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DAT 550 / DIT 978 Advanced Software Engineering for AI/ML-Enabled Systems



Lecture 3: On AI/ML System Architecture

Your teachers: Hans-Martin Heyn, Universitetslektor, Eric Knauss, Docent

Computer Science and Engineering Department, Göteborg University

What will you learn?

Architectures and patterns for AI/ML-enabled systems

- How can we get from (prototyping) models to production systems
- Modularity and the problem of ML components in larger software systems
- An introduction to an architecture framework for distributed AI-enabled systems

- Explain how ML fits into the larger pictures of building and maintaining systems
- Explain the modularity implications
- Understand the need for architecture frameworks in AI system development



What will you learn?

Architectures and patterns for AI/ML-enabled systems

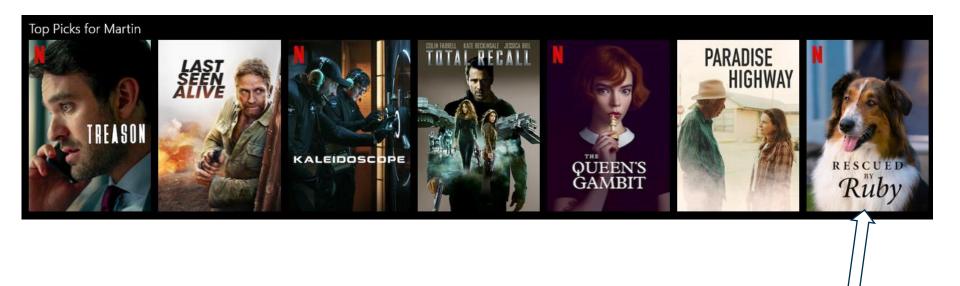
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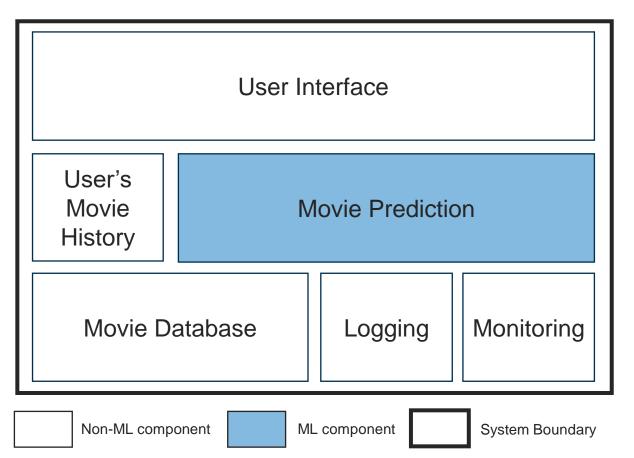


System: Movie Recommendation





System: Movie Recommendation



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Environment

System: Credit Rating



Your credit rating is...



Great news! Our AI predicts a low probability of credit default based on your personal data. We can offer you a loan for your house of 3.5 MSEK. Print out your loan application here.

LOW

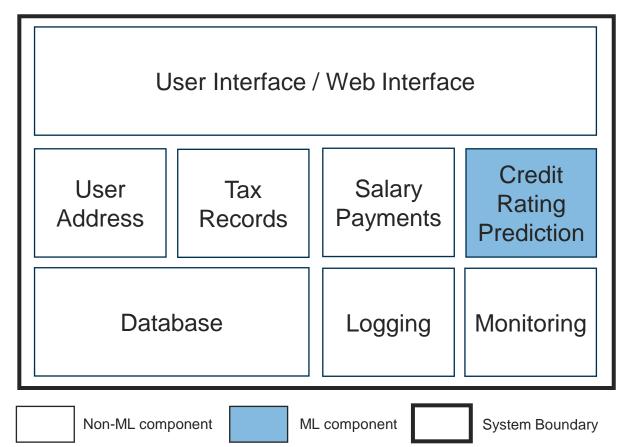
Bolånekalkyl - räkna på bolån

Räkna ut hur mycket du kan låna

- Se vad ditt lån kommer att kosta varje månad
- Räkna på din lånekostnad om räntan ändras

