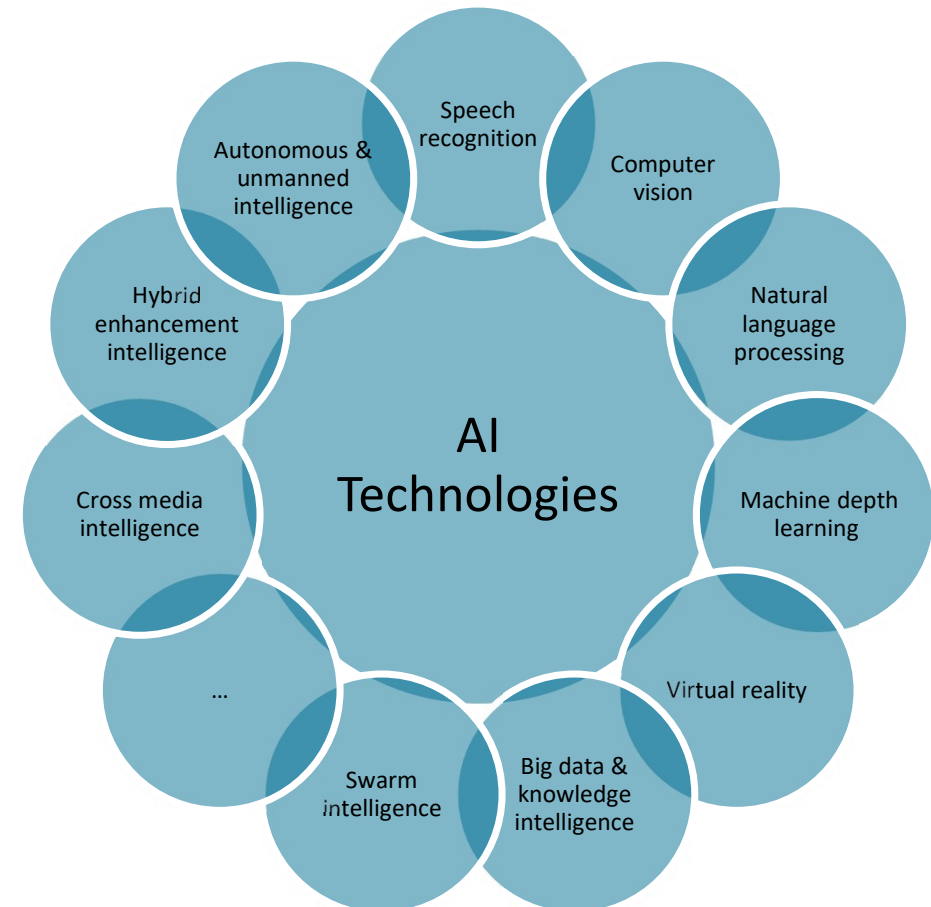


Ansari, F.; Kohl, L.; Giner J. & Meier, H. (2021). Text mining for AI enhanced failure detection and availability optimization in production systems.

Industrial AI as an Enabling Technology for Industry 4.0

Definition & Views

I-AI is a deep integration of AI technology and industrial process, in which industrial **enterprises** take AI technologies to achieve **intelligent function** in all stages of **industrial value chain**, including customer demand, R & D design, operation management, production and processing, service, and other activities.



Zhang, Xianyu, et al. "A reference framework and overall planning of industrial artificial intelligence (I-AI) for new application scenarios." The International Journal of Advanced Manufacturing Technology 101.9-12 (2019): 2367-2389.

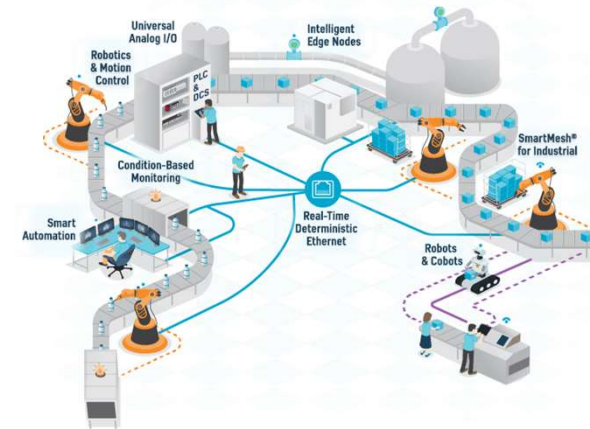
Industrial AI

What is Industrial AI?

Industrial AI can be defined as a systematic discipline focusing on the:

- **development**
- **validation**
- **deployment and**
- **maintenance**

of AI solutions for industrial applications with sustainable performance



From an industrial point of view, AI technologies can be seen as enablers for systems to

- **perceive their environment**
- **process the data they acquire and**
- **solve complex problems and make decisions**

as well as to **learn from experience** in order to improve their capability to solve specific tasks

The 5 dimensions of Industrial AI

Industrial AI distinguishes itself within the field of AI in...

1. Infrastructures

Regarding hardware and software, there is a large emphasis on real-time processing capabilities, ensuring reliability with high security requirements and interconnectivity

2. Data

Industrial AI requires data characterized by its large volume, high velocity variety, originating from various units, products, etc.

3. Algorithms

It requires the integration of physical, digital and heuristic knowledge. High complexity derived from model management, deployment and governance

Peres, R., et al. (2020). Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook.

The 5 dimensions of Industrial AI

Industrial AI distinguishes itself within the field of AI in...

4. Decision-making

Given the industrial setting, tolerance for error is generally very low. Efficiency is of special importance for large-scale optimization problems

5. Objectives

Industrial AI addresses mostly concrete value creation through a combination of factors such as scrap reduction, improved quality, augmented operator performance or accelerated ramp-up times

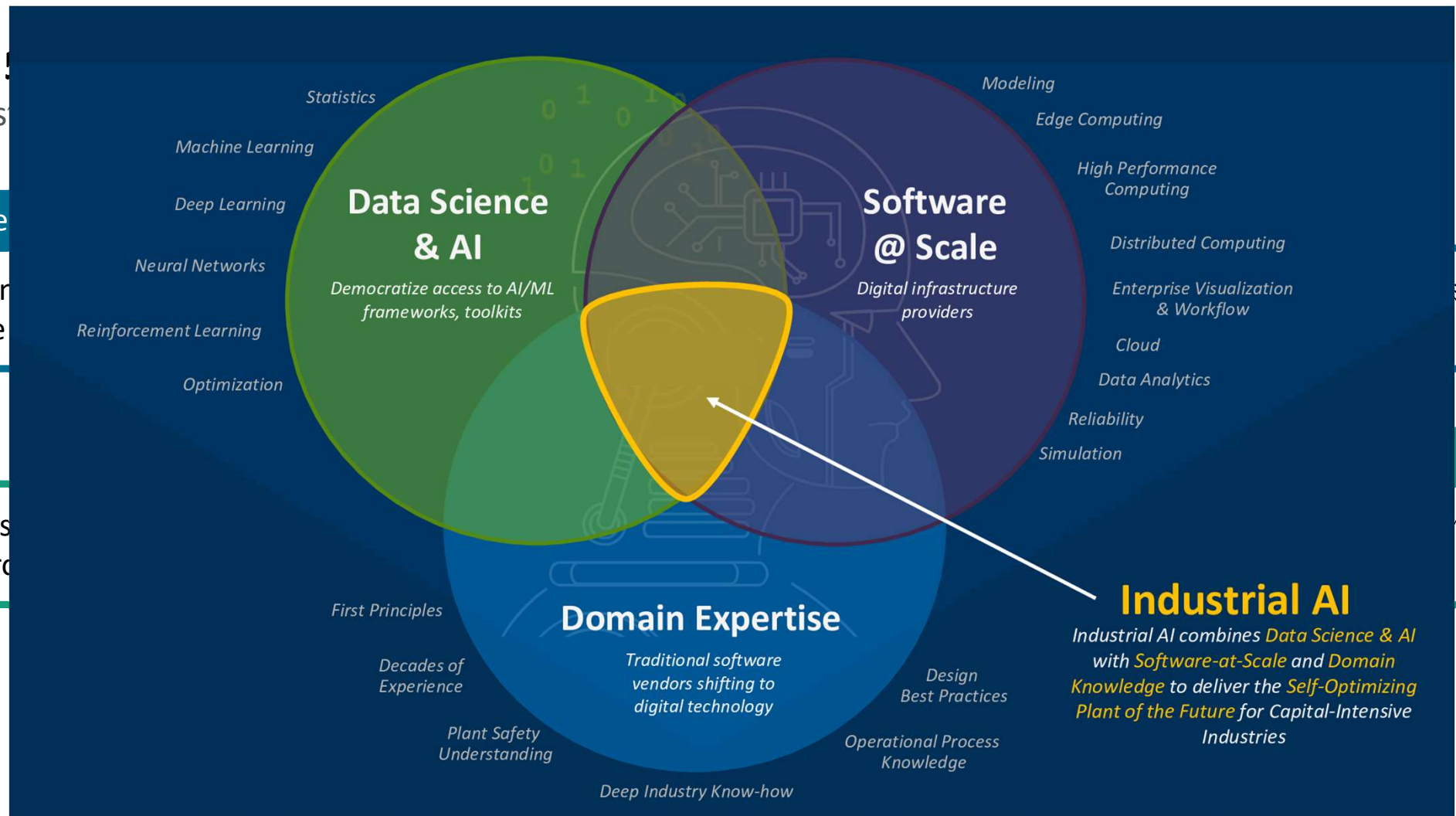
Peres, R., et al. (2020). Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook.

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<https://www.technologyreview.com/2021/06/28/1026960/the-future-starts-with-industrial-ai/>

Data in Manufacturing

Facts and Numbers

An effective use

- data and i
- data quali
- correct int

1TB

of **data is generated**
in an average factory
today

91%

of industrial
companies **invest in**
the development of
Smart Factories

20%

increase in
productivity is
possible through
Smart Factories

<1%

of data collected in
factories is **currently**

39%

of factories today
already use

66%

of factories will rely
on **predictive**

<1%

of data collected in
factories is **currently**
being evaluated
and used

39%

of factories today
already use
interconnected
sensors

66%

of factories will rely
on **predictive**
maintenance in the
future

Source: Microsoft, IBM, PWC

acquired from

(e.g., machines, pr
and additiona

very noisy


complete, incorrect,
onsistent)

Data in Manufacturing

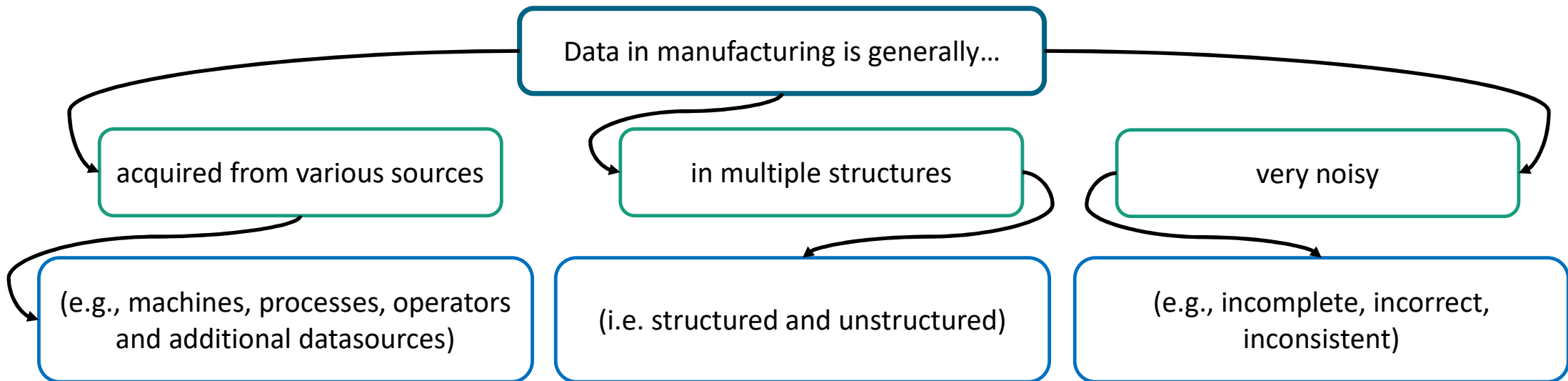
Facts and Numbers

An effective use of AI technologies depends largely on the existence of

- data and its structure
- data quality
- correct interpretation of discovered knowledge



Therefore, data pre-processing and feature selection are crucial to achieving optimal results with the developed algorithms



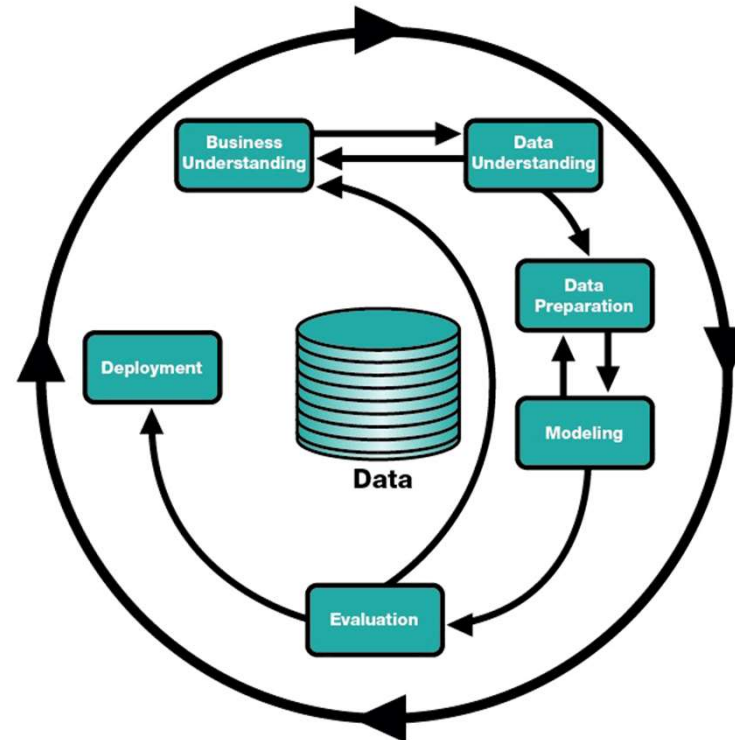
Ansari, F.; Kohl, L.; Giner J. & Meier, H. (2021). Text mining for AI enhanced failure detection and availability optimization in production systems.

