



Auditability in ML Systems v1.0.0

Gastvortrag - Software Engineering in KI Systemen –
Universität Leipzig

12.06.2023

Agenda

DB



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About me

About me



Jürgen Stary

*Solution Architect MLOps @
AI Factory DB Systel GmbH*

- Since 2015 worked in various roles with a focus on building and operating ML Systems and applications
- My favorite question is „Why?“



Perception vs Reality ☺



#gernePerDu
#prototypingInEnterprise
#systemsThinking
#challengeMe

/jaystary

About Rachel



Dr. Rachel Hagemann

*Senior AI Specialist @
AI Factory DB AG*

- Spent the last 10+ years building, applying and testing mathematical/ML algorithms.
- Drive to understand the strengths and weaknesses of the ‚OG algorithms‘ and ‚new Sheet‘ tools in the ML tool box.
- Motivated to see what makes an algorithm break.
- #SafeAI

Background - What do architects do?



Product



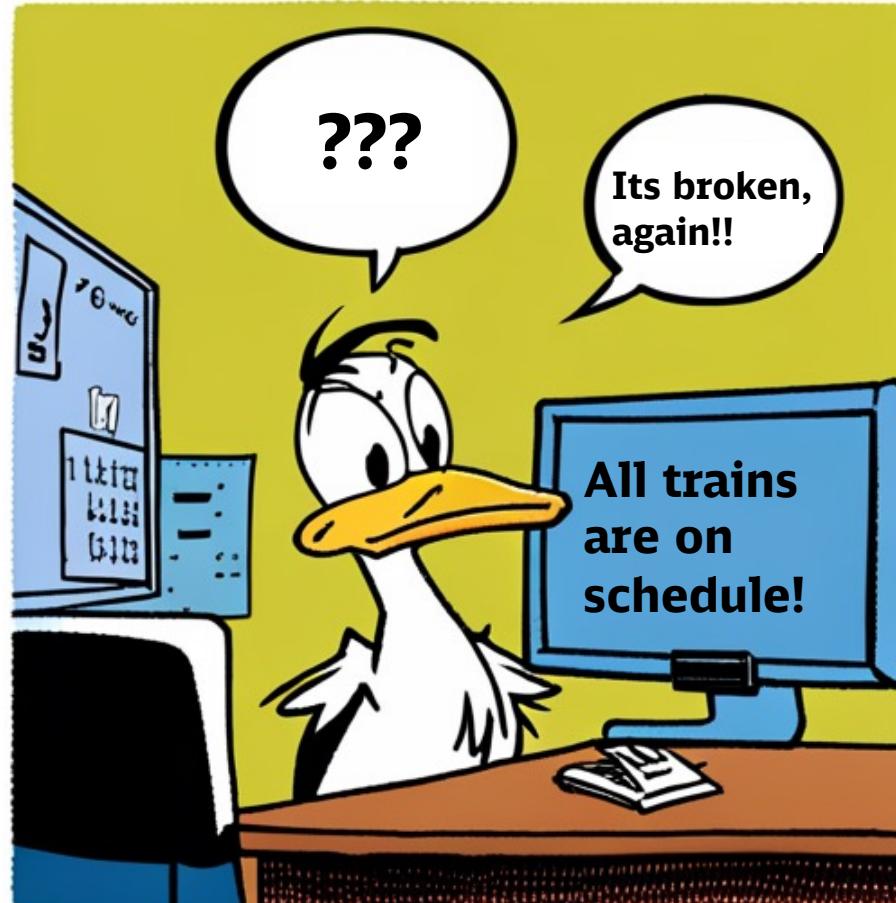
ENTERPRISE ARCHITECT (EA)	SOLUTION ARCHITECT (SA)	TECHNICAL ARCHITECT (TA)
Technology Focus 	Technology Focus 	Technology Focus
Strategy Focus 	Strategy Focus 	Strategy Focus
Key Competencies <ul style="list-style-type: none">✓ Master of EA Frameworks (i.e. TOGAF, Zachman Framework)✓ Uncovers operational gaps✓ Analyzes information through data models and architecture diagrams✓ Communicates the value of new IT strategies and keeps stakeholders informed of ongoing initiatives <p>https://www.leanix.net/de/ty/comparing-it-architecture-roles-poster</p>	Key Competencies <ul style="list-style-type: none">✓ Coordinates ongoing activities✓ Translates the design concept to IT operations✓ Defines a best-fit solution for existing problems✓ Ensures technological risks are accounted for and solutions meet necessary requirements	Key Competencies <ul style="list-style-type: none">✓ High level of in-depth expertise (i.e. Python, Java)✓ Provides recommendations to address potential threats✓ Implements technical processes to roll out solutions✓ Delivers fully functional products in a timely manner for the end user