🕨 Räkna på bolån

System: Credit Rating



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Environment

© Christian Kaestner 2022 ²⁰²³⁻⁰³⁻²⁴

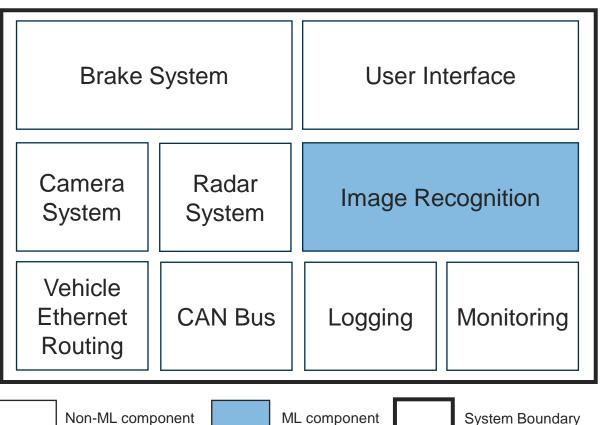
System: Obstacle Detection





Picture by AI Sweden

System: Obstacle Detection

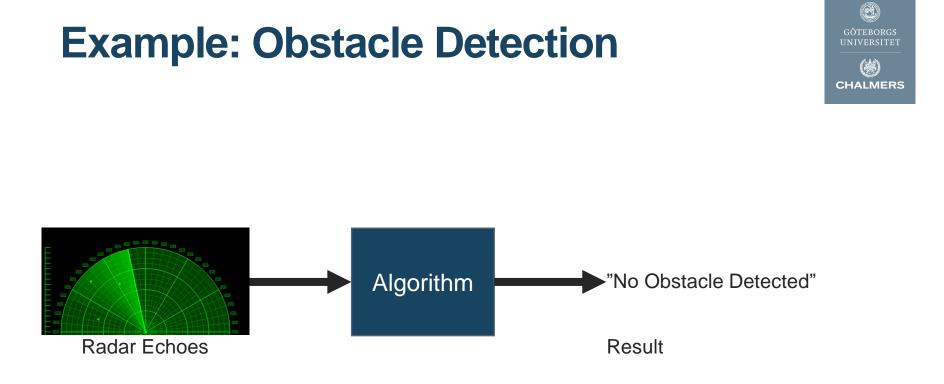


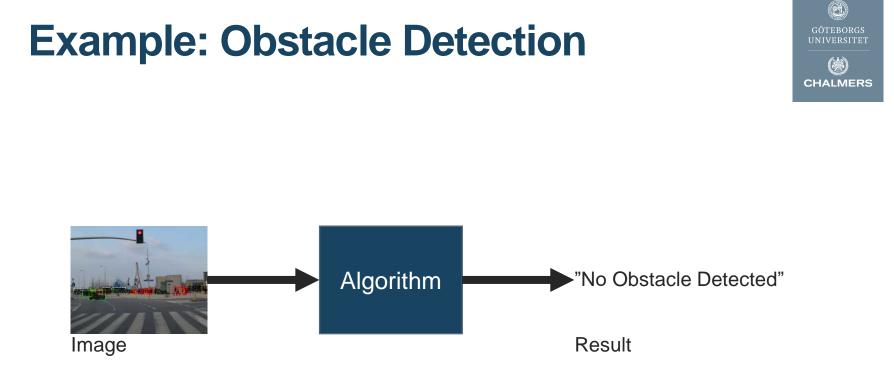
Environment

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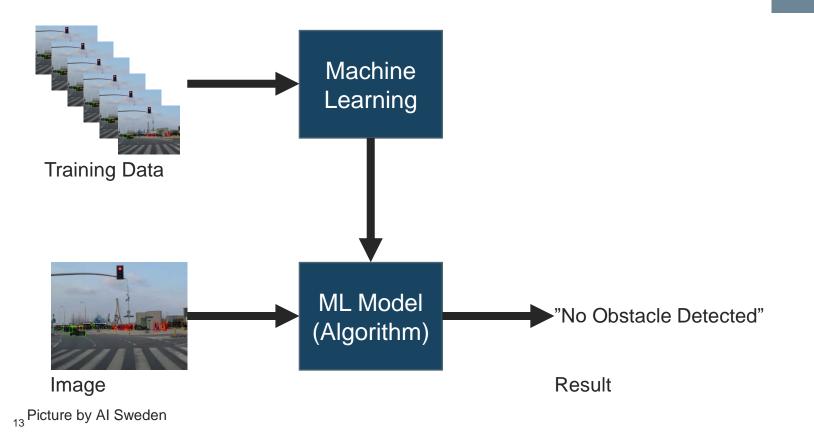
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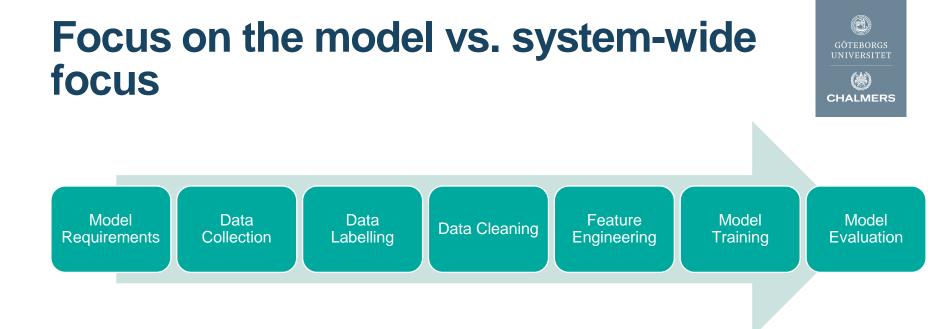


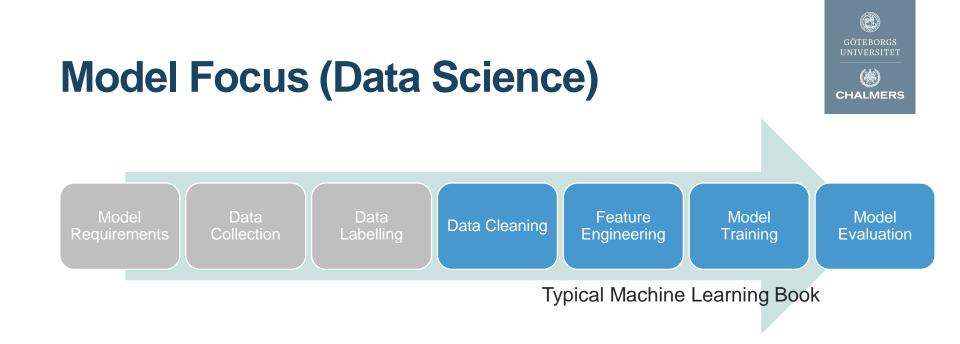


Example: Obstacle Detection

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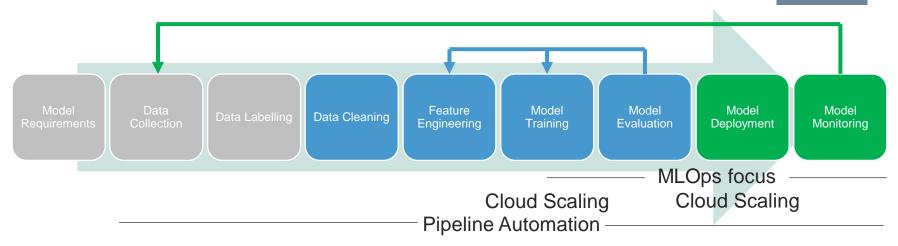




• The (traditional) focus in data science is building models from given data and evaluate the resulting accuracy. Small, prototype style of systems.



