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Testing the Untestable

Risikobasierte Qualitätssicherung für Machine-Learning Systeme

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Agenda

- Motivation
- Classical Risk-Based Testing
- Testing Machine-Learning-Based Systems
- Data Testing
- Online Testing

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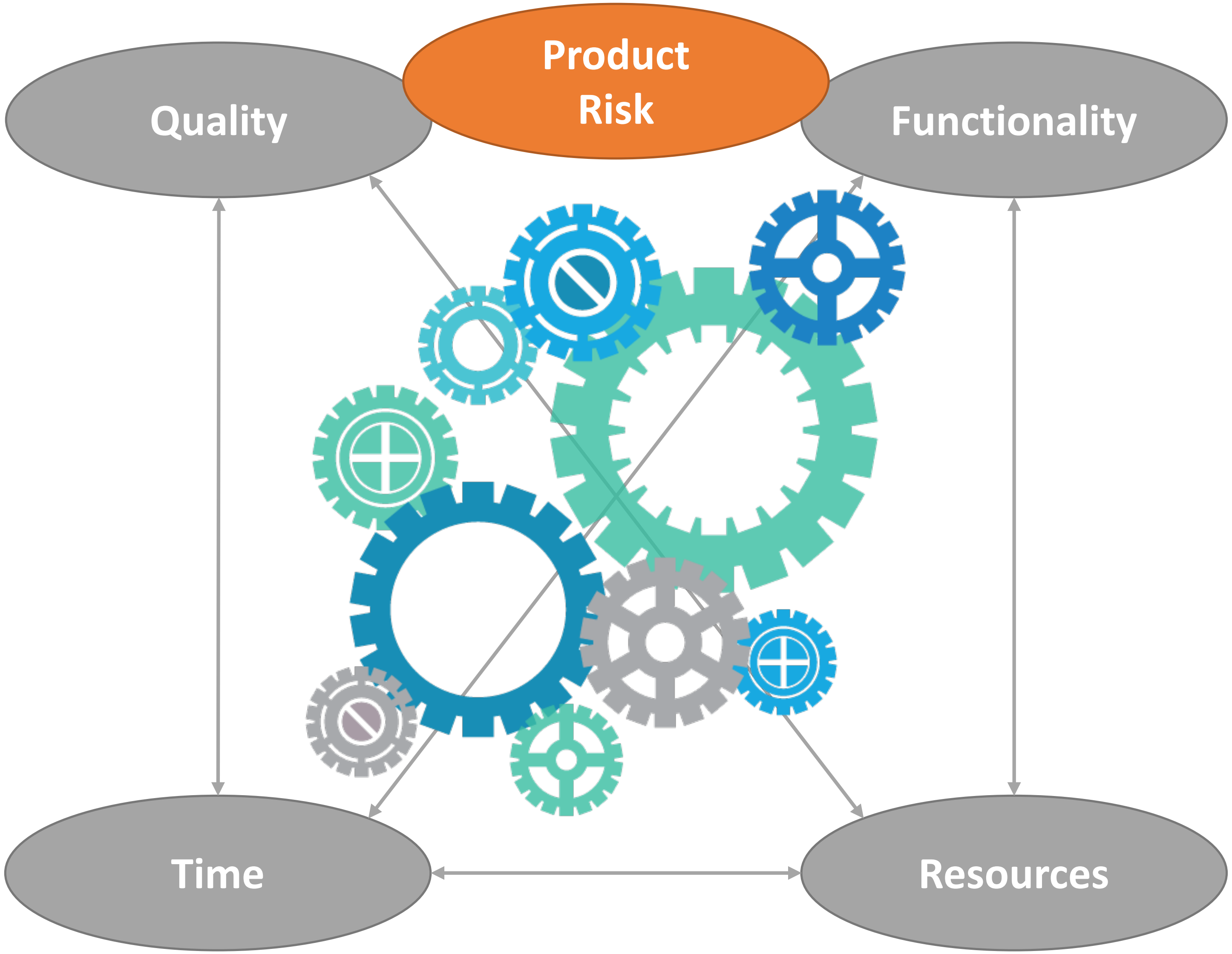
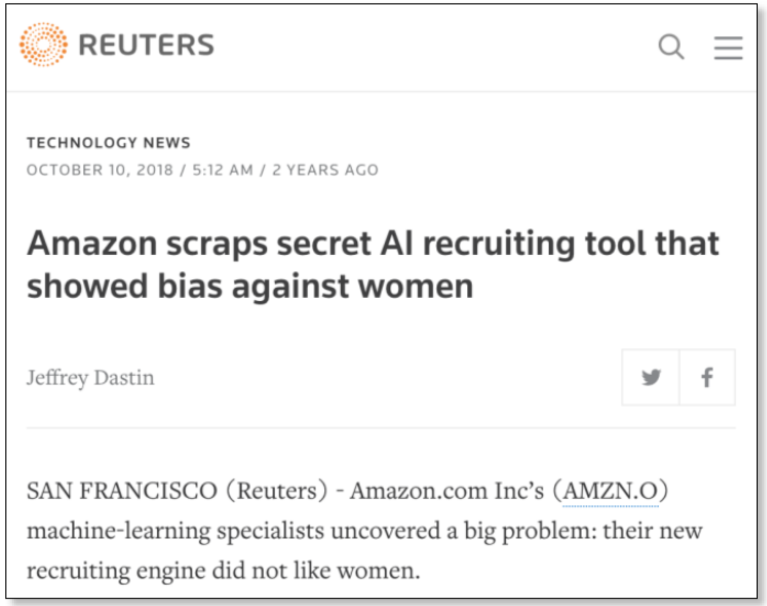
Quality and Risk in Software Development