Engineering

Why do we want auditable systems

“Anything that can go wrong, will go wrong” v1.0.0

DB



AI generated

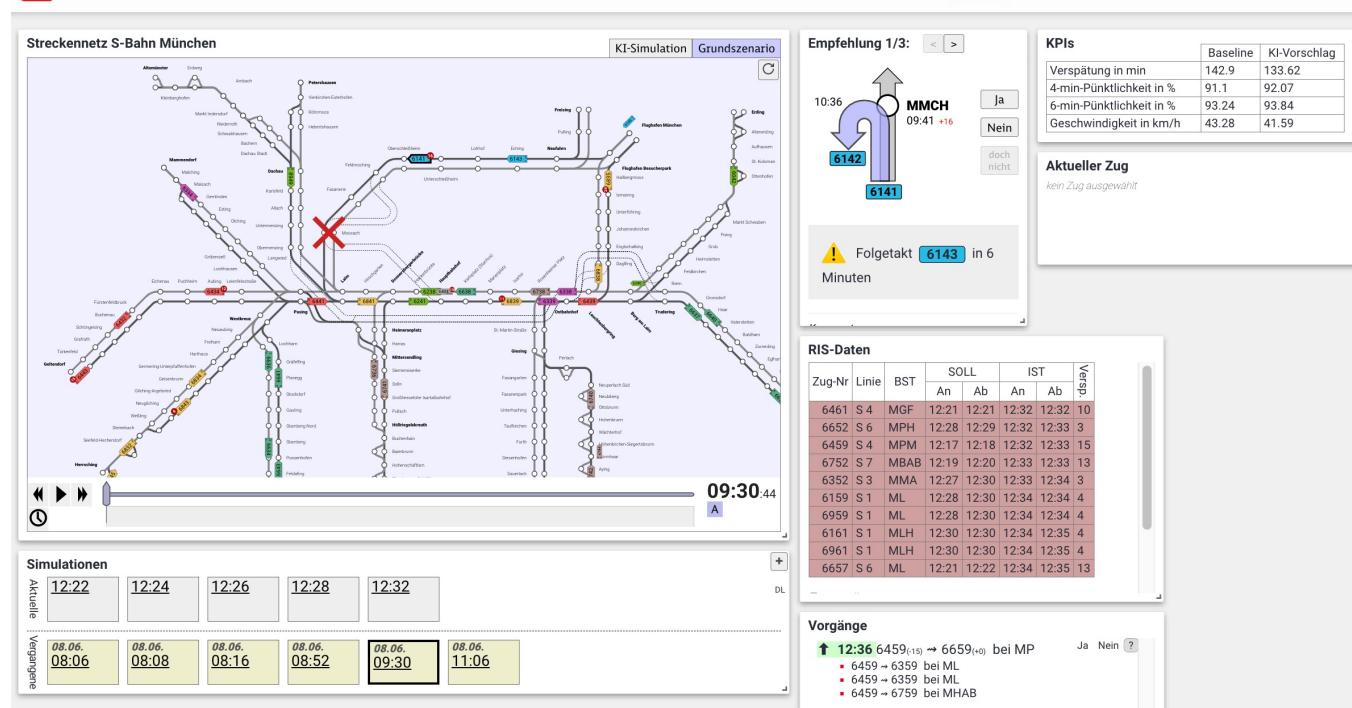
A ML System - KI in der Disposition



Reinforcement learning algorithms support human decision making in complex environments to minimize train delay / increase „Netzfrequenz“

Frontend

DB KI in der Disposition - S-Bahn München



Monitoring



<https://digitale-schiene-deutschland.de/AI-Prototyping>

<https://www.handelsblatt.com/unternehmen/handel-konsumgueter/schienenverkehr-bahn-bringt-kuenstliche-intelligenz-aufs-gleis/27222608.html>

Foundations of auditable ML Systems



Extrinsic

AI Act

- Provides a framework for **regulation** of AI systems for the selling, trading and operation of AI within the EU
- Lists specific requirements and limits on certain AI systems.

Operational Excellence

- Constructing a system with a strong emphasis on auditability from the outset leads to valuable by-products, including key aspects of operational excellence, while minimizing technical debt and concealed issues.

Intrinsic

Transparency

Reproducibility

Accountability

Trust &
Confidence

Long Term
Stability

Robustness

Definitions

Definition of auditability



A good auditable system is **accessible** and **transparent** to each respective stakeholder.

External Stakeholders

Requires:

- An overview of all AI/applications Systems at the company
- Designation for each AI application (high risk/moderate risk/low risk)
- Documentation of the processes, rolls and responsibilities for the 'high risk' systems
- Documentations of compliance to current laws and regulations

Developer

Requires:

- Technical documentation on
 - Data/Data quality/Restrictions/Contacts
 - Tooling
 - Feature Integration
 -
- Standards and processes for working with data, deploying models ...
- Limitations (IP/Licenses/Security) on tools/code/opensource etc.

1

External Stakeholders (Extrinsic)

- EU/Country Government
- Regulatory Authorities
- Customers / Users
- Third-Party Auditors
- ...

Concerns

- ... revolve around:
 - compliance with laws/regulations
 - system performance
 - impact on society
 - upholding values and human rights
 - ...



2

Internal Stakeholders (Intrinsic)

- Management
- Data Scientists / ML Engineers
- DevOpsSec/MLOps Teams
- Compliance (Liability)
- ...