CRISP-DM

Cross-Industry Standard Process for Data Mining

CRISP-DM an industry-independent process model for applying data mining projects

It is a six-phase cycle of discovery and action that describes the data mining life cycle



Machine-learning (ML) algorithms are often used when modelling concrete processes on the basis of CRISP-DM

The sequence of these phases is not rigid. There is always interaction between the phases

Artificial Intelligence (AI) vs. Machine Learning (ML) vs. Deep Learning (DL)

An Overview



AI

Computer system(s) that mimics and/or replicates human intelligence



ML

Allows computers to learn on their own (“computers write their own programs”)



DL

Algorithms attempting to model high level abstractions in data, to determine a high level meaning



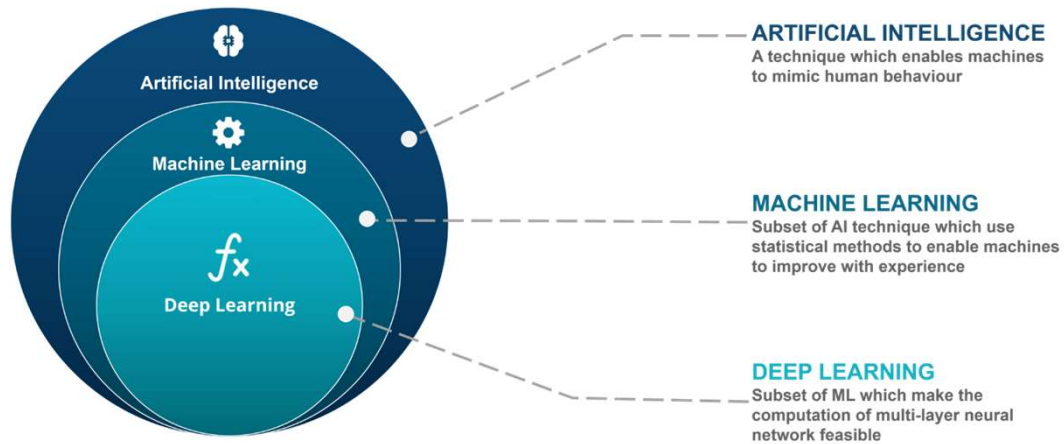
Example

If AI is being used to recognize people’s emotions in pictures, machine learning algorithms would generate thousands of pictures of faces, based on relearned rules, into the system. Deep learning would then help the system recognize patterns in the faces and emotions they share.

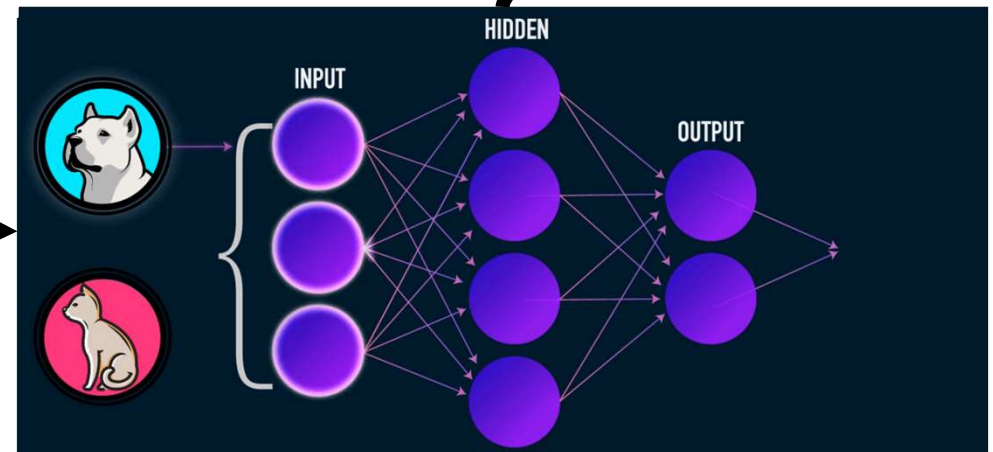
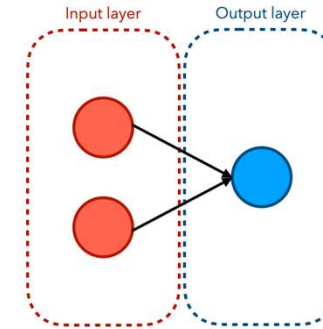
<https://medium.com/@GabriellaLeone/the-best-explanation-machine-learning-vs-deep-learning-d5c123405b11>

Artificial Intelligence (AI) vs. Machine Learning (ML) vs. Deep Learning (DL)

An Overview



<https://cognitive.la/blog/machine-learning-vs-deep-learning>



Machine Learning

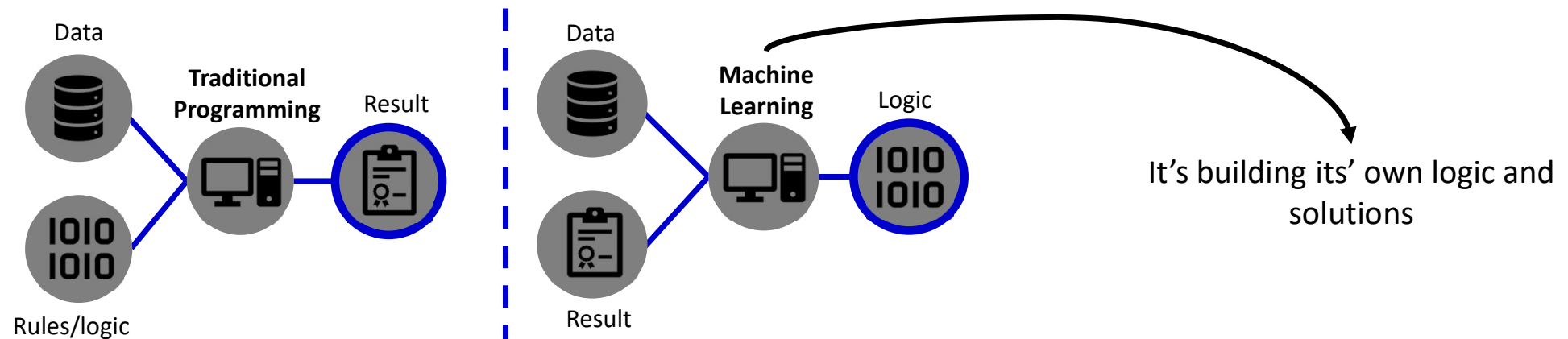
An Overview

Machine Learning

- analyzes data
- learns from it

and uses that to make a prediction/truth/determination depending on the scenario

The machine is training itself, on how to perform a task correctly after learning from all the data it has analyzed

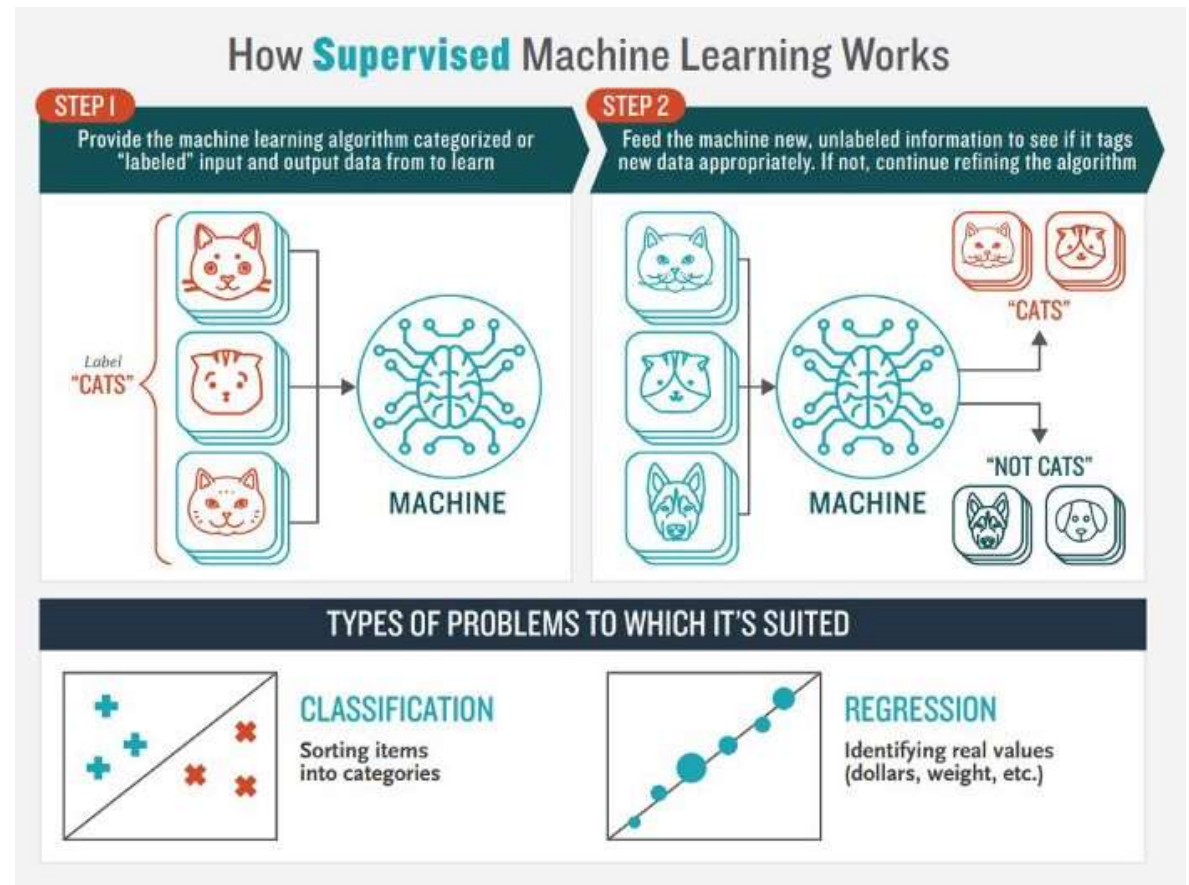


Machine Learning

ML Algorithms

Supervised Learning

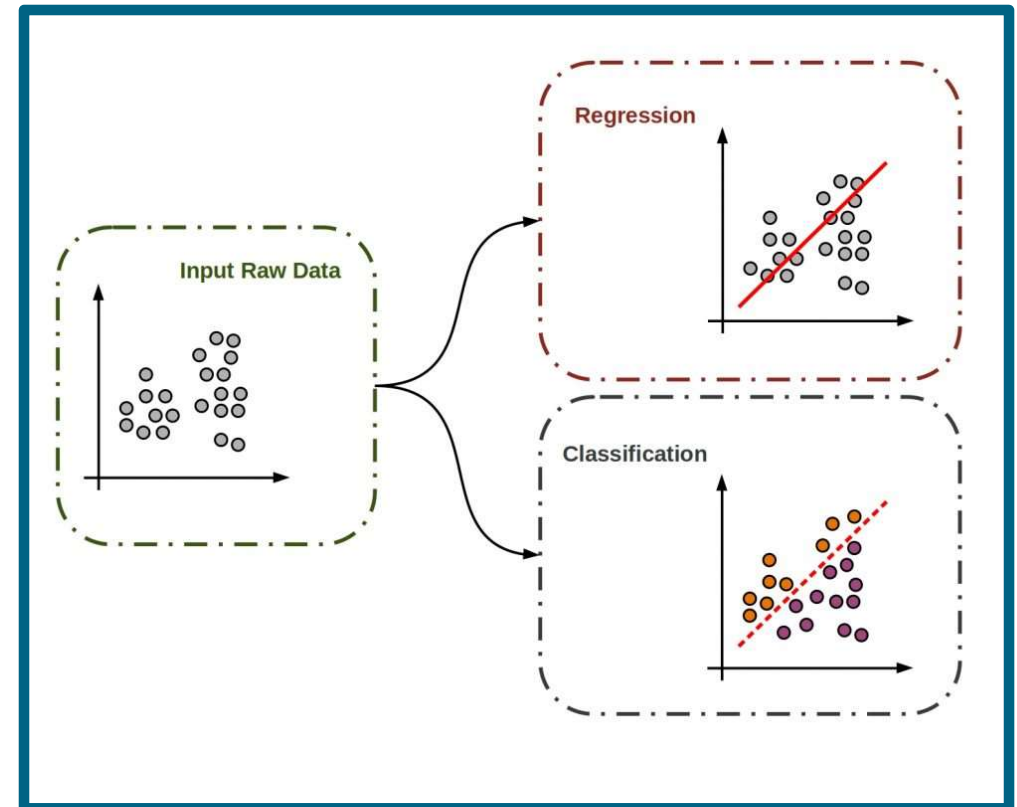
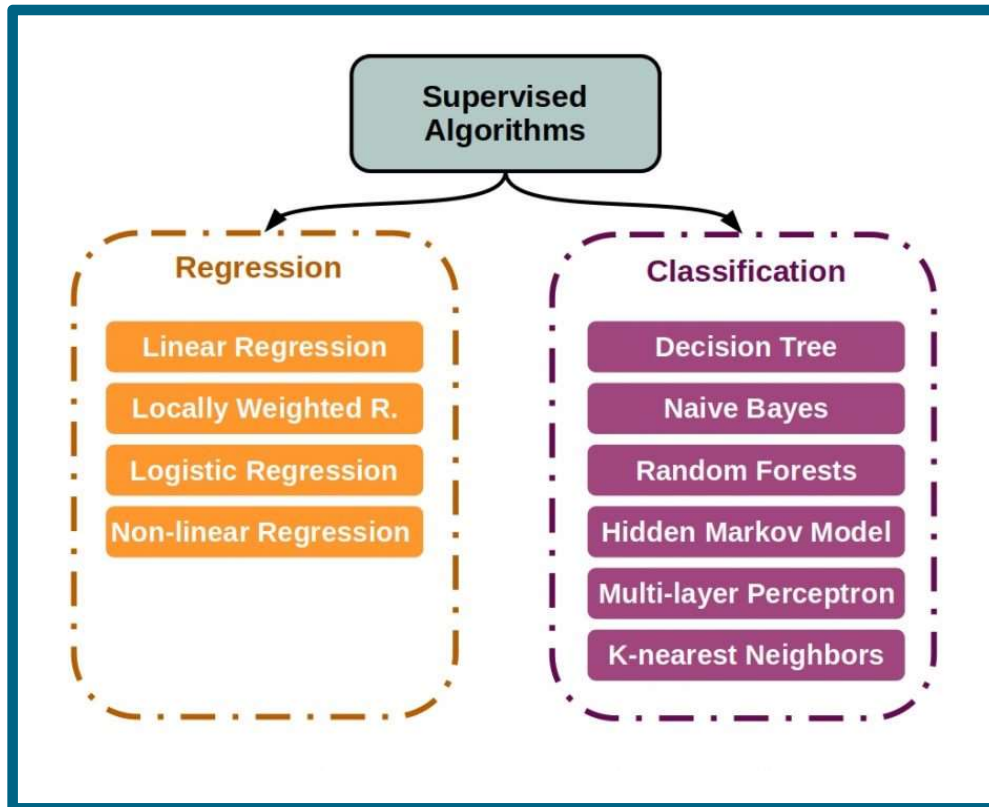
Requires a human to input the data and the correct solution, but allows the machine to figure out the relationship between the two



<https://medium.datadriveninvestor.com/supervised-and-unsupervised-learning-7281050992a0>