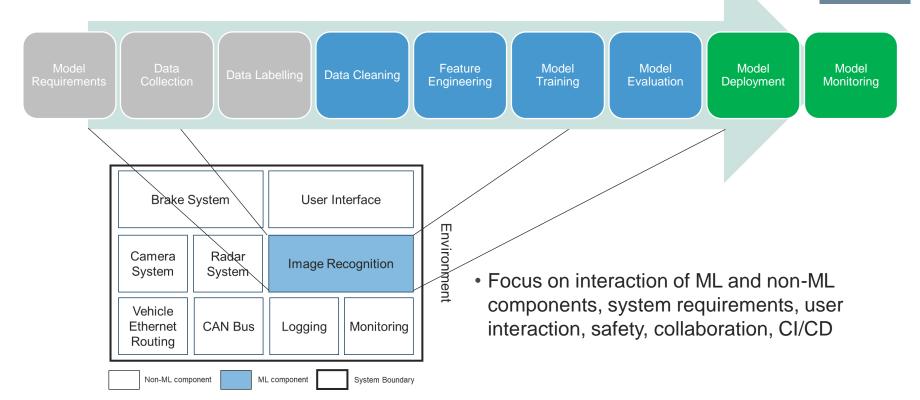
Let's automatise (ML Engineer)



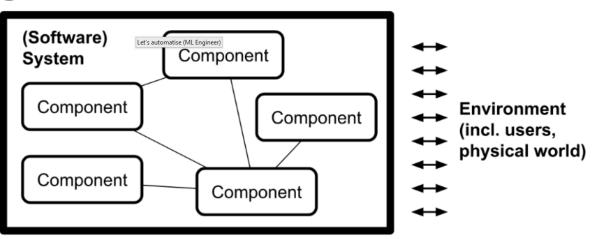
• ML Engineering focuses more on deploying, scaling training and deploying, model monitoring and updating (during operations)

ML in Production





High level system requirements and goals



- Systems basically never consist of a single component.
- The ML model is only one of many other components in a system.
- How does it communicate with other components?
- A system architecture brings all components together.

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3 Groups: System Goals

Environment

Environment

Environment

User Interface				
User's Movie History	Movie Prediction			
Movie Database		Logging	Monitoring	

User Interface / Web Interface				
User Address	Tax Records	Salary Payments	Credit Rating Prediction	
Database		Logging	Monitoring	

Brake System		User Interface	
Camera System	Radar System	Image Recognition	
Vehicle Ethernet Routing	CAN Bus	Logging	Monitoring

Exp Picks for Murth



Movie Prediction

Goal 1

Goal 2

Credit Rating Prediction

- Goal 1
- Goal 2

Automatic Emergency Braking

- Goal 1
- Goal 2

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We can define properties / nonfunctional goals for the system, e.g., safety is a system property

Environment



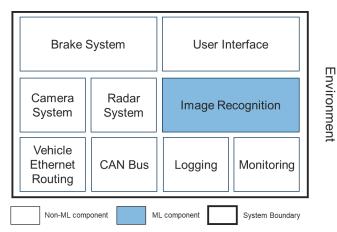
Brake System		User Interface		
Camera System	Radar System	Image Recognition		
Vehicle Ethernet Routing	CAN Bus	Logging	Monitoring	
Non-ML component ML component System Boundary				

Example of Safety Goals:

- The system shall not trigger an unwanted braking request (ASIL C).
- The system shall not trigger a brake request too late (ASIL B).

How to translate this into model data requirements, accuracy needs, testing conditions?

System goals and model requirements



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Example of Safety Goals:

- The system shall not trigger an unwanted braking request (ASIL C).
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On one hand we want a "conservative" model that only triggers the brakes when it is <u>very certain</u> about an obstacle ahead.

On the other hand, we do not want to trigger the brakes too late. We also need to consider artifacts or noise in the image for example.

A narrow focus only on model accuracy that ignores how the model interacts with the rest of the system might compromise the ability to balance various desired quality aspects.

How to ensure the safety goals (Safety Assurance)



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• For / in the model

- Ensure correct / sufficient training data (how?)
- Check that operational context (ODD) is as expected (how?)
- Optimise prediction speed
- Use confidence checks (what?)
- Outside the model
 - Add redundant non-ML system (radar)
 - Train a redundant independent second model (consequences?)
 - Move responsibility to the user

New Early Access Software Update

Full Self-Driving (Beta)

Full Self-Driving is in early limited access Beta and must be used with additional caution. It may do the wrong thing at the worst time, so you must always keep your hands on the wheel and pay extra attention to the road. Do not become complacent.