Concerns

- ... revolve around:
 - Risk assessment
 - Efficient development, deployment and ops
 - Internal guidelines and policies
 - System performance & reliability
 - Organizational goals & objectives

AI Act – Requirements

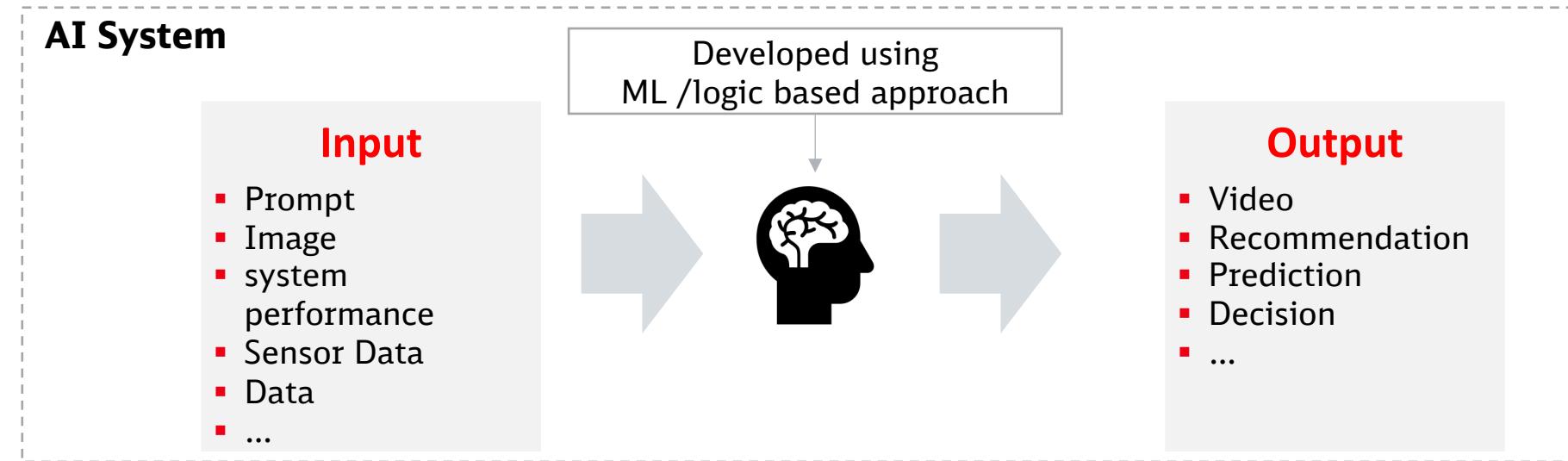
Highlights – AI Act

- Regulates the use of AI Systems that are of:
Inacceptable risk
 - social scoring
 - remote biometric identification
 - ...
- **High risk**
 - critical infrastructure
 - employment
 - safety components
 - ...
- Excludes scientific and product research
- Final voting expected at the end of 2024
- Estimated Costs for non-compliance up to*:
 - max(30 000 000 EUR , 6 % total worldwide annual turnover)
 - SMEs & start-ups, 3% of worldwide annual turnover



* Proposal is still in negotiations, however foundational aspects are not expected to change

Definition of AI (17.05.2023) – AI Act



Current (paraphrased) General definition of AI system (6a, 6b)

AI systems should **infer** the way to achieve a given set of human-defined **objectives** based on **inputs** (data,prompt, image, video, ...) using **machine learning** and/or logic- and knowledge based approaches in order to produce an **output** (prediction, suggestion, video,decision...) .