Machine Learning

ML Algorithms

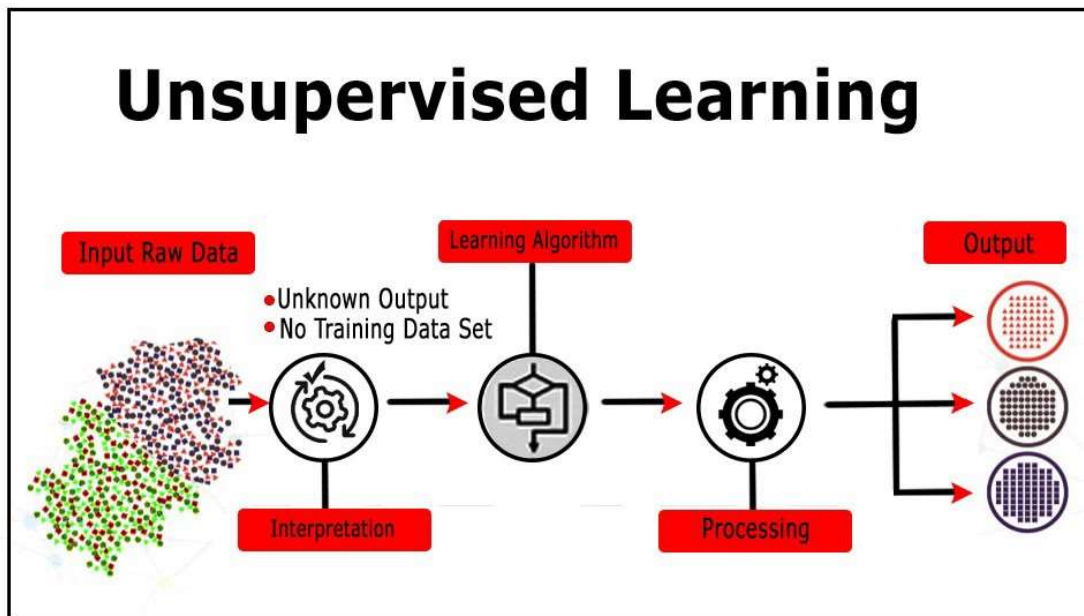


https://starship-knowledge.com/supervised-vs-unsupervised-vs-reinforcement#What_is_reinforcement_learning

Machine Learning

ML Algorithms

Unsupervised Learning



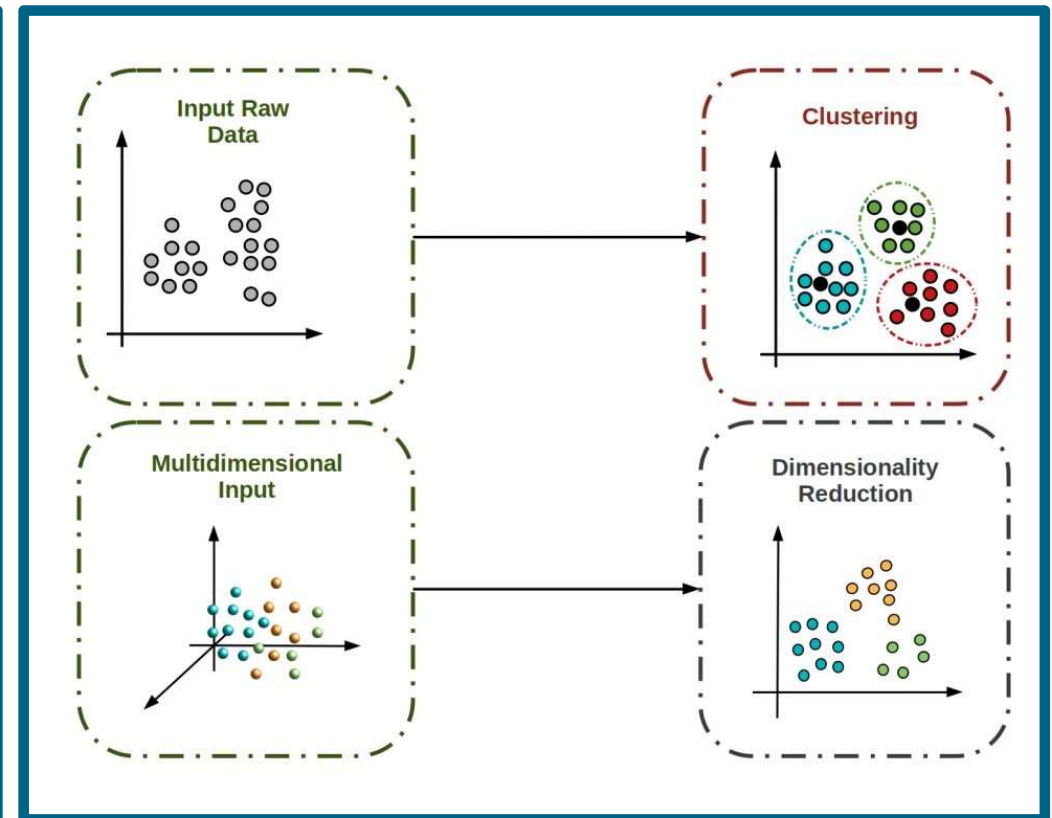
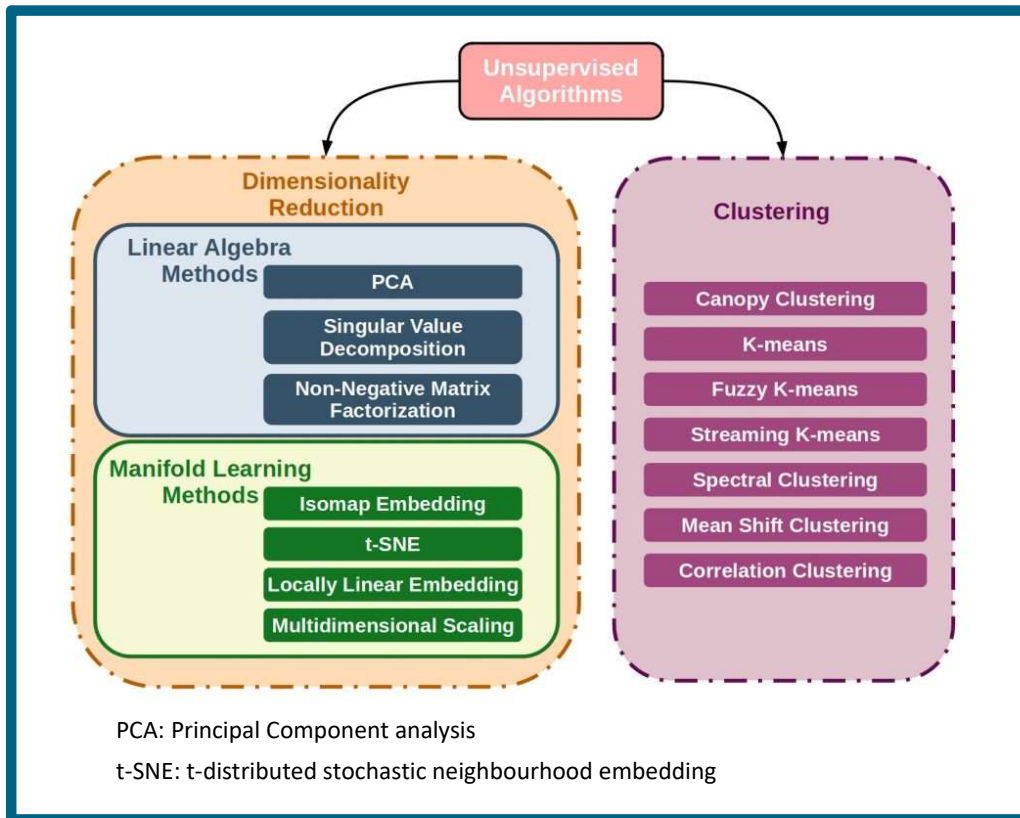
<https://medium.datadriveninvestor.com/supervised-and-unsupervised-learning-7281050992a0>

Unsupervised Learning

The model is handed the data set with no explicit instructions. The model tries to automatically find the structure in data by extracting the features and analyzing the structure.

Machine Learning

ML Algorithms



https://starship-knowledge.com/supervised-vs-unsupervised-vs-reinforcement#What_is_reinforcement_learning

Machine Learning

ML Algorithms

Supervised Learning

Requires a human to input the data and the correct solution, but allows the machine to figure out the relationship between them.

Unsupervised Learning

The model is handed the data set with no explicit instructions. The model tries to automatically find the structure in data by extracting the features and analyzing the structure.

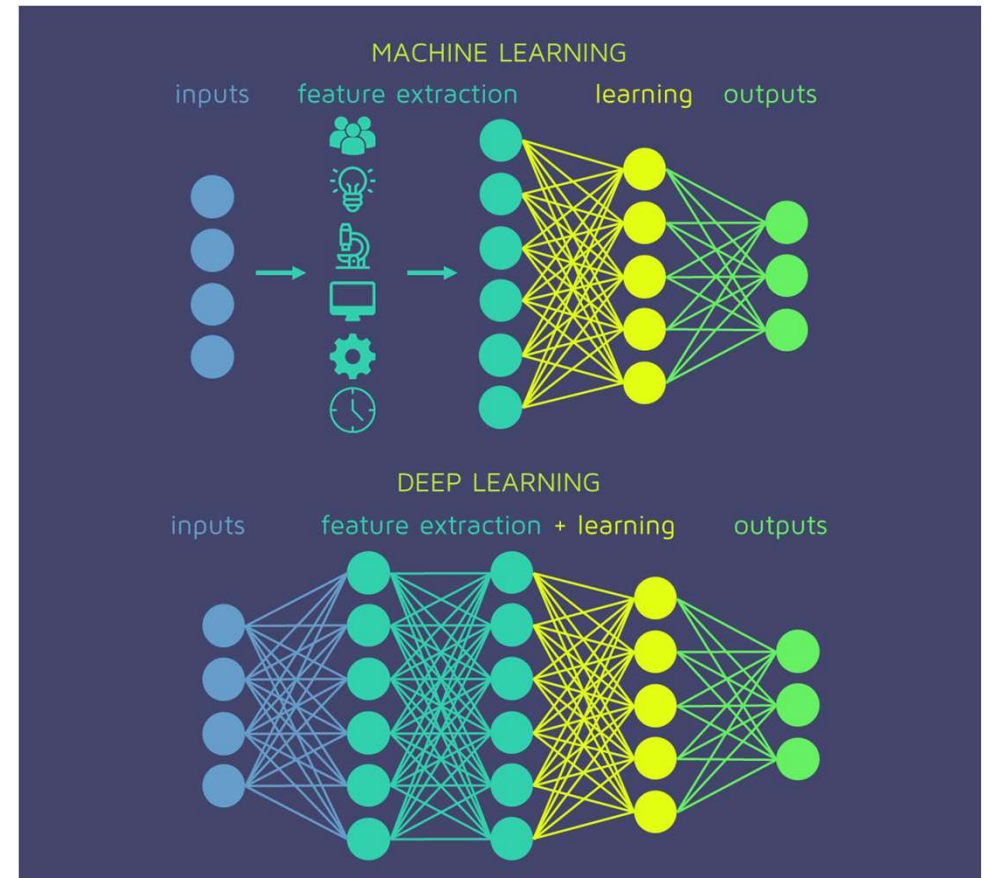
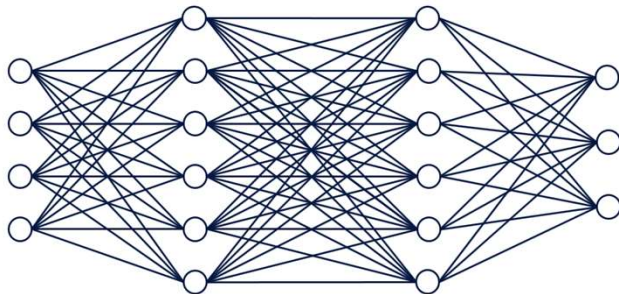
ML eliminates the need for someone to continuously code or analyze data themselves to solve a solution or present a logic

<https://medium.com/@GabriellaLeone/the-best-explanation-machine-learning-vs-deep-learning-d5c123405b11>

Deep Learning

An Overview

- Deep Learning (DL) is a discipline of ML based on deep convolutional neural networks
- Neural networks simulate human decision-making
- DL is best characterized by its layered structure, which is the foundation of artificial neural networks
- Each layer is adding to the knowledge of the previous layer



https://quantdare.com/what-is-the-difference-between-deep-learning-and-machine-learning/deep_learning/

Deep Learning

An Overview

Deep Learning processes more data than machine learning... that is the **main difference**

When you move on to Deep Learning



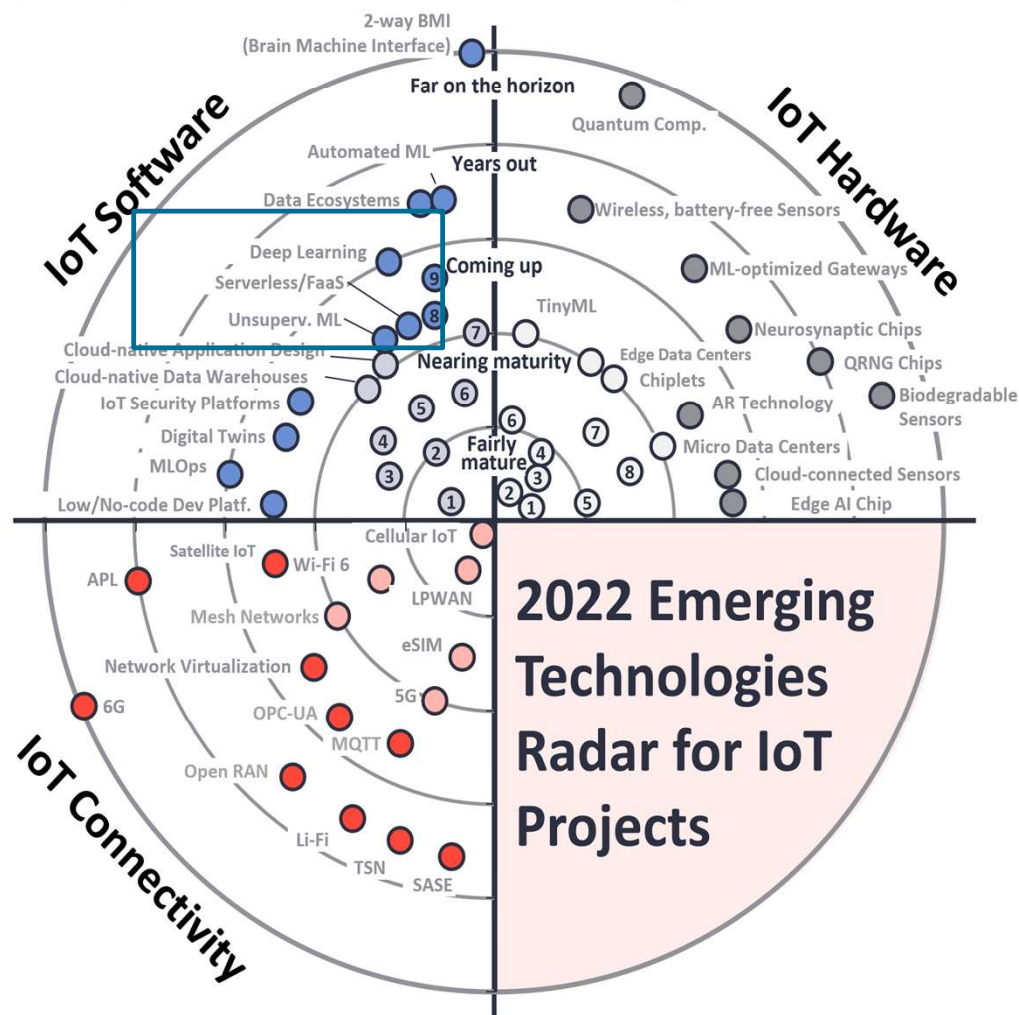
If there is not much data available, then machine learning is the way to go. However, if there is tons of data involved, deep learning is the answer.