When Full Self-Driving is enabled your vehicle will make lane changes off highway, select forks to follow your navigation route, navigate around other vehicles and objects, and make left and right turns. Use Full Self-Driving in limited Beta only if you will pay constant attention to the

road, and be prepared to act immediately, especially around blind corners, crossin intersections, and in narrow driving situations.

Picture by Forbes Magazine

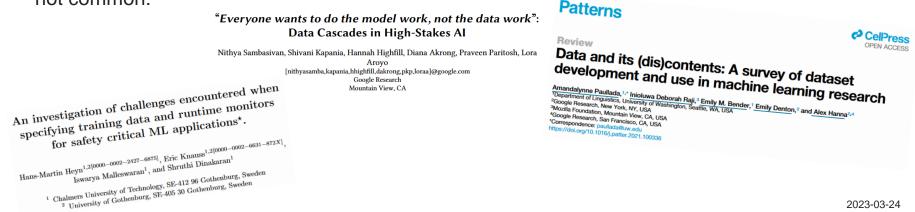


Model vs. System Properties

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- Similar to safety, many other (non-functuional) requirements / qualities should be discussed at <u>model and system level</u>
 - Security
 - Privacy
 - Transparency & Accountability
 - Maintainability
 - Scalability
 - Energy Efficiency

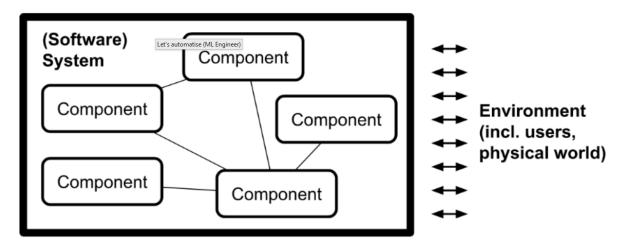
What data do we need?

- Often a model-centric view assumes we have (unlimited) pool of data available.
- In production systems, especially in industries outside of traditional software engineering (e.g., car industry, medical industry, environmental monitoring,...) creating data is actually expensive! Sometimes very very expensive!
- System designers therefore should also focus on how to collect data, label data, document data, plan experiments / data collection campaigns.
- However, defining clear data specifications for ML-enabled system development is not common:



Managing complexity





- Abstraction: Focus first on high-level behaviour
- Reuse: Define small units / packages that are reusable and define interfaces (Divide & Conquer)
- Composition: Build larger components out of smaller ones

Time for a break



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What will you learn?

Architectures and patterns for AI/ML-enabled systems

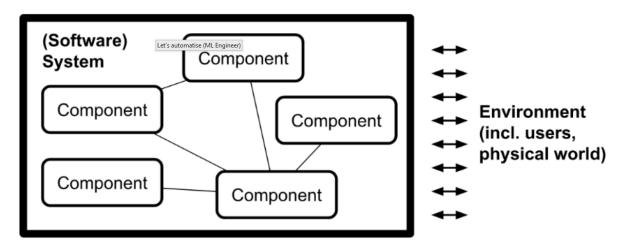
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Managing complexity





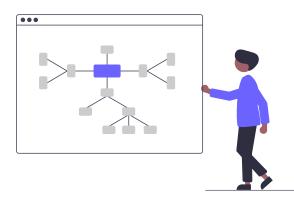
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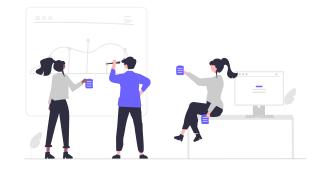
Co-Design of a system



- Designing a complex and distributed system is a hierarchical process of integration.
 - Several, sometimes highly specialized views allow for decomposition of the design task.
 - Requirements and architecture often co-evolve (Twin Peaks).

• Developing complex system is a **highly collaborative** act between many stakeholders.



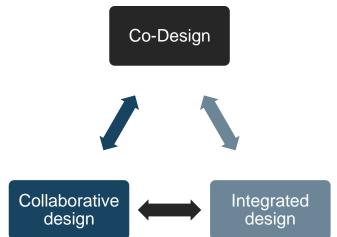


Problem Definition

Finding an architectural framework that works with AI/ML enabled systems

- We needed to define an architectural framework, that supports both aspects of co-design.
- The framework must support explicitly aspects AI system development but also of other aspects such as connectivity
 - Learning and data
- A special focus lies on the support of nonfunctional requirements / quality views
- Traceability of design decisions



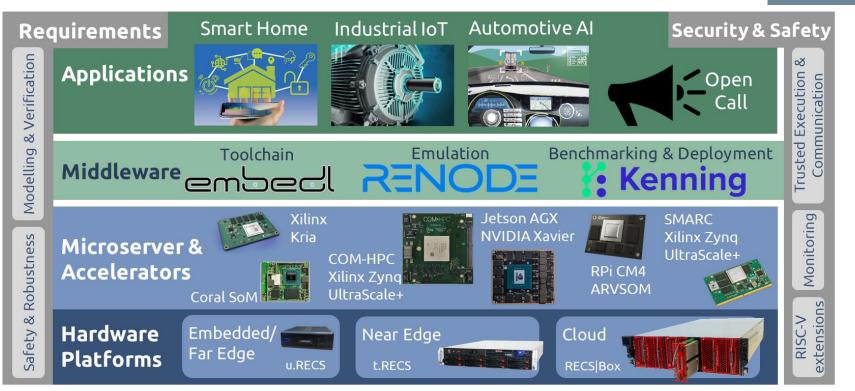


A bit of context

Building distributed systems with AI

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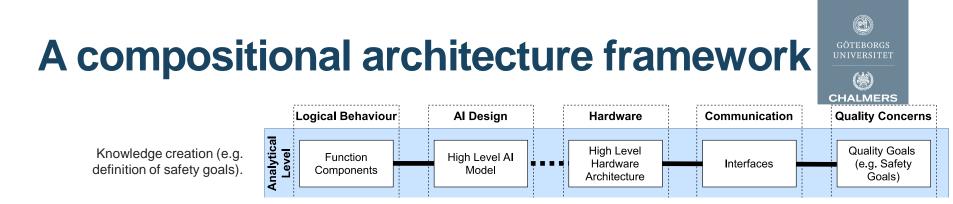