Autonomy

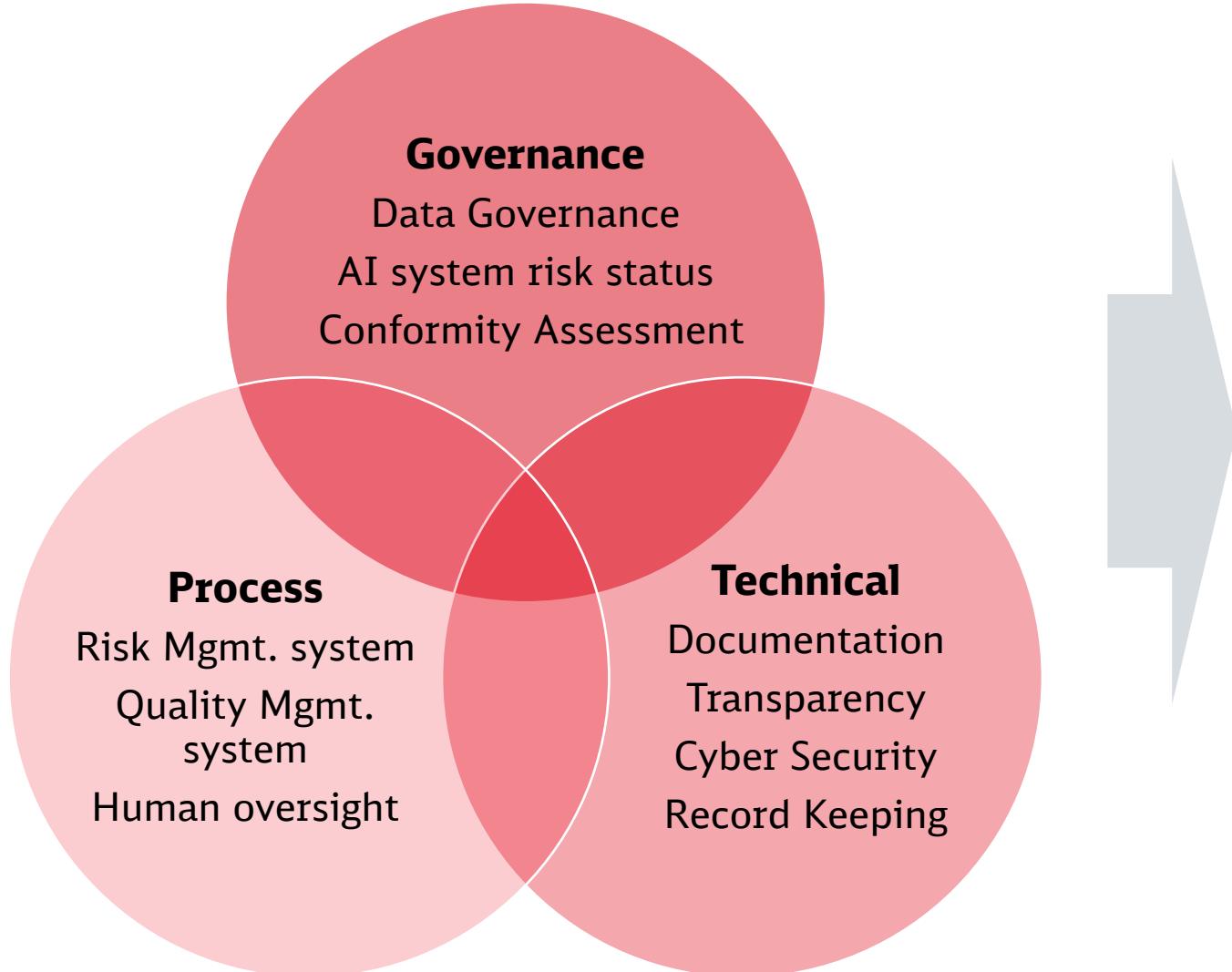
The concept of the autonomy of an AI system relates to the degree to which such a system functions without external influence human involvement.

Distinction with ‘classical’ software

The definition should make a distinction between the software of **artificial intelligence** and more **classic** simpler software systems and programming approaches.

Out of scope

A system that uses **rules defined solely by natural persons** to automatically execute operations should not be considered an AI system.