Since DL algorithms are very powerful and they need a lot of data to give the best solution/outcome, powerful machines are needed (not the case for ML).

Some of the reasons are...

- Deep Learning algorithms **do complicated things** (e.g. matrix multiplications), which require a graphic processing unit (GPUs).
- DL algorithms try to **learn high-level features** (e.g. in the case of facial recognition the algorithm will get the image pretty close to the RAW version in replication, whereas machine learning's images would be blurry).
- Deep learning takes a **long time to process** data and find solutions thus needs **powerful computational infrastructure**.

Emerging IoT Technologies Radar 2022



- ① Cloud Computing
- ② IoT Platforms
- ③ Containers
- ④ Supervised ML
- ⑤ IoT-based Streaming Analytics
- ⑥ Edge AI
- ⑦ Real-time Databases
- ⑧ IoT Marketplace
- ⑨ Edge Data and App Platforms

- ① CPUs
- ② MCUs
- ③ GPUs
- ④ Security Chips
- ⑤ Edge Gateway
- ⑥ FPGA
- ⑦ ASICs
- ⑧ Intelligent Sensors

Disclaimer: The 2022 Emerging Technologies Radar for IoT projects represents the analyst view of the IoT Analytics' research team under the disclaimer that, depending on the context, the classification and perception of the project may be different in reality. IoT software refers to middleware, analytics, storage, platforms, and applications. The only relevant positioning of each topic is its distance to the center. The positioning on the axes plays no role.

Source: IoT Analytics Research—April 2022. We welcome republishing of images but ask for source citation with a link to the original post and company website.



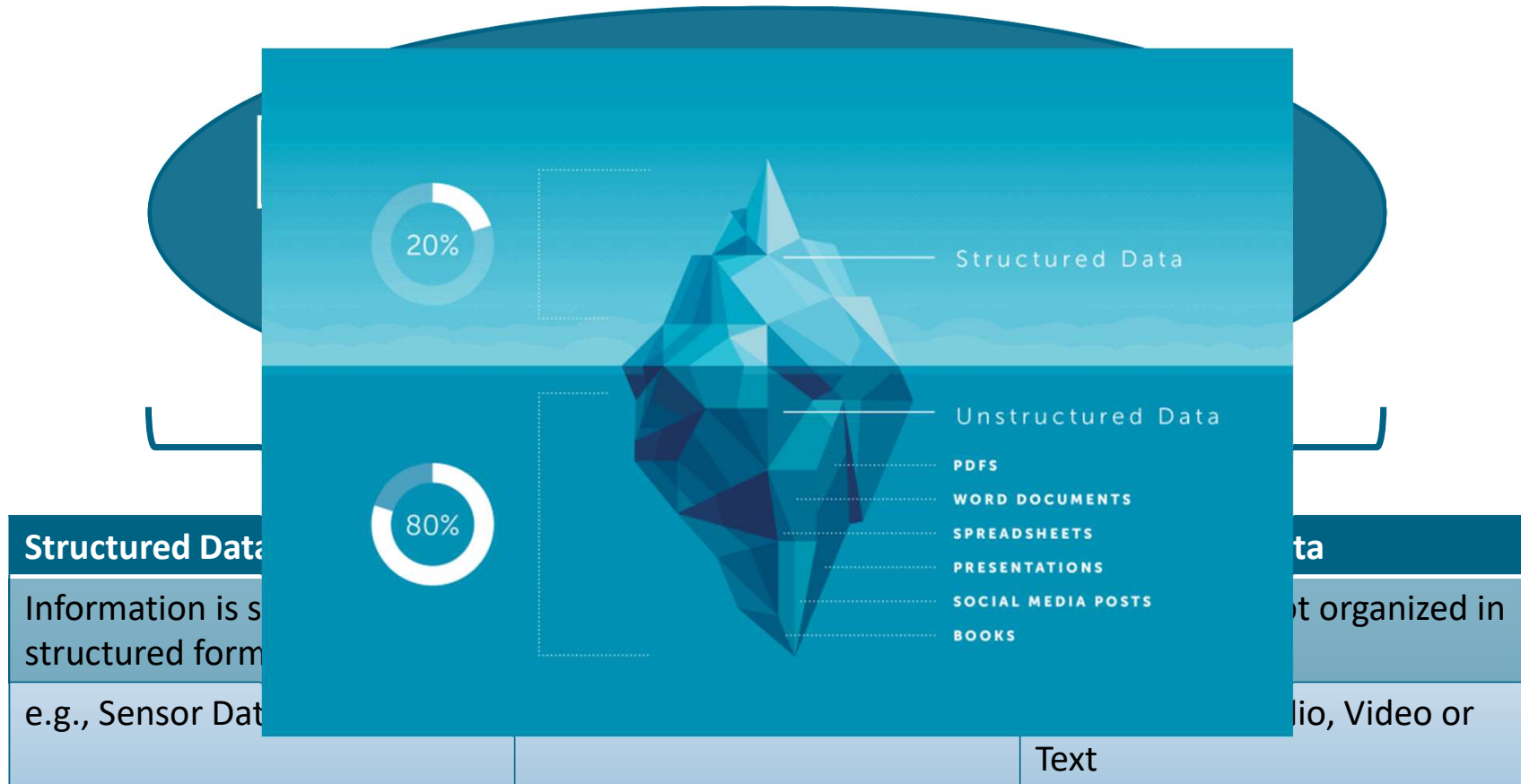


WHAT IS TECHNICAL LANGUAGE PROCESSING?

– INTRODUCTION & INTERACTION

Data Sources

Formats of data



<https://k21academy.com/microsoft-azure/dp-900/structured-data-vs-unstructured-data-vs-semi-structured-data/>

Unstructured Data

Text, the most common unstructured data format



Text ...

- is the most common unstructured data type
- can not be displayed in rows and columns
- contains a lot of implicit and explicit human knowledge
- can be brought into a structured format using Text Mining



What is Text ?

Existing Definitions

Linguistic

*“verbal record of
communicative art”*

- Brown & Yule (1983)

*“Any passage spoken or written,
independent of the length forming a
unified whole”*

- Halliday & Hasan (1976)



<https://www.gov.uk/guidance/pathways-text-analysis>

Computational Linguistic

*„unstructured form of data that can be interpreted as
human-readable text, consisting of sequence of words,
called strings”*

- OXFORD Dictionary

*“string together words, which can only be interpreted
and understood by the appliance of a wide range of
rules called grammar”*

- Jo (2019)

What is Text Mining (TM)

An Overview

- TM is a **subfield of AI/ML** concerned with giving computers the ability to **understand, process** and **analyze** natural language
- TM combines **computational linguistics** with **statistical, machine learning, and deep learning models**
- These technologies **enable computers to process human language** in the form of text data and to “understand” its full meaning
- TM enables the possibility to **convert unstructured text to a structured format**



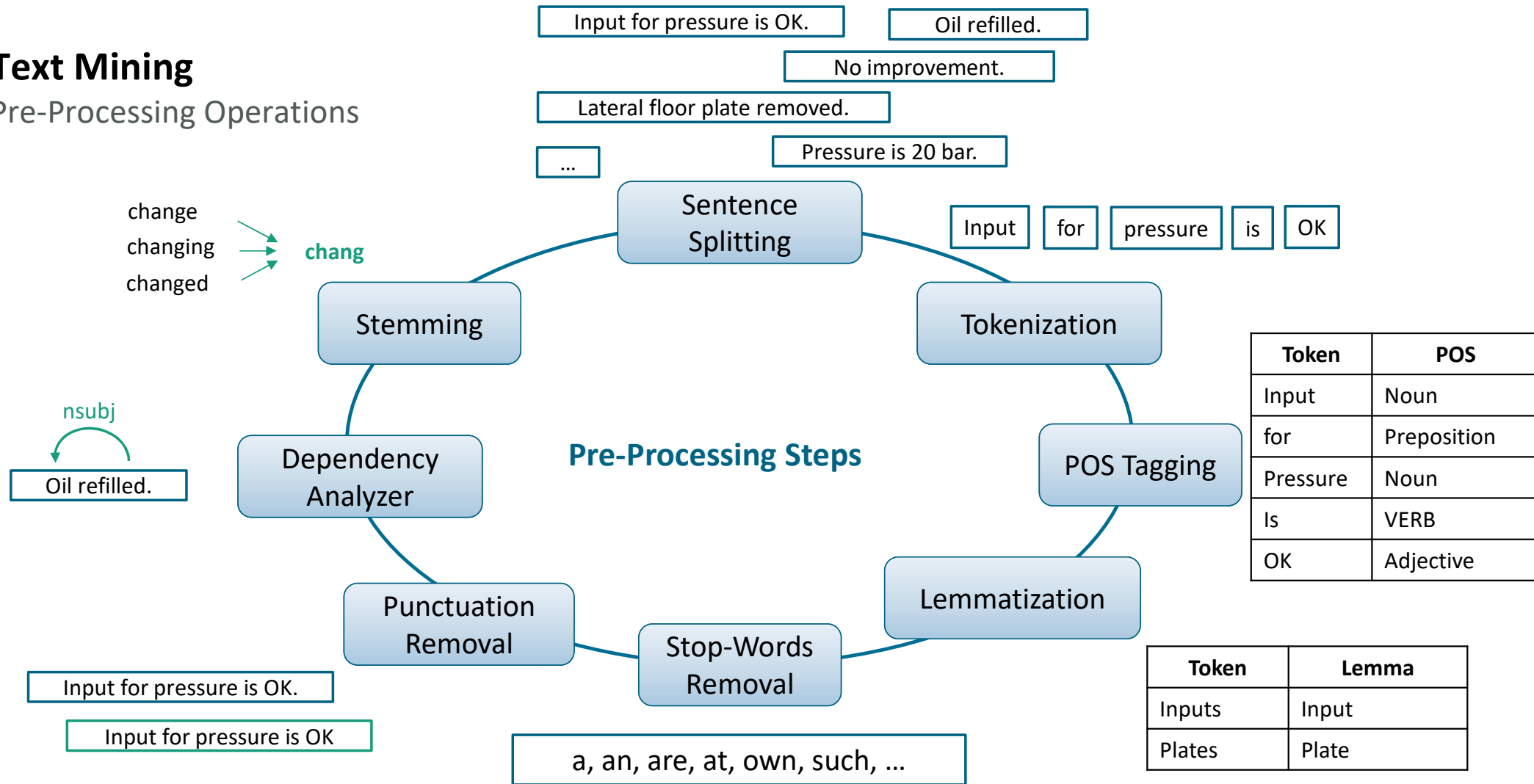
<https://www.ibm.com/cloud/learn/natural-language-processing>

<https://www.alexanderthamm.com/de/blog/natural-language-processing-nlp-natuerliche-sprache-fuer-maschinen/>

<https://textmining.nu/2019/04/28/finding-relevant-information-without-knowing-exactly-what-is-available-or-what-you-are-looking-for/>

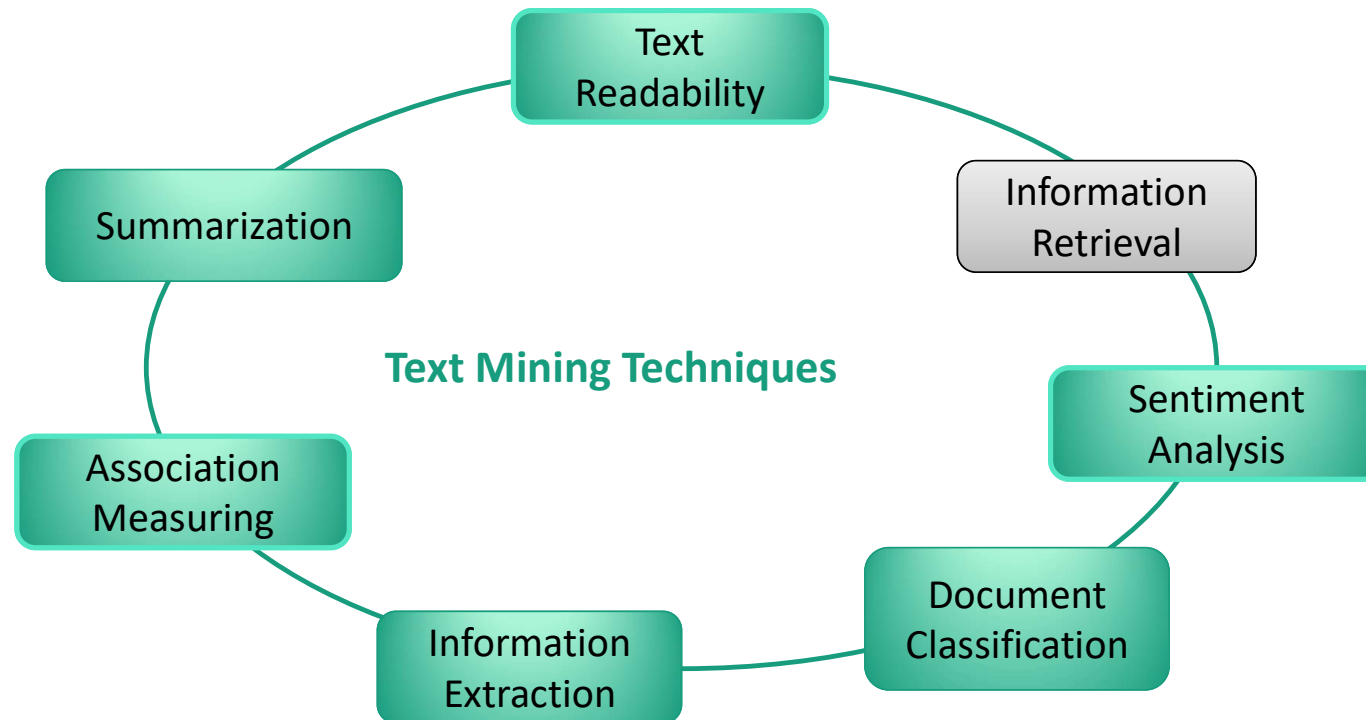
Text Mining

Pre-Processing Operations



Text Mining

Text Mining Techniques



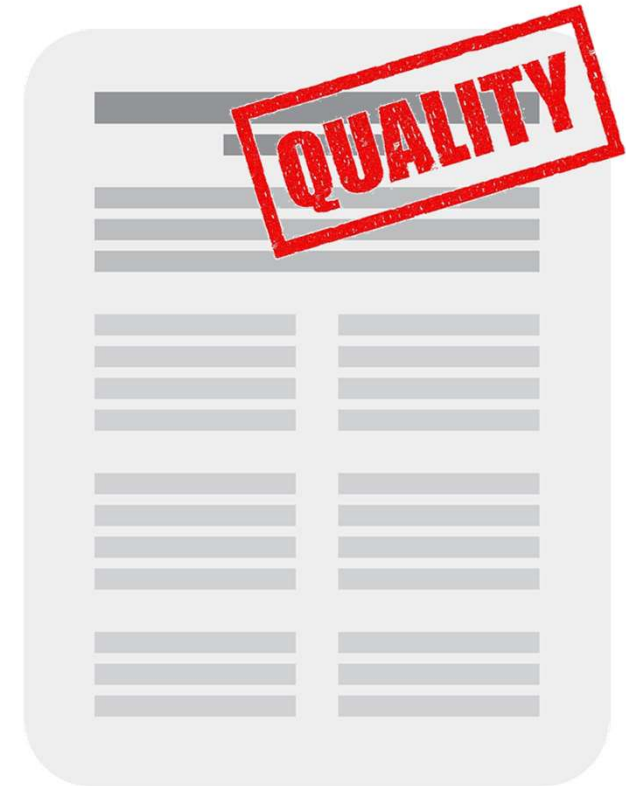
Text Mining Techniques

Text Readability

- Assures the **interpretability** of text
- **Extraction of information** from text **requires** basic **readability** criteria
- Text Readability evaluation **depends on information** that needs to be extracted from text

$$0.39 * \frac{|words|}{|sentences|} + \frac{|syllables|}{words} - 15.59$$

Flesch-Kincaid Grade Level Formula



Text Mining Techniques

Sentiment Analysis

- Determines whether text is **positive**, **neutral** or **negative**
- **Application Fields:**
 - Political Science
 - Marketing and Advertising
 - Customer Support
- **Underlying Techniques:**
 - ML-Algorithms
 - Sentiment-Lexicon