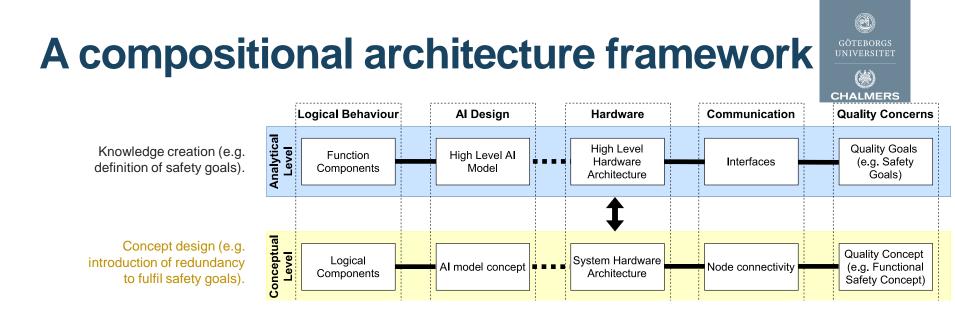


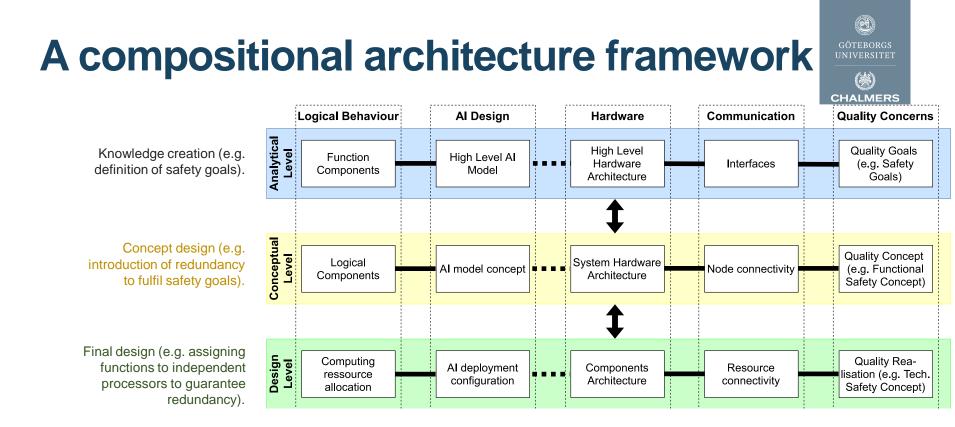
Current approaches to architecture did not help



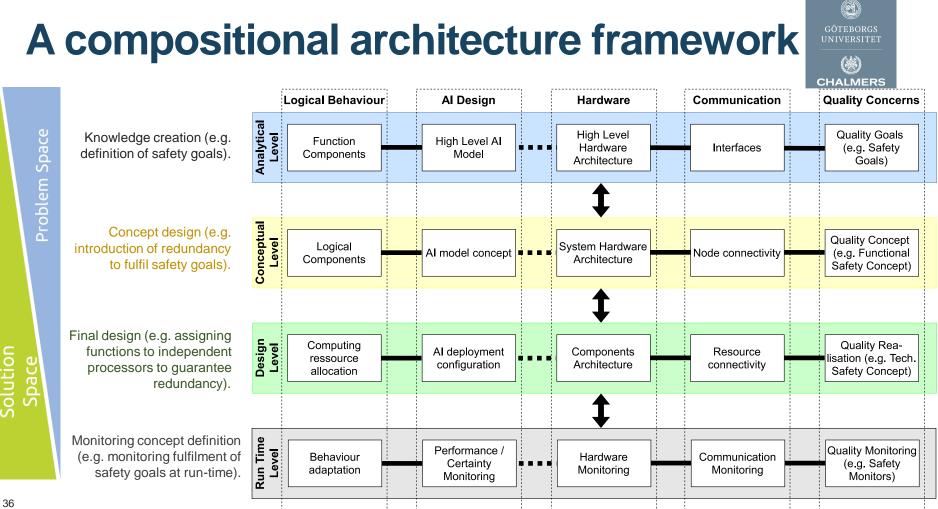
- Providing the right learning setting / training data
 - No explicit views on the learning perspective of an AI system in common architecture approaches (Bosch et al., 2020, Muccini et al., 2021).
- Monitoring solutions must be represented explicitly in the architecture
 - Some flaws can only be detected after deployment
 - Therefore, monitoring is needed to ensure functional, and non-functional aspects of an AI system (Bernadri et al., 2019).
- New quality aspects arise, such as "explainability", or "data privacy"
 - Depending on the use case certain a wide set of quality aspects can be relevant (Habibullah and Horkoff, 2019)
 - New stakeholders need to be included with their own views on the system (Vogelsang and Borg, 2019)







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The full picture (for VEDLIoT)