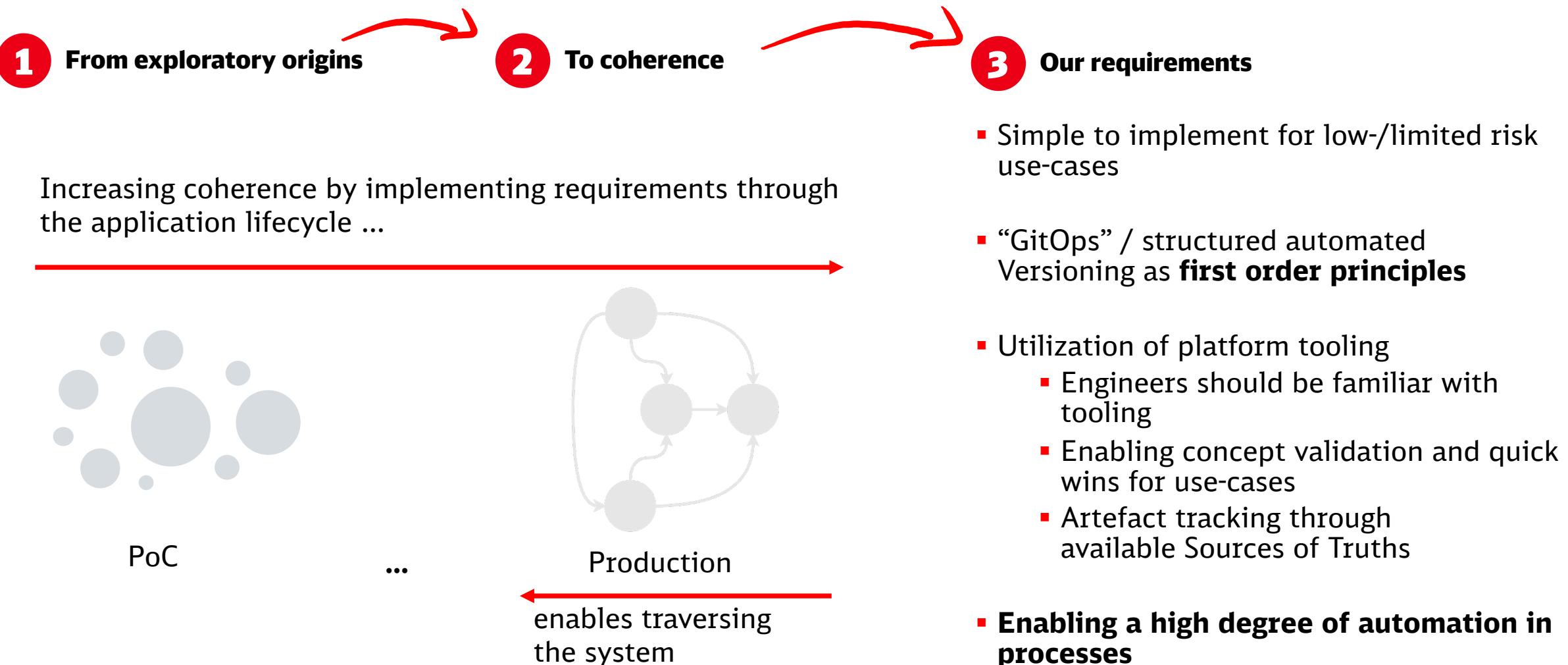


Transparency through Technology

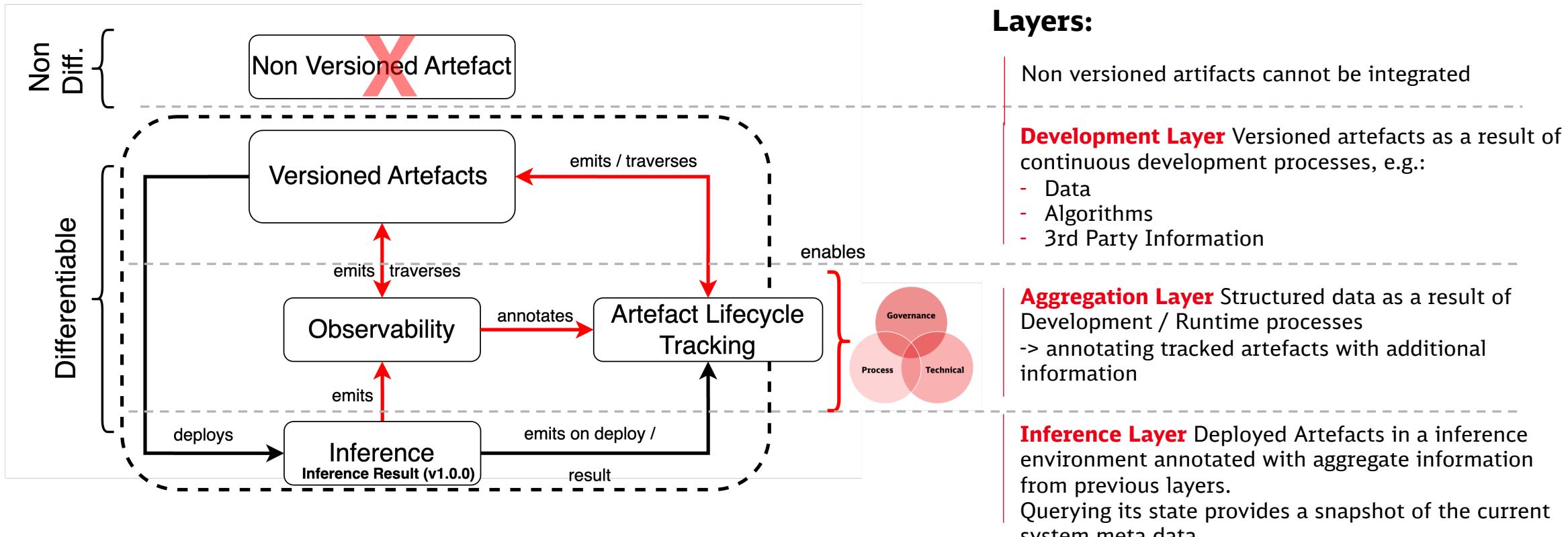
Solutions need
Automation and Integration
in the development process