Positive

Neutral

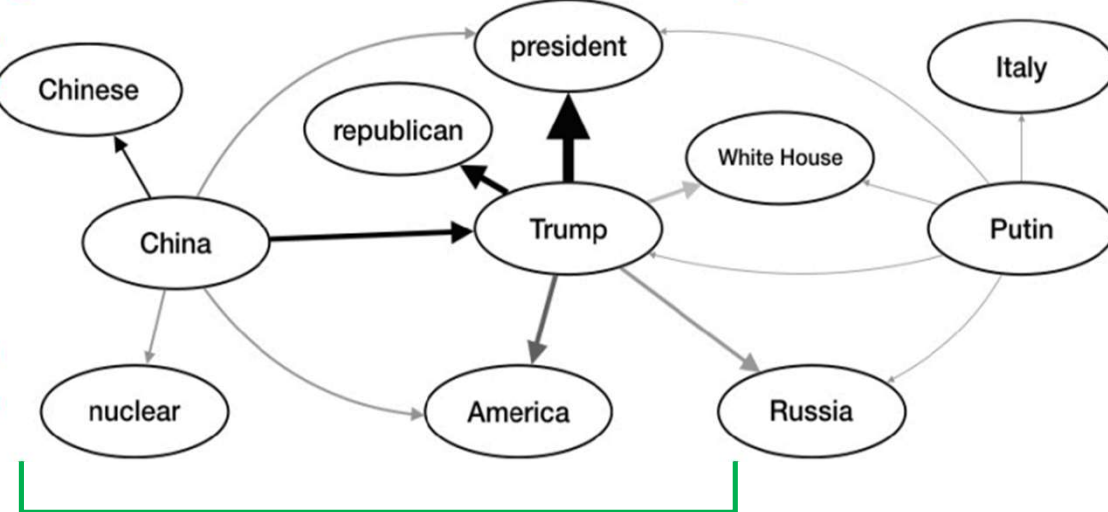
Negative

Text Mining Techniques

Association Measuring

cue	response	association strength (10^{-2})
Trump	president	1.915
	republican	1.028
	America	0.728
	Russia	0.703
	White House	0.689
China	Trump	0.847
	Chinese	0.506
	America	0.309
	president	0.256
	nuclear	0.232
Putin	Russia	0.080
	president	0.046
	Italy	0.039
	White House	0.032
	Trump	0.023

There are more articles focusing on the



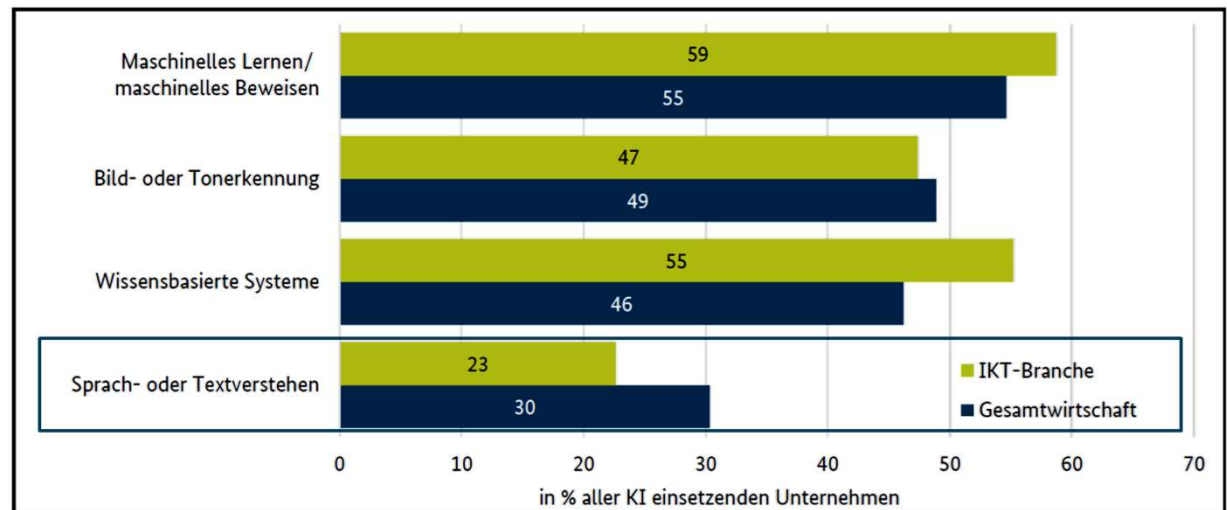
Hu, Z., Luo, J., Zhang, C., & Li, W, A Natural Language Process-Based Framework for Automatic Association Word Extraction. IEEE Access, 2020, 8, pp. 1986–1997

Industrial Application of Technical Language Processing

Do we have room for improvement!? Why TLP can generate added-values?

- According to IBM Research **85%** of business relevant information originates in **unstructured form, primarily text**.
- **Manufacturing companies use only 20-30% of the value of data** captured in their cooperate IT systems, according to McKinsey.
- Ernst & Young predict that an **intelligent document solution can reduce costs by 80%**. In maintenance and production, activities are stored primarily in log-book entries.

Eingesetzte KI-Verfahren in Unternehmen der deutschen Wirtschaft und der deutschen IKT-Branche 2019 (in %)



Quelle: Deutsche Innovationserhebung 2019. Zusatzbefragung KI 2019/2020. Berechnungen des ZEW

However, still practical challenges are:

- **Low quality of documentations**
- **Economic and technical plausibility**
- **Proper use of multiple data sources**
- **Multi-modality of data (semantic correlation of information)**

Source: ftp://public.dhe.ibm.com/software/in/events/softwareuniverse/resources/Content_Analytics_and_the_High_Performing_Enterprise.pdf, <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-age-of-analytics-competing-in-a-data-driven-world>, https://www.ey.com/en_my/alliances/how-ai-is-reshaping-the-document-review-and-processing-landscape

Technical Language Processing (TLP)

Why do we need TLP?



TM Tools

- Many TM tools are not designed for technical text in ways that address industrial business needs
- Standard TM tools often produce outcomes which fall short of engineering and business requirements

TLP Tools

“Technical language processing (TLP) is a human-in-the-loop, iterative approach to tailor TM tools to engineering data”

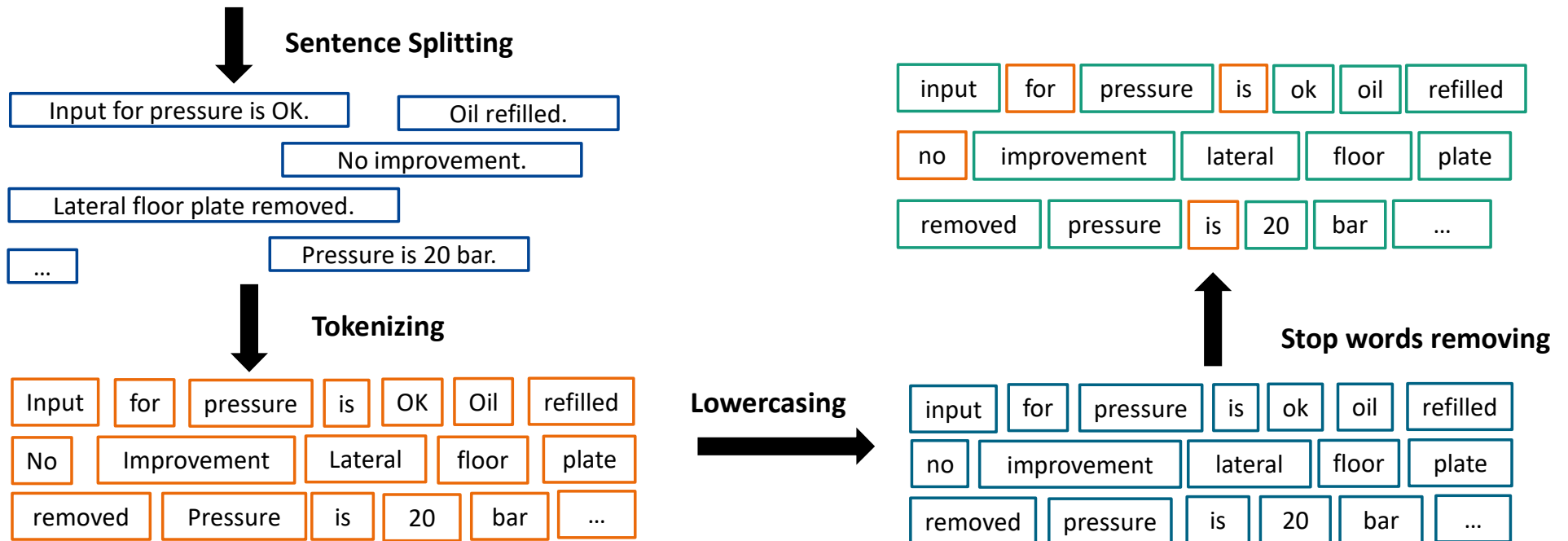
- TLP uses tools to meet engineering requirements
- TLP approaches are developed with industry use cases in mind
- It utilizes detailed domain-based taxonomies and data dictionaries to ensure that the system comprehends all relevant technical terms, abbreviations and acronyms which may appear in a file
- Some use cases in maintenance and reliability are:
 - ✓ Reduced Equipment Downtime
 - ✓ Earlier Failure Detection

Brundage, M. P., Sexton, T., Hodkiewicz, M., Dima, A., & Lukens, S. (2021). Technical language processing: Unlocking maintenance knowledge. In *Manufacturing Letters* (Vol. 27, pp. 42–46). Elsevier BV. <https://doi.org/10.1016/j.mfglet.2020.11.001>

How to understand a text?

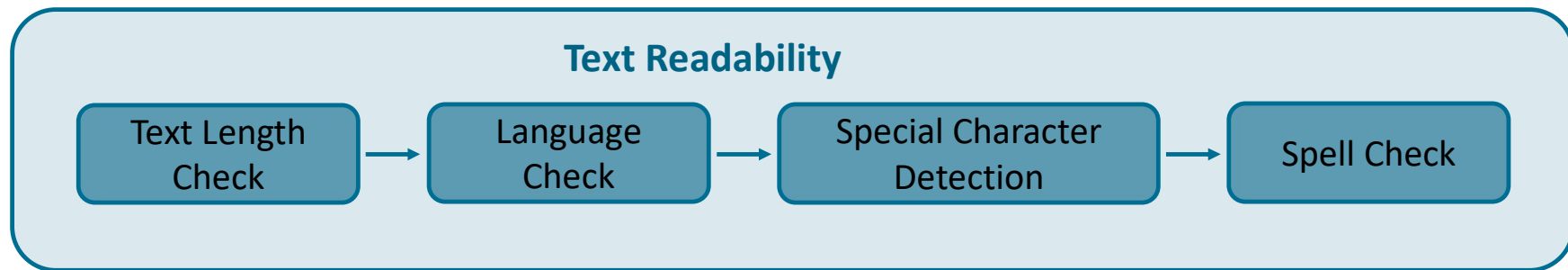
Step I: Preprocessing Steps of a Sample Text

Input for pressure is OK. Oil refilled. No improvement. Lateral floor plate removed. Pressure is 20 bar. Target pressure = 25 bar. Filter is changed. Pressure rises to 40 bar, and then again slowly drop to 20 bar. End of the bed bottom plate removed. Here is a drain tap, to drain separated water from the drip trays. Only water came, then a nondescript broth. Maybe an oil change should be made.

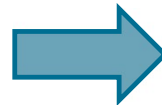


How to understand a text?

Step I: Text Readability



Input for pressure is OK. Oil
refilled. No improvement.
Lateral floor plate removed.
Pressure is 20 bar. ...