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Business Goals and Use Cases Behaviour and Context Means and Resources Communication Quality Concerns Hardware Information Con-Al Model Ethics Security Safety Logical Process Context & Data Learning Privacv Behaviour Behaviour Constraints Strategy nectivity High level Analytical Function Context Privacy Threat Hazard Level Data Training High level hardware Com-Ethic analysis analysis Interfaces impact Interaction assumcomingestion obiectives 📗 Al model archipilation principles analvsis (TARA) (HARA) ponents ptions tecture Conceptual System Logical Logical Infor-Cyber-Functional Level Context Data Training Al model hardware Node con-Ethic Privacy security mation safety comsedefinition selection concept concept archinectivity concept concept model concept ponents auences concept tecture Level Com-Com-Con-Data pre-Technical Technical Technical Resource Al model ponent Comm-Resource Ethic paration / Optimiser straints / cyberputing unication 븜 technical solutions safetv Design sehardware 🖶 concon-Design settings security maniressource figuration archinectivity realisation model for privacy quences concept allocation Domain pulation concept tecture Runtime Assess-Assess-Security Safety Manage Al model Hardware Run Time ment of Level data Conment / monitoring monitoring Be-Adaptive Context continous Data perpernectivity auditing of privacy haviour monitorina monitoring behaviour monitoring improveformance formance monitoring and monitorina AI comthreat safetv demonitoring monitoring ments collection decisions pliance aradition response

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3 Groups: Cluster of Concerns

Environment

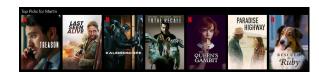
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Environment

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Data	base	Logging	Monitoring

Brake S	System	User In	iterface
Camera System	Radar System	Image Recognition	
Vehicle Ethernet Routing	CAN Bus	Logging	Monitoring



Your credit rating is...



Movie Prediction

- Cluster 1
- Cluster 2

• ...

Credit Rating Prediction

- Cluster 1
- Cluster 2

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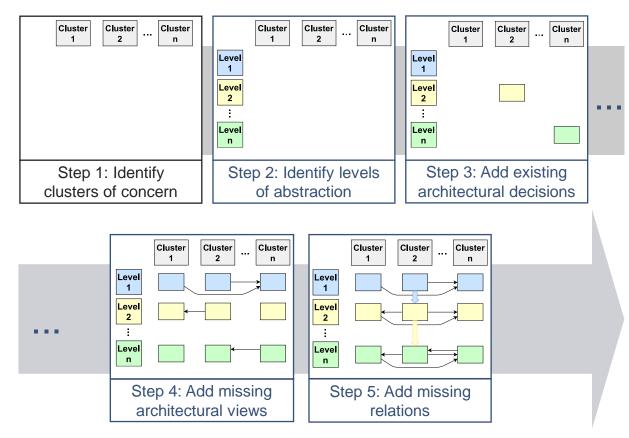
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Automatic Emergency Braking

- Cluster 1
- Cluster 2

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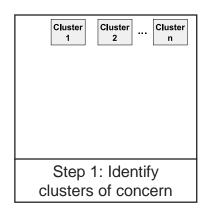


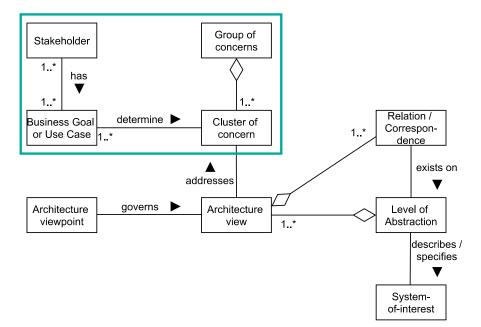


- Step 1: Identify clusters of concern
- Step 2: Identify levels of abstraction
- Step 3: Add existing architectural decisions.
- Step 4: Add missing architectural views.
- Step 5: Add missing relations.
- Step 6: Iterate if needed.



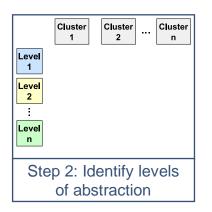
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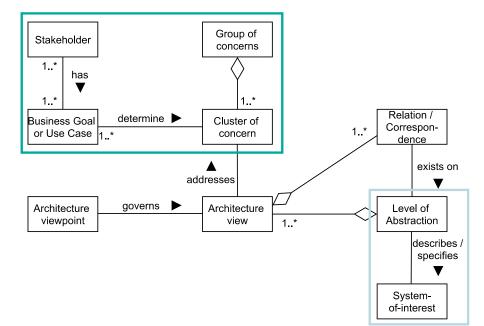