Auditability from a technical perspective

Modern ML Systems produce a wide variety of audit relevant artefacts



A mental model for working with artefacts



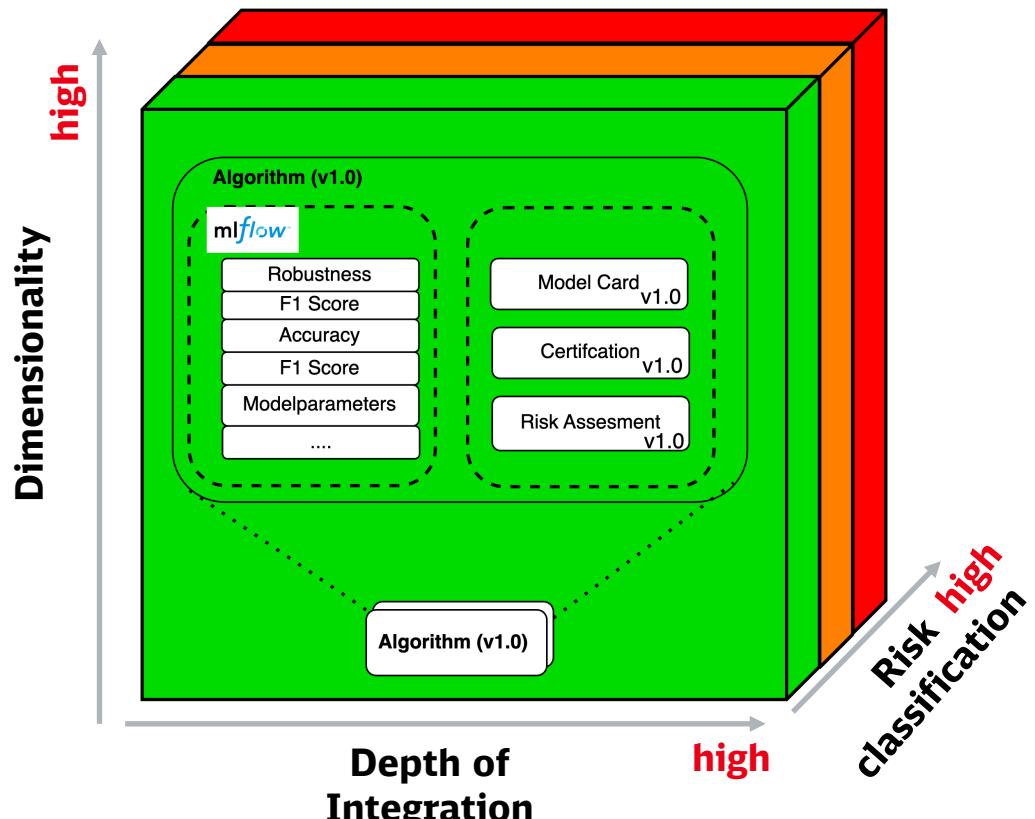
Coherence:

- Given a versioned artefact, we must be able to traverse the system, its artifacts and their history to ensure our defined foundations

Steps towards Coherence:

- Integrating versioned artefacts starting from the end adding them to tracking increases the degree of understanding about the system

Challenges with artefact tracking



Dimensionality

- The level of detail at which artifacts are tracked

Depth of Integration

- The extent to which artifacts within our system are tracked

Risk Categorization

- The criteria for determining which properties of artifacts require monitoring

Use-case specific requirements

- Industry specifics (e.g. regulated industries)
- Tamper proofness ...
- Multitenancy on a per project/user level ...
-

Capturing artefacts at higher dimensions requires specialized tooling

- Current market offerings still early phase
- Platform components >> OSS / Buy >> Make

Specialized tooling requires maintenance and additional education from users and engineers

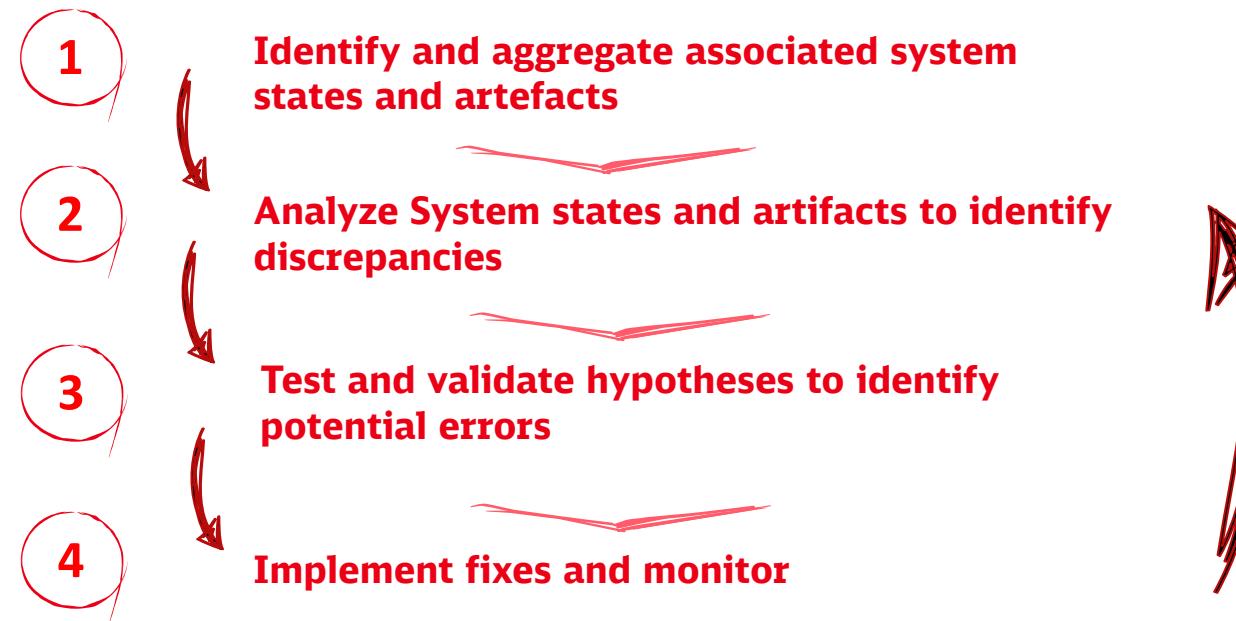
- Requires additional discipline, consistency embedded in workflows and culture
- Gaps in automation -> possibility for gaps in our DAG, impacting lower level integration