Text Readability Stats:

Text Length: 5 sentences || 17 words

Detected Language: English

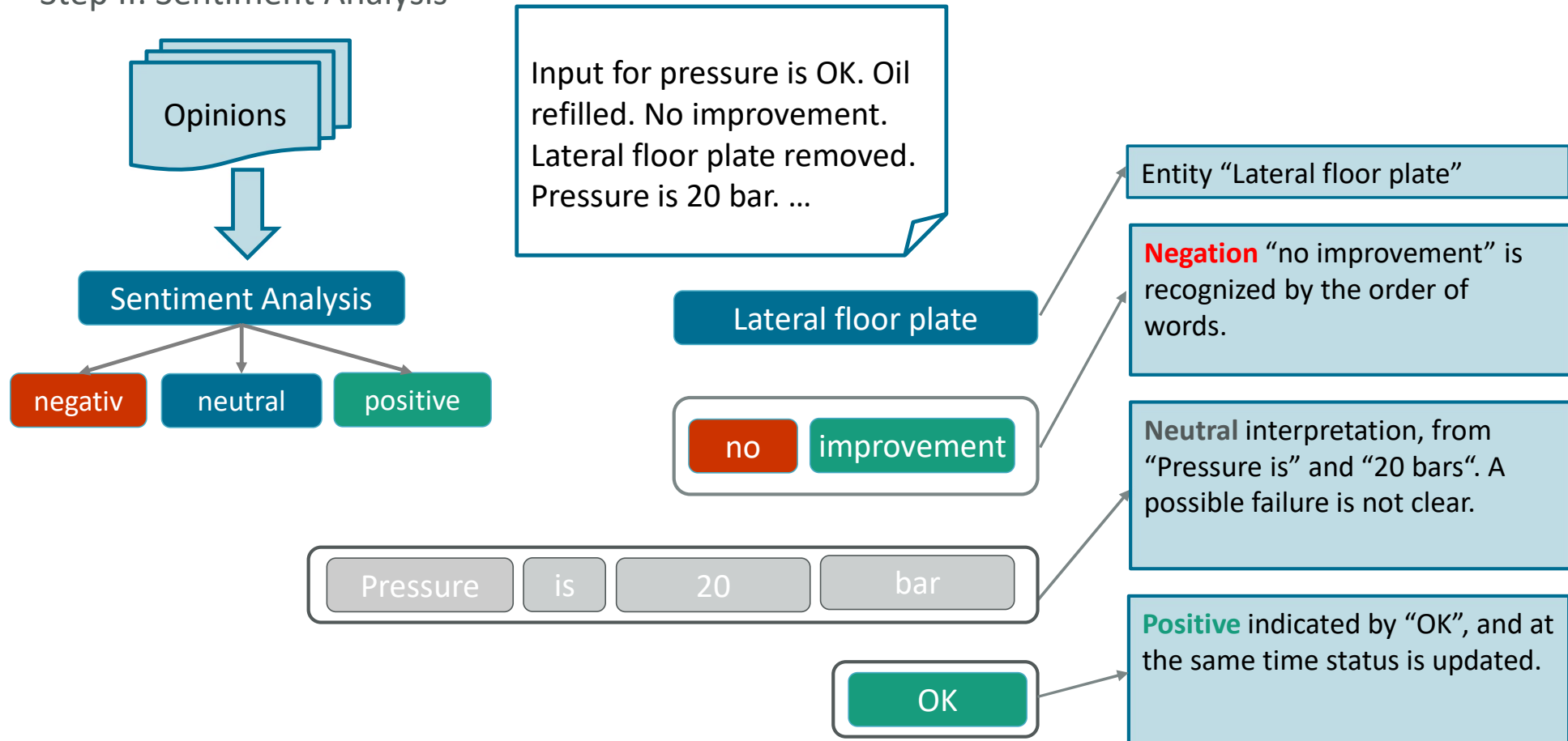
Spell Check: correct

Special Character Detection: non



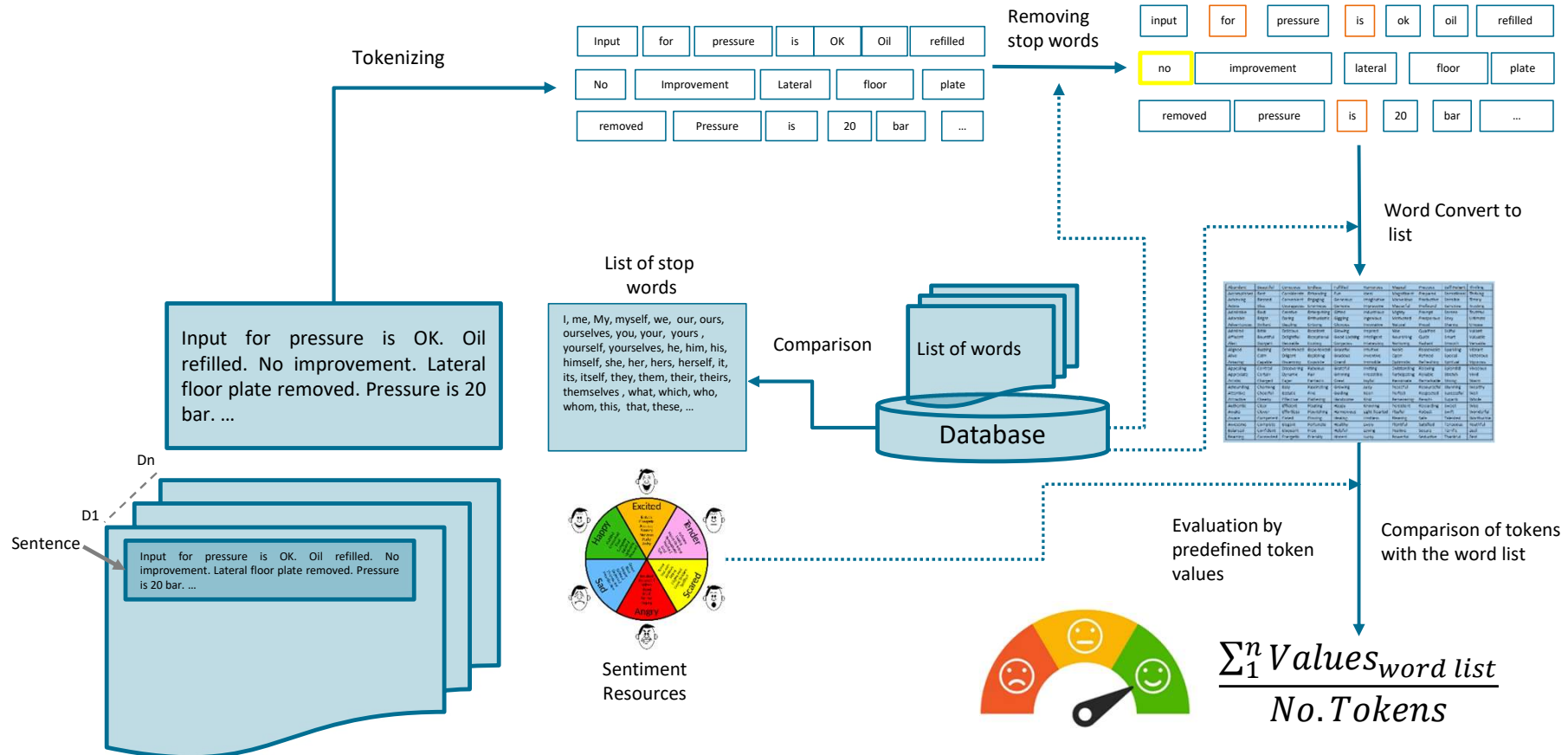
How to understand a text?

Step II: Sentiment Analysis



Sentiment Analysis

Basic Algorithm



How to understand a text?

Step III: Association Measuring

What is the first word coming into mind when one person is given the word *computer*?



“In psychology, association typically refers to a mental connection among different appearances due to some inducements, which can be perceived and revealed through the phenomenon of word association.”



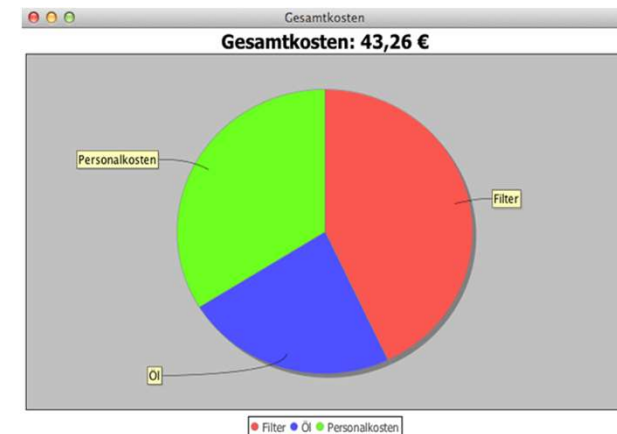
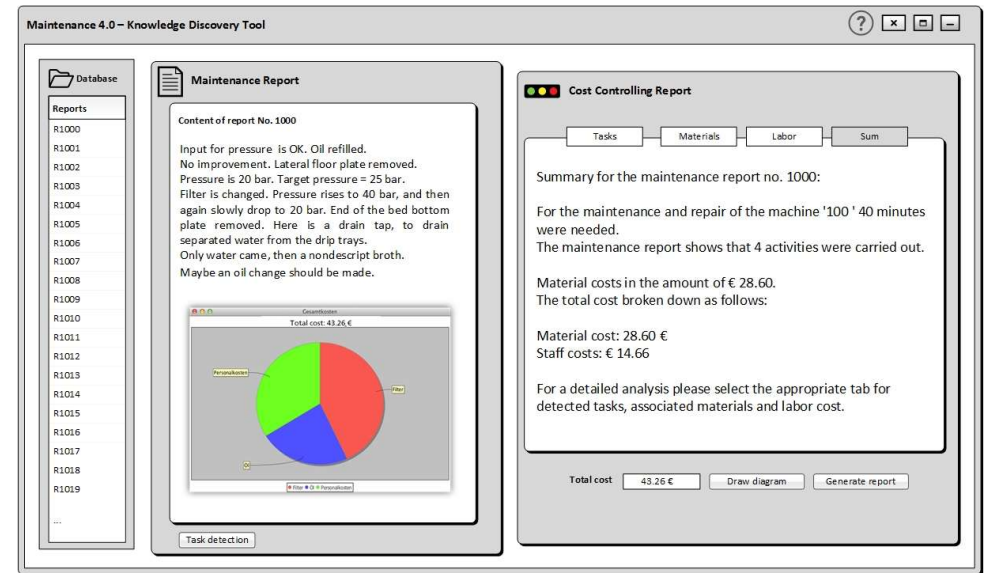
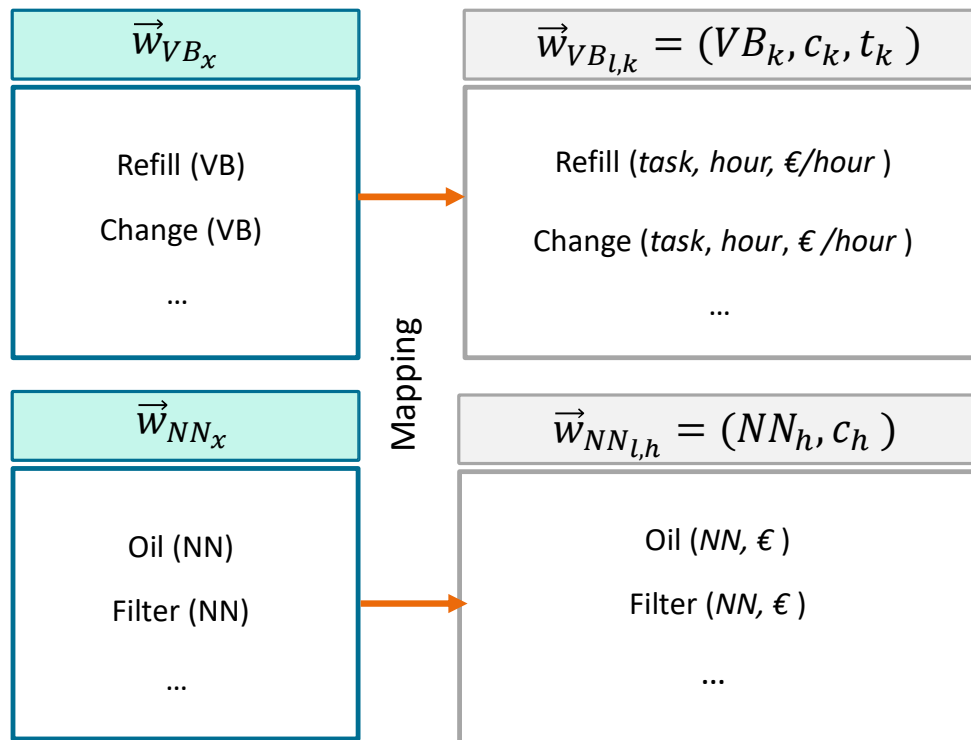
Psycholinguistic studies reveal that human brain distinguishes between association of $w1 \rightarrow w2$ and $w1 \leftarrow w2$. Therefore, the direction of association significantly affects the strengths of association between $w1$ and $w2$

Hu, Z., Luo, J., Zhang, C., & Li, W, A Natural Language Process-Based Framework for Automatic Association Word Extraction. IEEE Access, 2020, 8, pp. 1986–1997

F. Ansari, Cost-Based Text Understanding to Improve Maintenance Knowledge Intelligence in Manufacturing Enterprises, Journal of Computer and Industrial Engineering, Vol. 141, <https://doi.org/10.1016/j.cie.2020.106319>

How to understand a text?

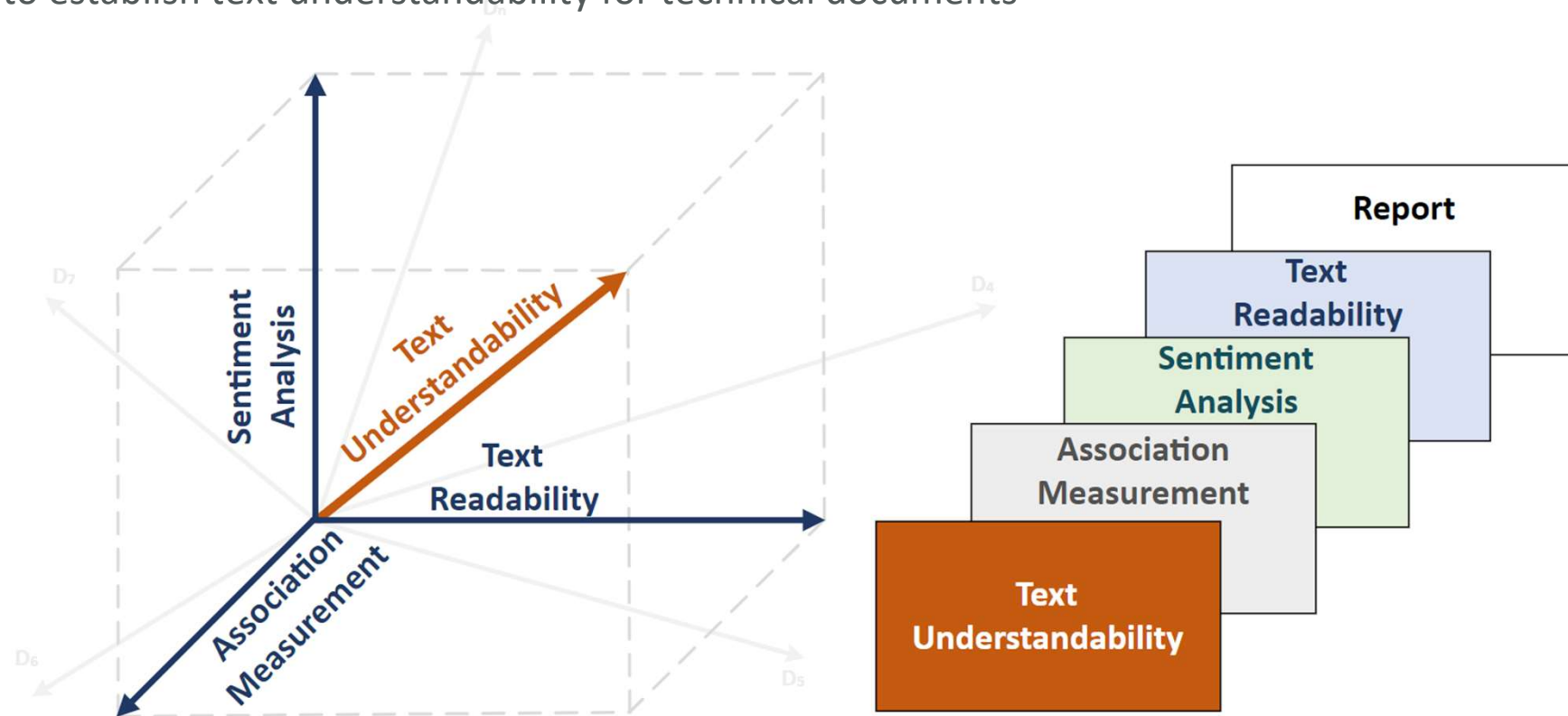
Step IV: Interpretation in terms of economic values



F. Ansari, Cost-Based Text Understanding to Improve Maintenance Knowledge Intelligence in Manufacturing Enterprises, Journal of Computer and Industrial Engineering, Vol. 141, <https://doi.org/10.1016/j.cie.2020.106319>

How to understand a text?