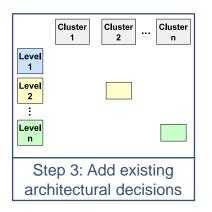


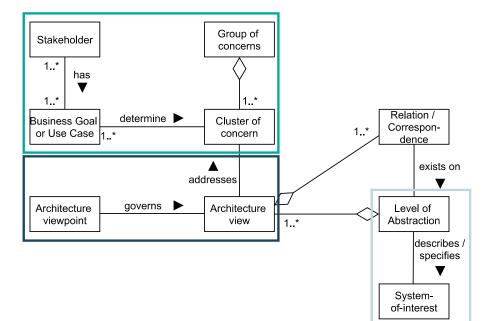


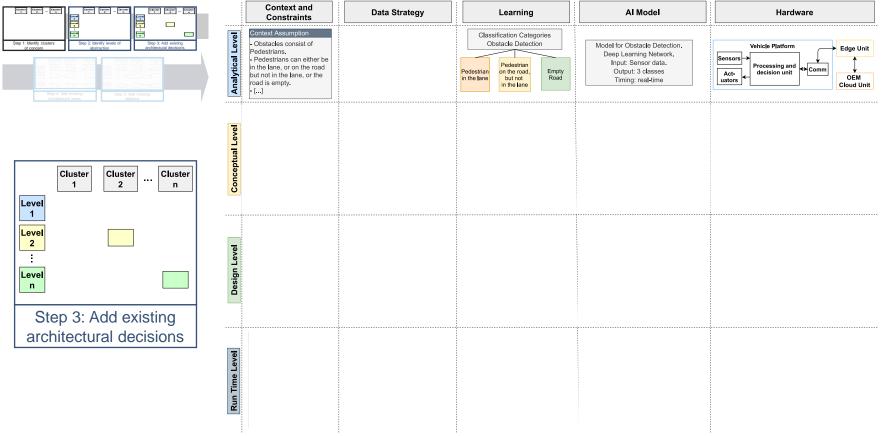


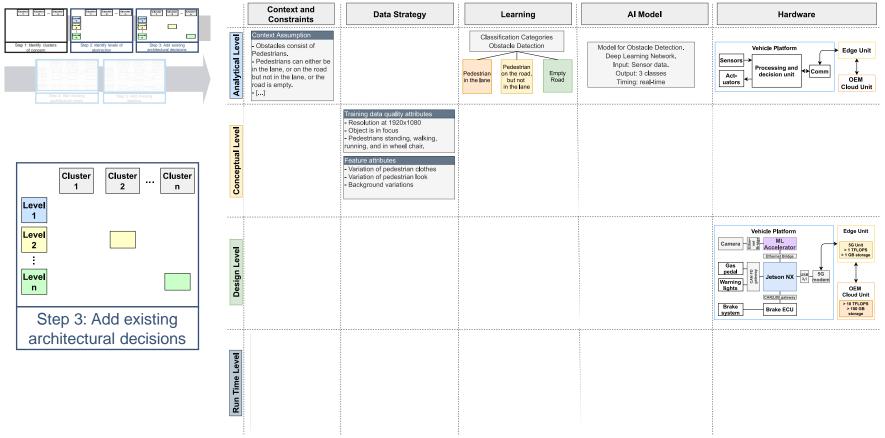






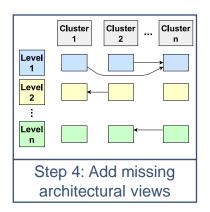


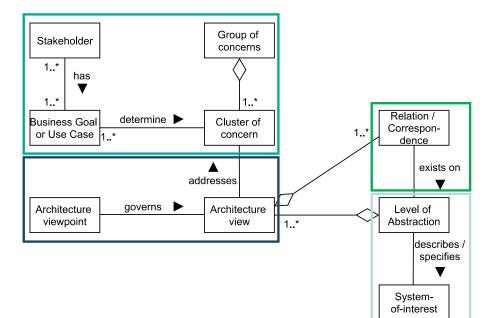


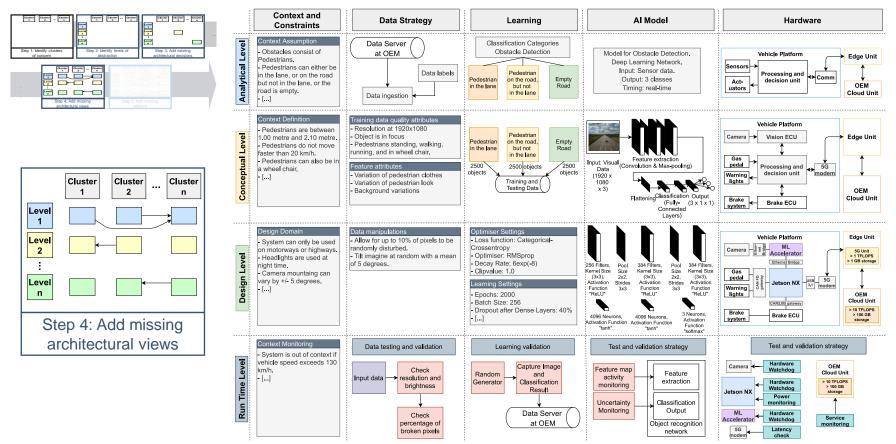






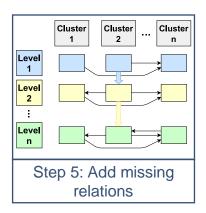


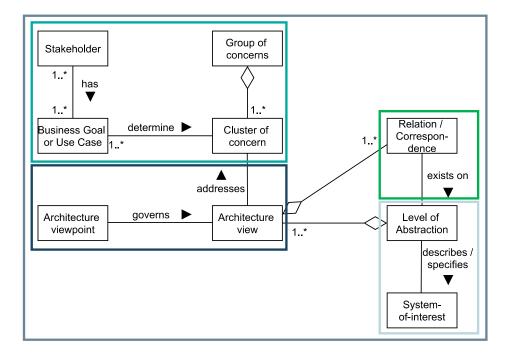




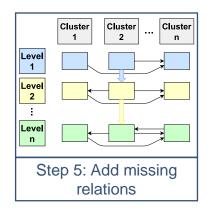


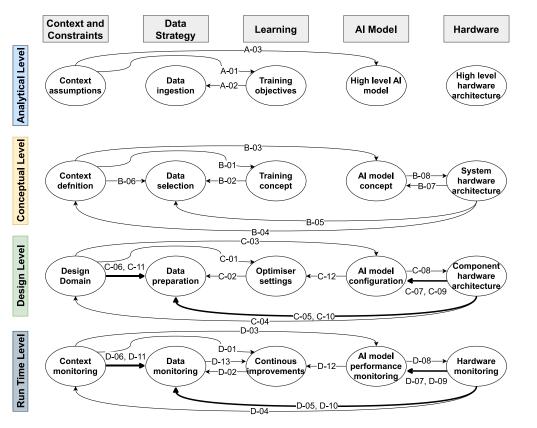




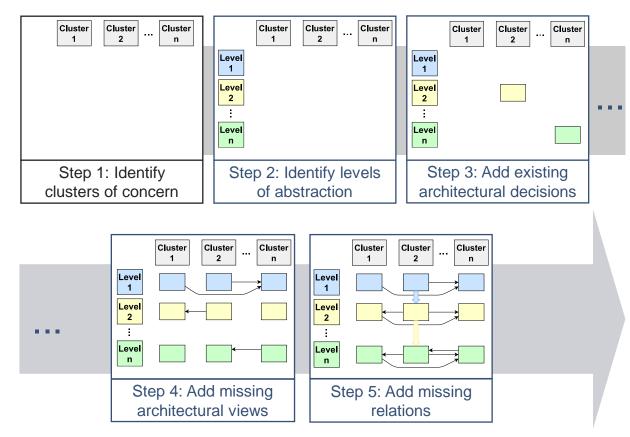








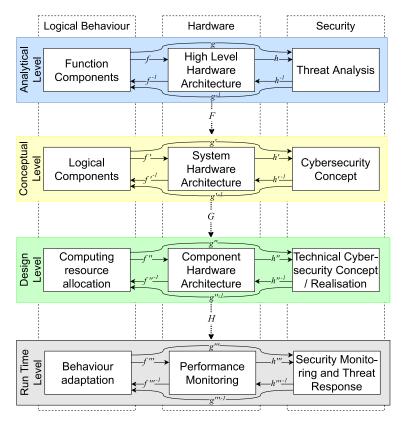
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A compositional approach to architecture framework





Rule 1: Clusters of concern shall contain architectural views with different levels of details of a certain aspect of the VEDLIoT system.

Rule 2: Architectural views shall be sorted into levels of abstractions, according to their level of details about the VEDLIoT system.

Rule 3: By using correspondence rules, it shall be possible to arrive at different architectural views of the VEDLIOT system without encountering inconsistencies.

Rule 4: Architectural views, and relations between them, shall be mapped to the next lower level of abstraction.

Heyn, H. M., Knauss E., & Pelliccione P. (2023). A Compositional Approach to Architecture Frameworks for distributed AI Systems. *In Elsevier Journal of Systems and Software (JSS)*.

Why?

- The architectural framework helps connecting different aspects of a larger system together.
- It allows for "middle-out" development, i.e., existing design decisions are explicitly considered.
- It allows to keep an overview over the necessary quality aspects, such as safety, security, ethical, or privacy aspects of the systems.
- The framework enforces a runtime concept for the system.
- The traceability of design decisions allows for compliance with upcoming AI regulations.



Proposal for a

REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL

LAYING DOWN HARMONISED RULES ON ARTIFICIAL INTELLIGENCE (ARTIFICIAL INTELLIGENCE ACT) AND AMENDING CERTAIN UNION LEGISLATIVE ACTS

{SEC(2021) 167 final} - {SWD(2021) 84 final} - {SWD(2021) 85 final}