Common artefacts in ML Systems



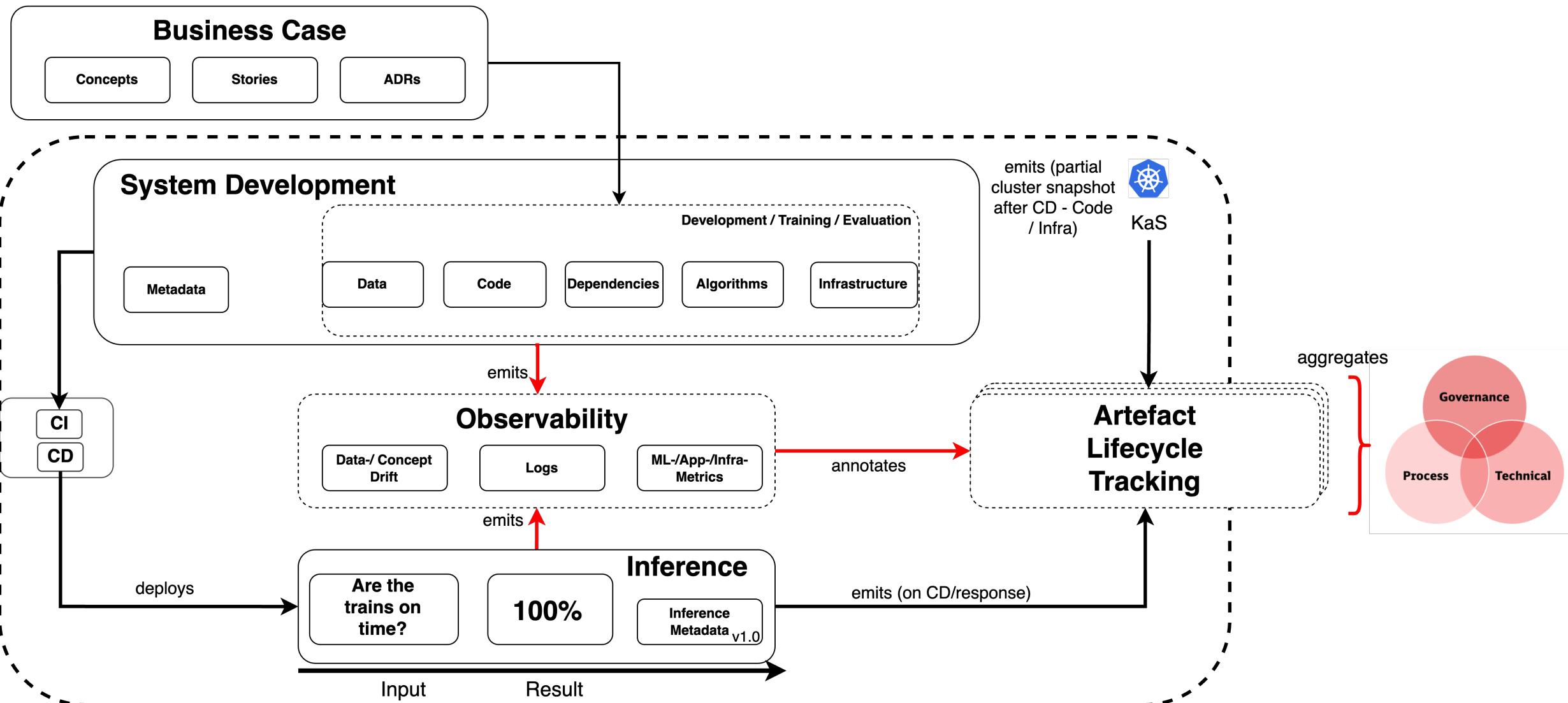
Artefact	Description	Source of Truth
Algorithm Input	./.	...
Inference Result	./.	...
Inference Metadata	Process information about Inference, e.g. Algorithm Version, Latency, Telemetry,
Observability	Logs and Emits from Development / Inference Layer	...
Data	References datasets, data slices, ... on a data source	...
Code	./.	...
Dependencies	Utilized package and/or engine dependencies	...
Algorithms	Aggregation of Code, Data, Parameters, Certifications as a result of the algorithm development process	...
Metadata	References ML related artefact metadata	...
Infrastructure Metadata	References to training / evaluation infrastructure	...
CICD	References to Pipelines, Qualitygates, owners of a deployment,
Concepts / Stories / ADRs ...	Planning & Documentation artefacts that result in development	...

Navigating the system



An ML system built upon defined principles inherently facilitates a coherent environment. This allows both external and internal stakeholders to readily discover answers to their specific inquiries.