Quality and Risk of ML-based Systems


REUTERS

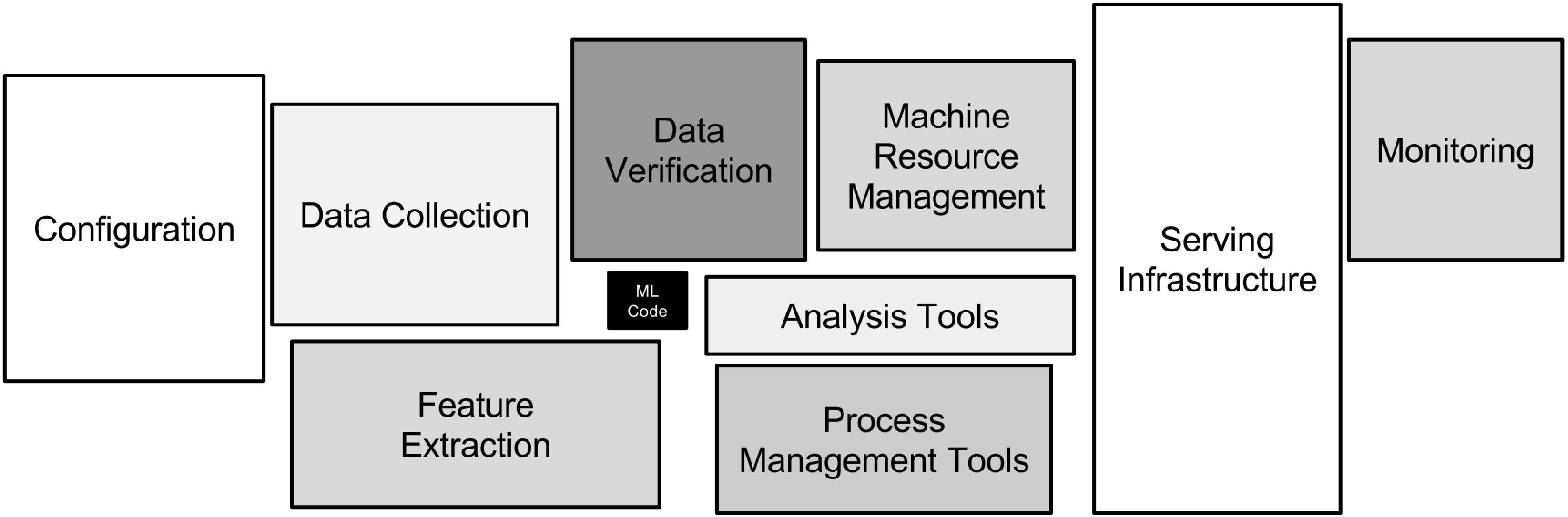
TECHNOLOGY NEWS
OCTOBER 10, 2018 / 5:12 AM / 2 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin

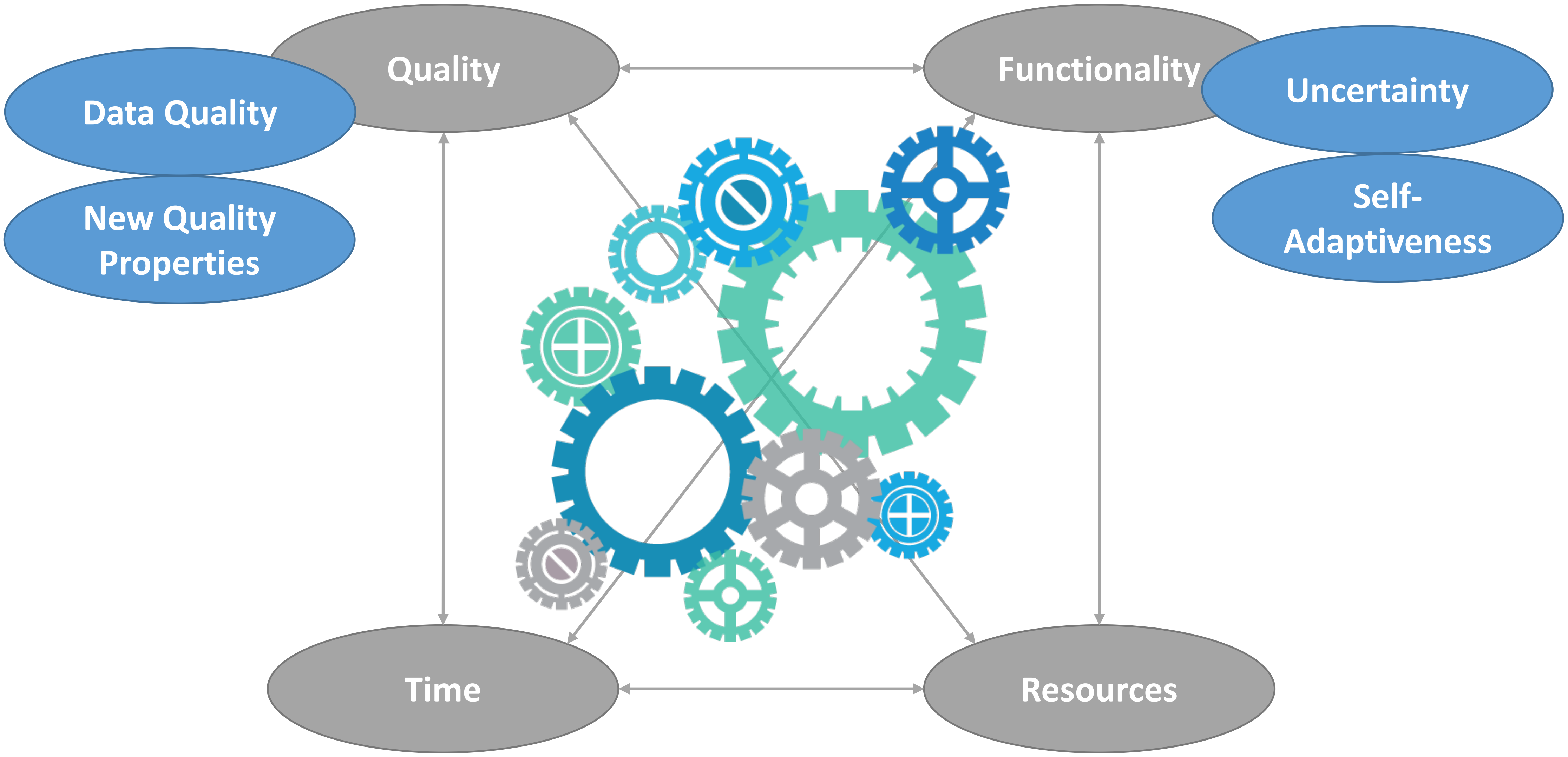
SAN FRANCISCO (Reuters) - Amazon.com Inc's (AMZN.O) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