Some reading recommendations



Bosch, J., Olsson, H. H., & Crnkovic, I. (2021). Engineering ai systems: A research agenda. In Artificial Intelligence Paradigms for Smart Cyber-Physical Systems (pp. 1-19). IGI global.

Bernardi, L., Mavridis, T., & Estevez, P. (2019). 150 successful machine learning models: 6 lessons learned at booking. com. In Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining (pp. 1743-1751).

Paullada, A., Raji, I. D., Bender, E. M., Denton, E., & Hanna, A. (2021). Data and its (dis) contents: A survey of dataset development and use in machine learning research. Patterns, 2(11)

Heyn, H. M., Knauss, E., & Pelliccione, P. (2023). A compositional approach to creating architecture frameworks with an application to distributed AI systems. Journal of Systems and Software, 111604.

Jackson, M. (1995). The world and the machine. In Proceedings of the 17th international conference on Software engineering (pp. 283-292).

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Hulten, G. (2019). Building Intelligent Systems. Berkeley, CA: Apress., Chapter 5 and Chapter 7

More literature (if you are interested)



Muccini, H., & Vaidhyanathan, K. (2021, May). Software architecture for ml-based systems: what exists and what lies ahead. In 2021 IEEE/ACM 1st Workshop on AI Engineering-Software Engineering for AI (WAIN) (pp. 121-128). IEEE.

Habibullah, K. M., & Horkoff, J. (2021, September). Non-functional requirements for machine learning: understanding current use and challenges in industry. In 2021 IEEE 29th International Requirements Engineering Conference (RE) (pp. 13-23). IEEE.

Vogelsang, A., & Borg, M. (2019, September). Requirements engineering for machine learning: Perspectives from data scientists. In 2019 IEEE 27th International Requirements Engineering Conference Workshops (REW) (pp. 245-251). IEEE.

What did you learn?

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In the next lecture...



- Example of how the compositional architecture framework can be applied.
- Responsible Software Engineering for / with AI/MLenabled systems





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