Filling our mental model with artefacts

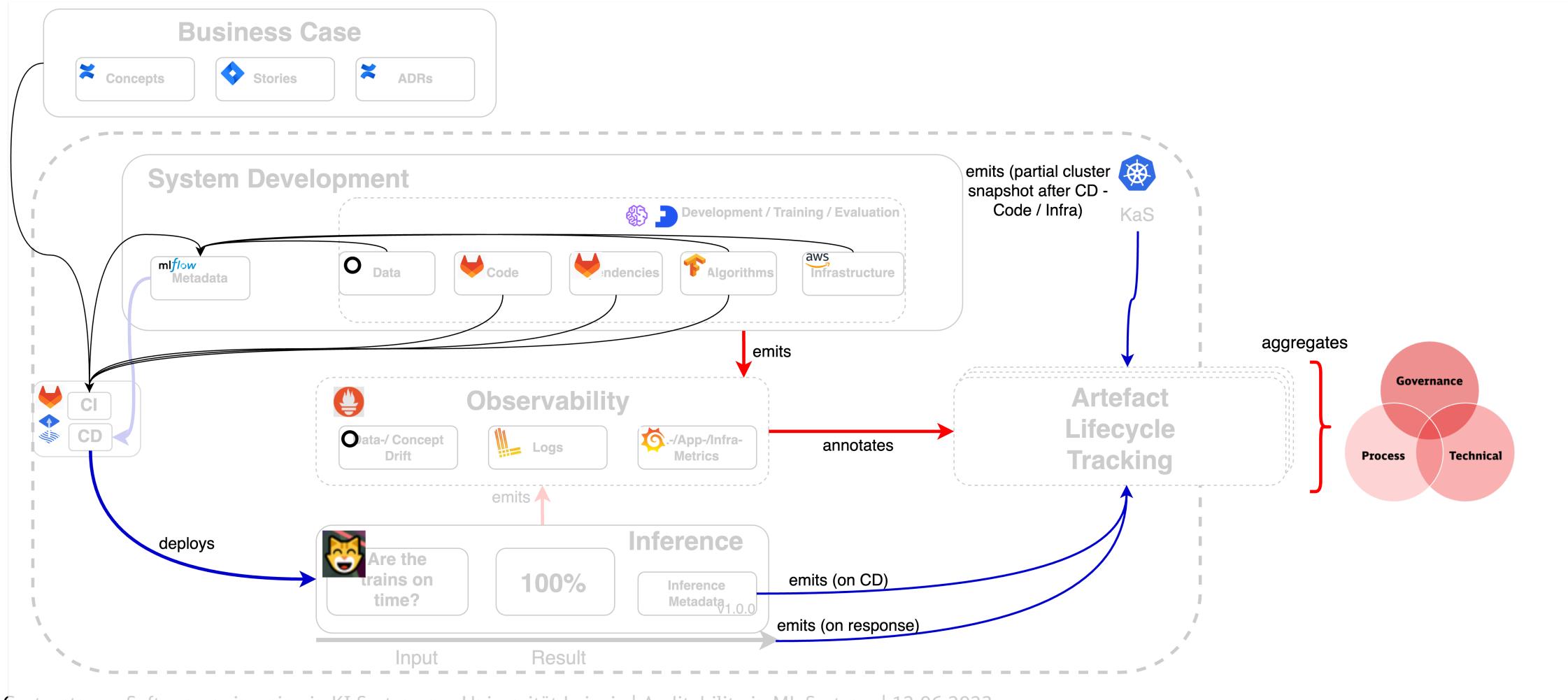


All streets must lead to Rome eventually...



Additional considerations for implementation:

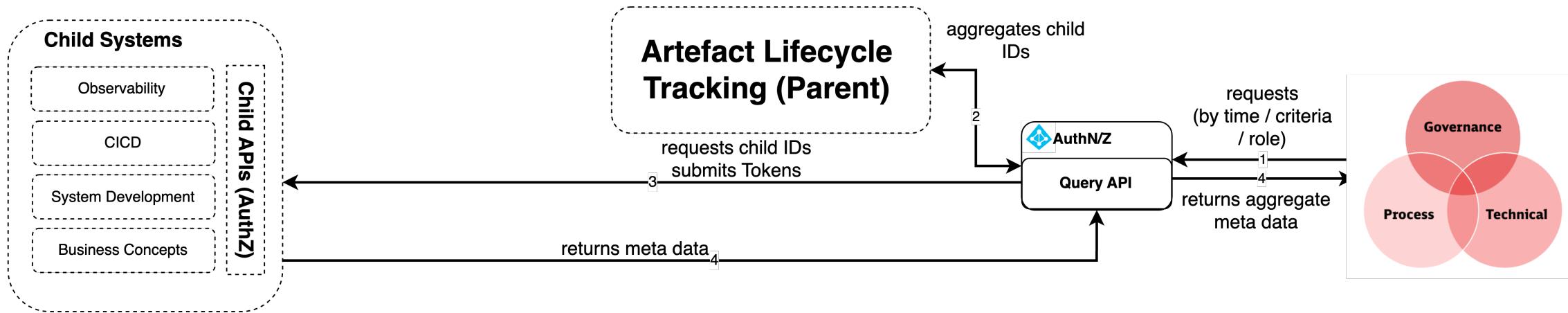
- Running everything in a common/integrated environment (e.g. K8s) simplifies tracking and process implementation
- Minimizing Sources of Truth simplifies data aggregation and traceability
- Being able to capture all state changes in the system (e.g. on / after a CD / declarative Infra) simplifies understanding



Retrieving our system state



By adding a permissioned query api in front of the overall application we can query all components and aggregate the relevant meta data by defined criteria





AI generated

**Thank you for
your interest!**

P.S. db.de/ai-jobs