Trying to establish text understandability for technical documents



Madreiter, Theresa, Linus Kohl, and Fazel Ansari. "A Text Understandability Approach for Improving Reliability-Centered Maintenance in Manufacturing Enterprises."

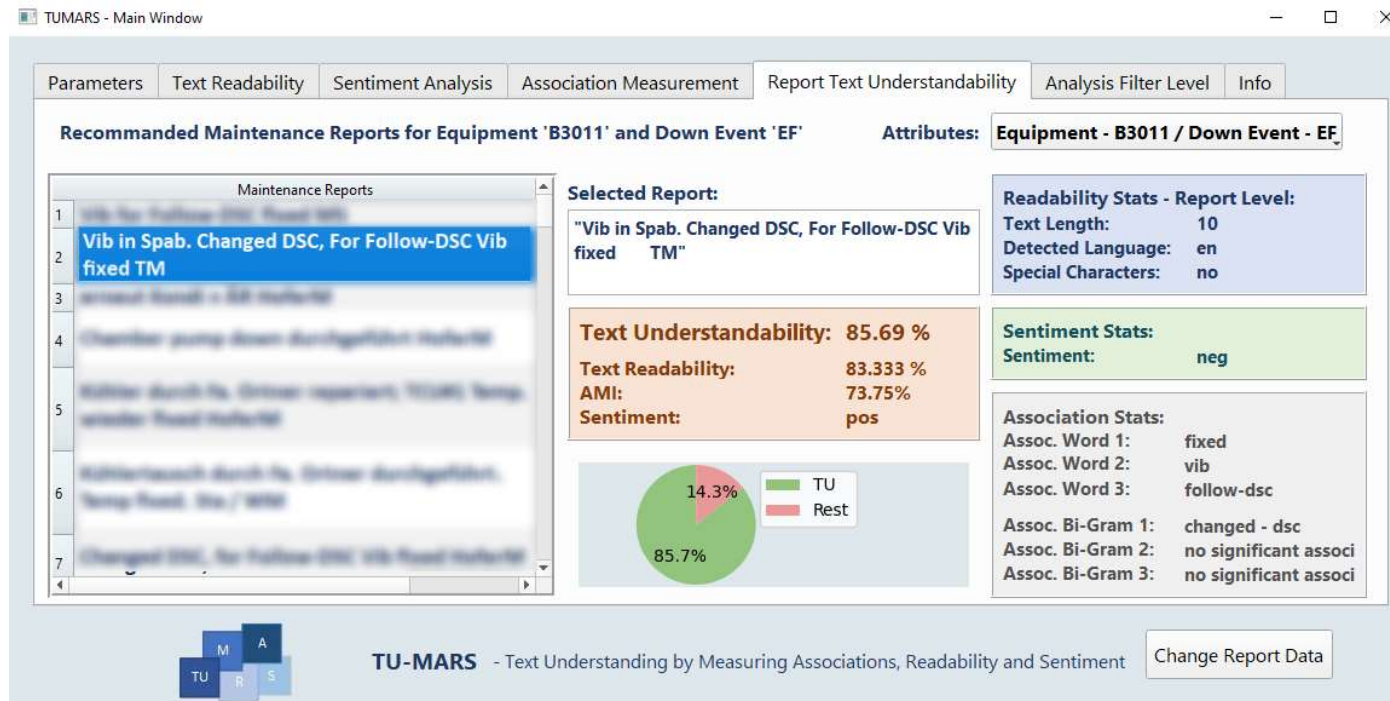
https://doi.org/10.1007/978-3-030-85874-2_17

SKBM Text Mining Dashboard Solution

TU MARS

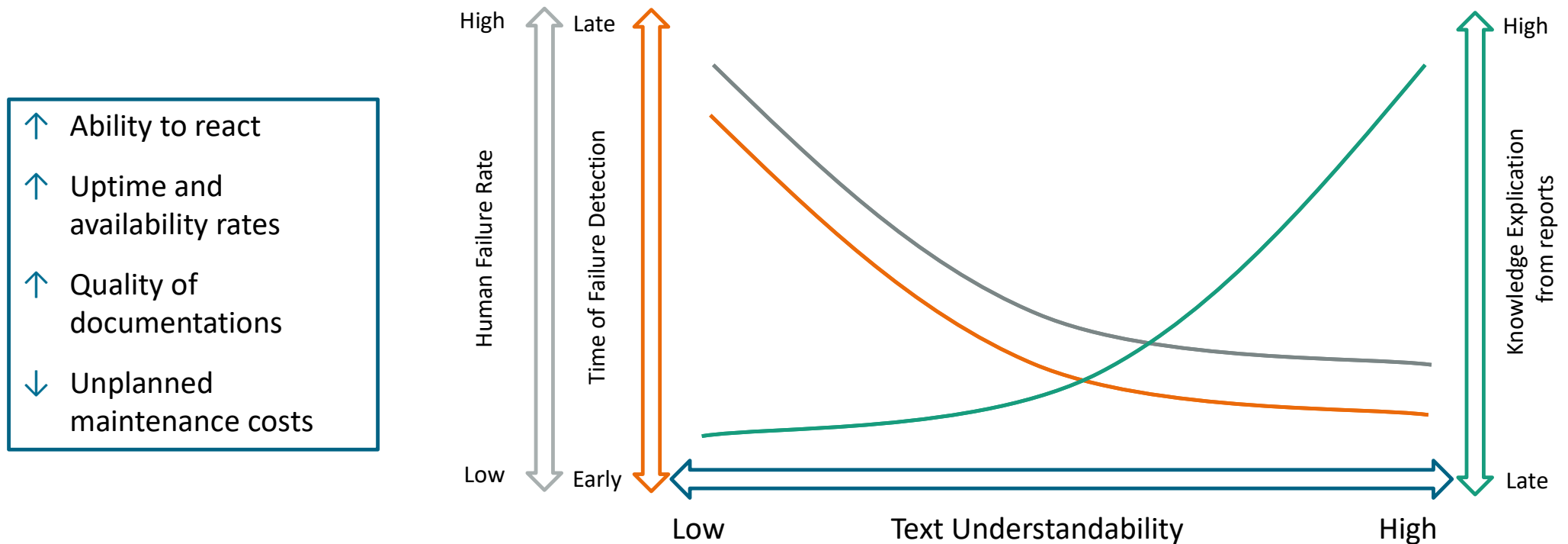


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Text Mining in Industrial Maintenance

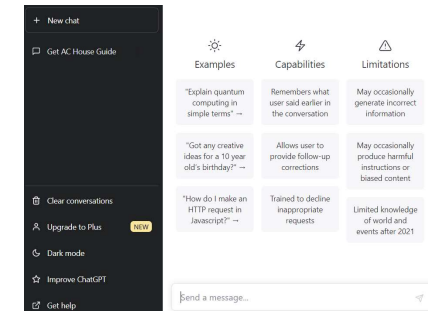
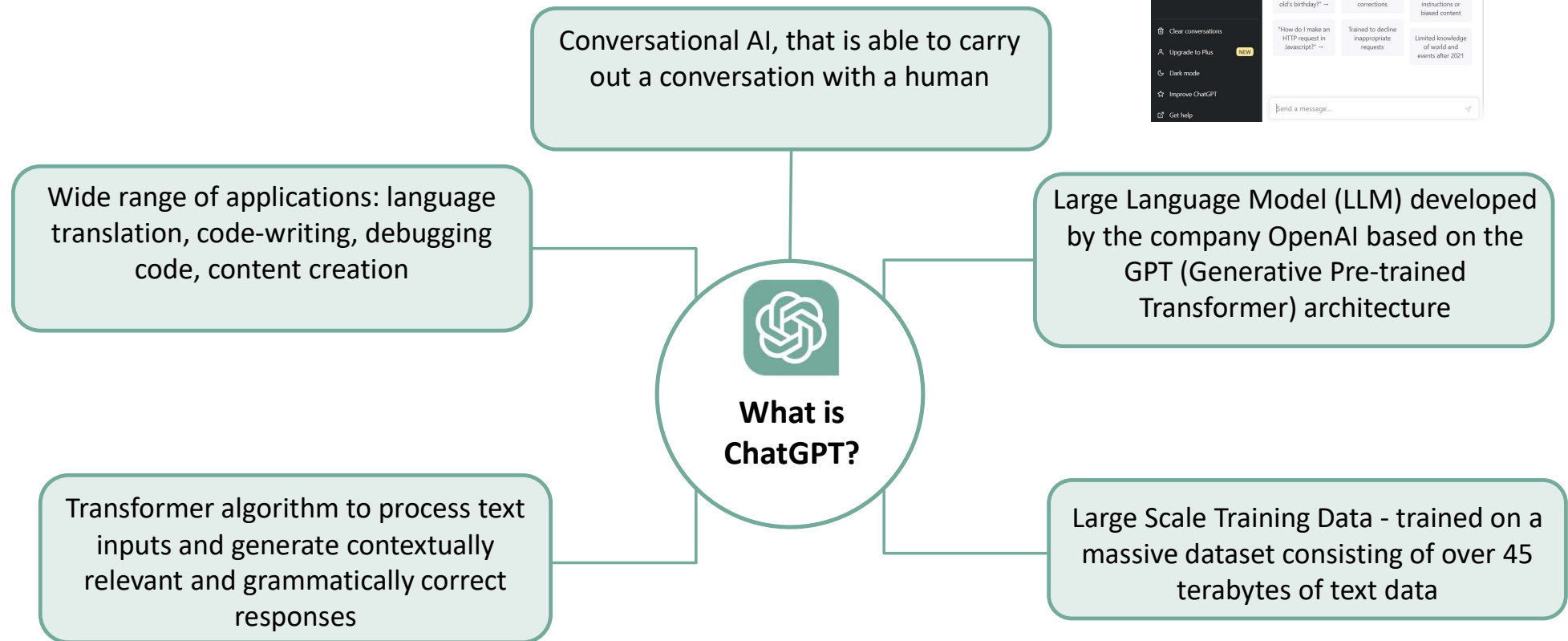
What can be the added value for industrial applications?



In fact, the proposed approach is not limited to maintenance and can be applied in other areas like HRM (Competency Management), QM, logistics, etc.

ChatGPT and Technical Language Processing?

Introduction to ChatGPT

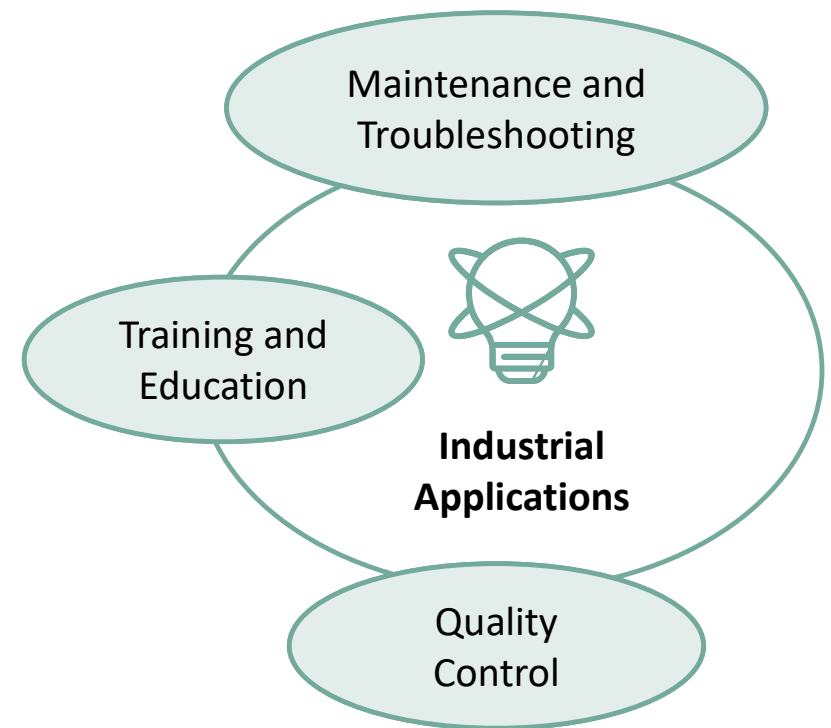


ChatGPT and Technical Language Processing?

How does ChatGPT work and how can it be applied in industry?



- **Natural Language Processing (NLP):** ChatGPT uses NLP algorithms to understand and generate human-like language
- **Pre-training:** ChatGPT has been pre-trained on a large corpus of text data, including books, articles, and websites, to learn the nuances of language
- **Fine-tuning:** After pre-training, ChatGPT can be fine-tuned on specific tasks or domains to further improve its performance
- **Contextual Awareness:** ChatGPT is contextually aware, meaning it takes into account the conversation history and context when generating responses
- **Feedback Loop:** Finally, ChatGPT uses a feedback loop to continuously improve its performance



To Sum Up

what are other
words for
to sum up?



finally, in conclusion,
to conclude, ultimately,
all in all, at last, summarize,
tot, tot up, total



 Thesaurus.plus

Looking for a Seminar or Project Work?



Project Relevant Topics:

- Data-Driven Sustainability in Manufacturing
- Twin Transition
- Large Language Models
- Individualizable Work Systems
- Maintenance Free Factory

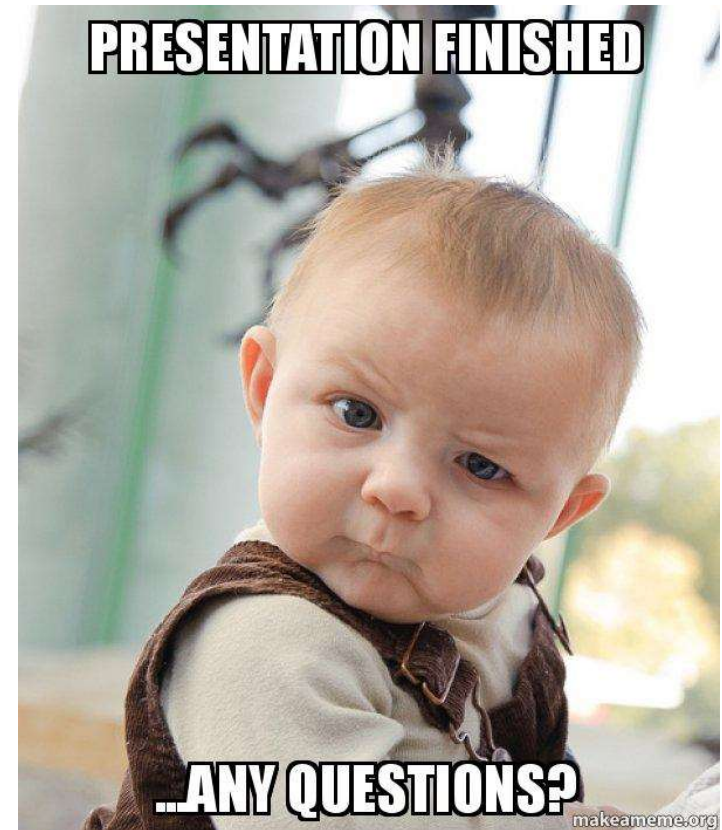
Contact Details:

Name: Dipl.-Ing. Theresa Madreiter

Mail: theresa.Madreiter@tuwien.ac.at

Q&A?

- Any question so far?
- Next Lecture: 25.04.2022 on „Knowledge Management 4.0: Theories and Foundation“





Technik für Menschen.

Technology for People!



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Further Readings

- C. Schröer, F. Kruse & J. Gomez, A Systematic Literature Review on Applying CRISP-DM Process Model. *Procedia Computer Science*, 2021, 181, pp.526-534
- F. Ansari, L. Kohl, J. Giner & H. Meier, Text mining for AI enhanced failure detection and availability optimization in production systems. *CIRP Annals*, 2021, 70, pp.373-376
- F. Ansari, Cost-Based Text Understanding to Improve Maintenance Knowledge Intelligence in Manufacturing Enterprises, *Journal of Computer and Industrial Engineering*, 2020, 141
- M. Brundage, T. Sexton, M. Hodkiewicz, A. Dima, and S. Lukens, Technical language processing: unlocking maintenance knowledge. *Manufacturing Letters*, 2021, 27, pp. 42–46
- M. Magnanini & T. Tolio, A model-based Digital Twin to support responsive manufacturing systems. *CIRP Annals*, 2021, 70, pp.353-356
- R. Peres, X. Jia, J. Lee, K. Sun, A. Colombo, J. Barata, Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook. *IEEE Access*, 2020, 8, pp. 220121–220139
- R. Peres, A. Dionisio Rocha, P. Leitao, and J. Barata, IDARTS— Towards intelligent data analysis and real-time supervision for industry 4.0. *Comput. Ind.*, 2018, 101, pp. 138–146
- X. Zhang, X. Ming, Z. Liu, D. Yin, Z. Chen, and Y. Chang, A reference framework and overall planning of industrial artificial intelligence (I-AI) for new application scenarios,. *Int. J. Adv. Manuf. Technol.*, 2019, 101, pp. 2367–2389

List of References

- E. Lee and S. A. Seshia, Introduction to Embedded Systems, A Cyber-Physical Systems Approach, 2nd Edition, 2015.
- F. Y. Wang, The Emergence of Intelligent Enterprises: From CPS to CPSS, IEEE Intelligent Systems, Vol. 25, Issue: 4, 2010, pp. 85-88.
- H. Zhuge, Semantic Linking through Spaces for Cyber-physical-socio Intelligence: A Methodology, Artificial Intelligence, Vol. 175, Issues 5-6, Elsevier, 2011, pp. 988-1019.
- E. Geisberger and M. Broy (Ed.): Agenda CPS - Integrated Research Agenda for Cyber Physical Systems, acatech Study, Springer, 2012.
- Acatech, Final report of the Industry 4.0 Working Group: Recommendations for implementing the Strategic Initiative Industry 4.0, acatech – National Academy of Science and Engineering, Sponsored by BMBF, Germany, 2013.
- L. Monostori, B. Kádár, T. Bauernhansl, S. Kondoh, S. Kumara, G. Reinhart, O. Sauer, G. Schuh, W. Sihn and K. Ueda, Cyber-physical systems in manufacturing, CIRP Annals-Manufacturing Technology, Vol. 65, Issue: 2, 2016, pp. 621-641.
- J. Lee, B. Bagheri and H.-A. Kao, A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems, Manufacturing Letters 3, 2015, pp. 18–23.

List of References

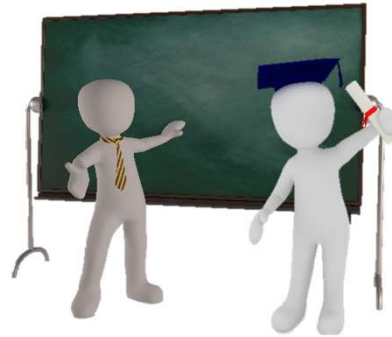
- A. Jetter, K. Jeroen, H. Schröder and F. Wijnhoven, Knowledge Integration – The Practice of Knowledge Management in Small and Medium Enterprises, Physica Verlag, 2006.
- F. Ansari and U. Seidenberg, A Portfolio for Optimal Collaboration of Human and Cyber Physical Production Systems in Problem-Solving, In Proceedings of the 13th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2016), Mannheim, October 28-30, International Association for Development of the Information Society, pp. 311-315, 2016.
- CPS Summit, Report: Cyber-Physical Systems Summit, 2008.
- U. Seidenberg and F. Ansari, Qualitätsmanagement in der additiven Fertigung – Herausforderungen und Handlungsempfehlungen, 3D-Printing: Recht, Wirtschaft und Technik des industriellen 3D-Drucks, Handbook, A. Leupold and S. Glossner (Eds.), Verlag C.H.Beck, 2017, S. 159-214.
- F. Ansari, P. Hold and W. Sihn , Human-Centered Cyber Physical Production System: How Does Industry 4.0 impact on Decision-Making Tasks? IEEE TEMSOCN, 2018 (In Press)
- F. Ansari, L. Kohl, J. Giner & H. Meier, Text mining for AI enhanced failure detection and availability optimization in production systems. CIRP Annals, 2021, 70, pp.373-376
- F. Ansari, Cost-Based Text Understanding to Improve Maintenance Knowledge Intelligence in Manufacturing Enterprises, Journal of Computer and Industrial Engineering, 2020, 141

List of References

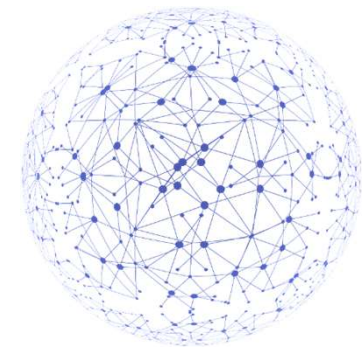
- M. Brundage, T. Sexton, M. Hodkiewicz, A. Dima, and S. Lukens, Technical language processing: unlocking maintenance knowledge. *Manufacturing Letters*, 2021, 27, pp. 42–46
- Madreiter, T., Kohl, L., Ansari, F. (2021). A Text Understandability Approach for Improving Reliability-Centered Maintenance in Manufacturing Enterprises. *Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems. APMS 2021. IFIP Advances in Information and Communication Technology*, vol 630. Springer, Cham.
https://doi.org/10.1007/978-3-030-85874-2_17
- Weiss, S.M., N. Indurkha, and T. Zhang. 2015. *Fundamentals of Predictive Text Mining*. London: Springer London.
- Mohammadi, H., and S.H. Khasteh. 2019. *Text as Environment: A Deep Reinforcement Learning Text Readability Assessment Model*



Industrial Innovation & Research



Teaching & Professional Training



Scientific Networking

ABOUT OUR PROJECTS!

AM4Rail (2021-2024)

Overview

AM4Rail

Multidimensional data pipeline for evaluating the potential of additive manufacturing of spare parts at EVU

Objectives

- Forcing the use of future-oriented AM in spare parts supply at the most important railroad operators in Austria to reduce costs, material and energy consumption
- Implementation of economically and ecologically oriented life cycle analyses
- Development of a sharing economy concept for a broader establishment of the use of AM and for the reduction of entry barriers in the industry

Contributions: Text Mining and Semantic Technologies, OCR (Optical Character Recognition) and Text Mining for Technical Drawings, Data linking through a semantic data hub



TEXCOM (2020)

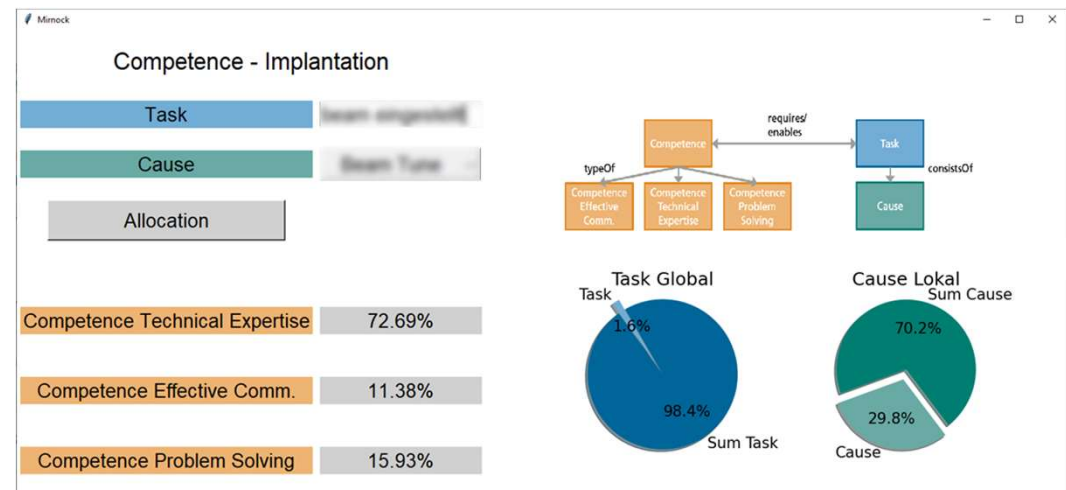
Overview

TEXCOM | Text Based Competency-Profiling

Objectives

- Improvement of data quality with support of AI-methods
- Qualitative and quantitative derivation of competences in maintenance tasks and comparison with job requirements
- Implementation of activity and competence trend analyzes
- Improvement of maintenance planning and personal development through identification of requirements on the shopfloor

Contributions: Definition of the data base, Text-Mining & Pre-Processing, competence taxonomy, competence model



Partners & Funding



Research Project True-Usage (2020-2023)

Overview

Product Design &
Construction Phase

Product-in-Use &
Operation Phase

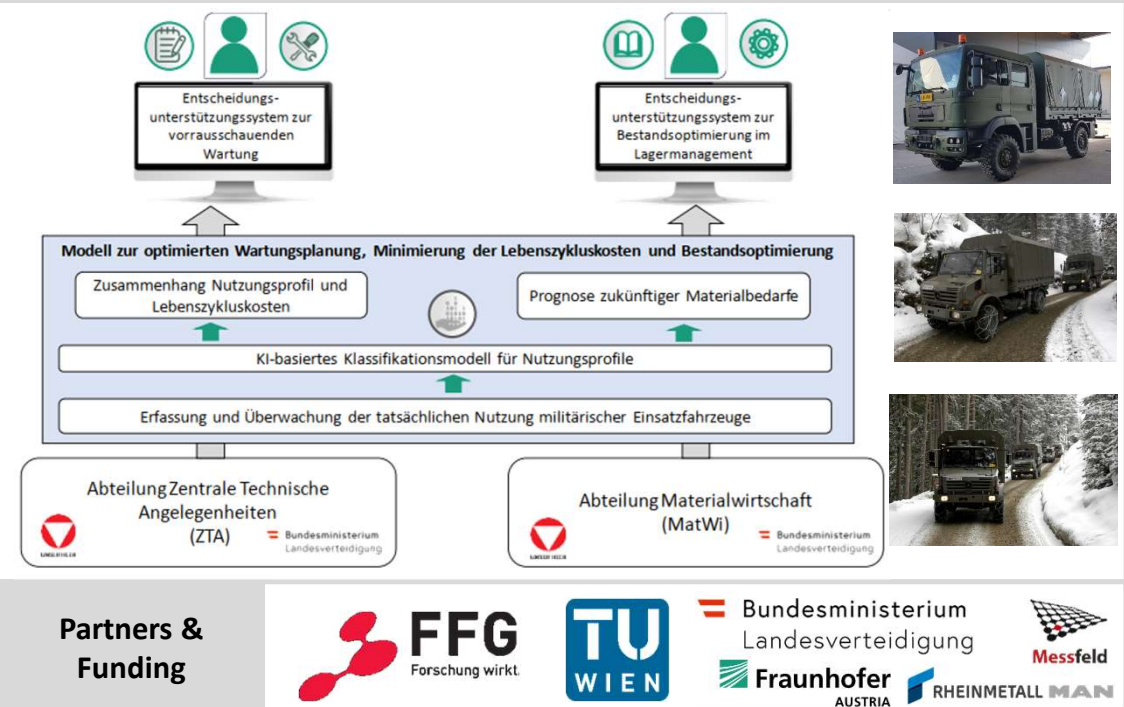
Service Phase

True-Usage | AI-enhanced Platform for Planning, Monitoring and Controlling “True-Usage” Profiles of Military Logistic Vehicles for Optimizing Maintenance and Inventory Plans

Research Objectives

- Adaptation and further development of **PriMa** for modeling “True-Usage” profile of military logistics vehicles
- **Multi-channel data** analysis using sensor, textual, environmental, and vehicle control data.
- Calculation and optimization of **True-Usage-life-cycle costs** considering various Road profiles, usage and stationary times.
- A **decision support system** for the predictive initiation of maintenance measures.

Contributions: Similarity-based Analysis, Case-Based Reasoning, Predictive Analytics, Text Mining, Case Study



* FFG: Österreichische Forschungsförderungsgesellschaft

Rhein-Plan

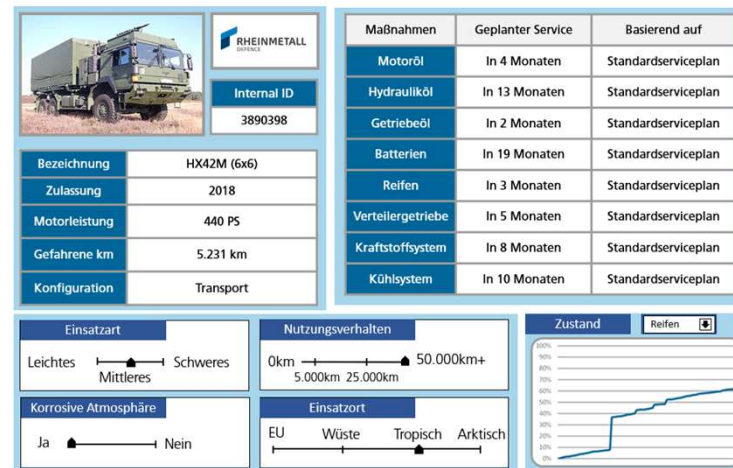
Overview

Rhein-Plan | A Rheinmetall-specific maintenance planning tool for military commercial vehicles

Objectives

- Derivation of maintenance measures, based on civilian specifications, in military commercial vehicle use
- Offer customers of RMMVÖ a cost-effective and waste-free vehicle maintenance adapted to real usage profiles
- Improvement of the competitive position of RMMVÖ through an improved, future-oriented maintenance concept

Rhein-Plan Digital Dashboard Mock-up



Contributions: Design of a PoC for the development of a Rhine-Plan Recommender System, Content based filtering approach, Construction of a Bayesian Classifier for individual components

Partners & Funding



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