ML Systems are IT Systems not only Algorithms



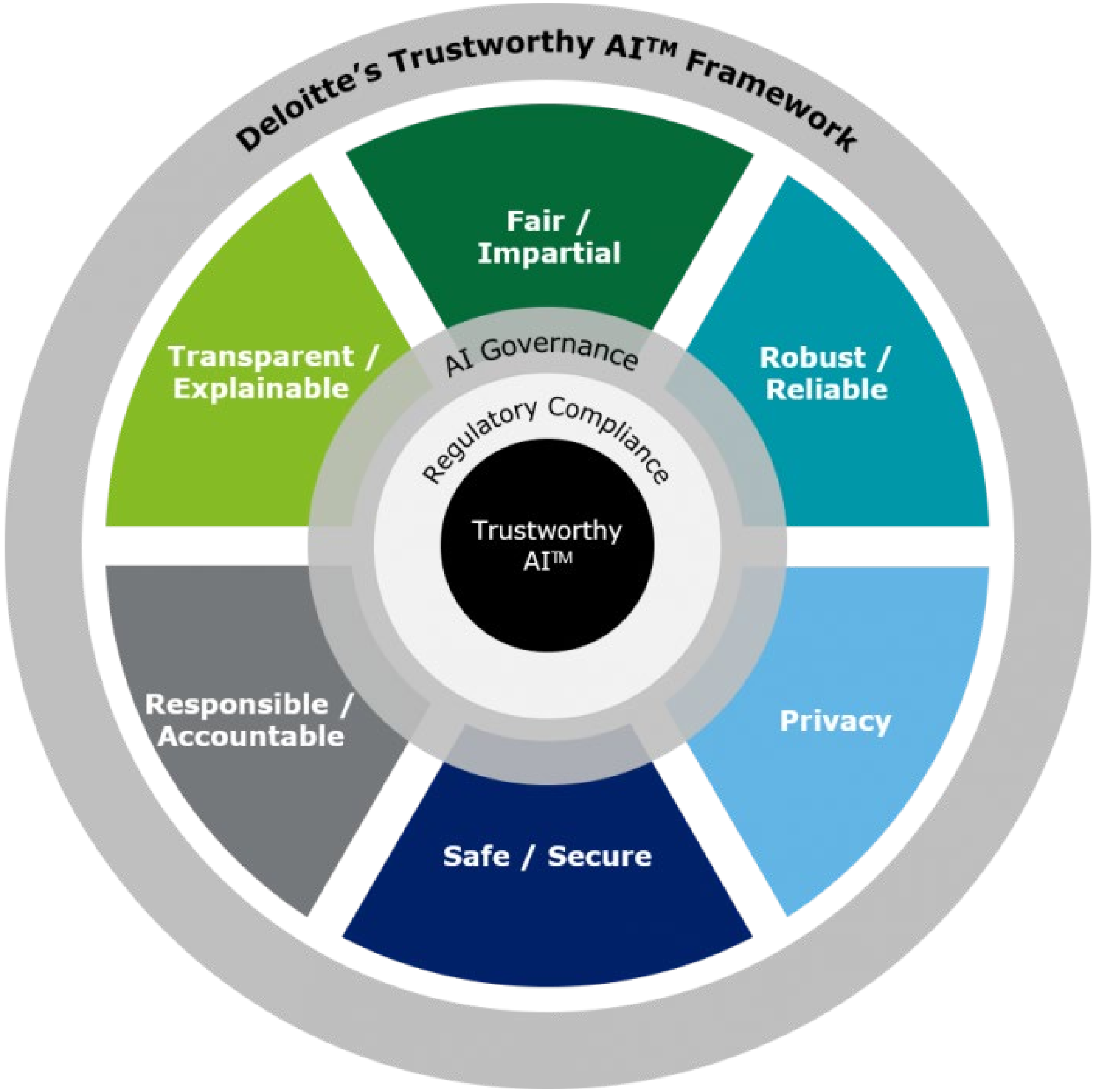
Sculley et al.: Hidden Technical Debt in Machine Learning Systems, NIPS 2012

What Makes (AI)ML-Based Systems Different?



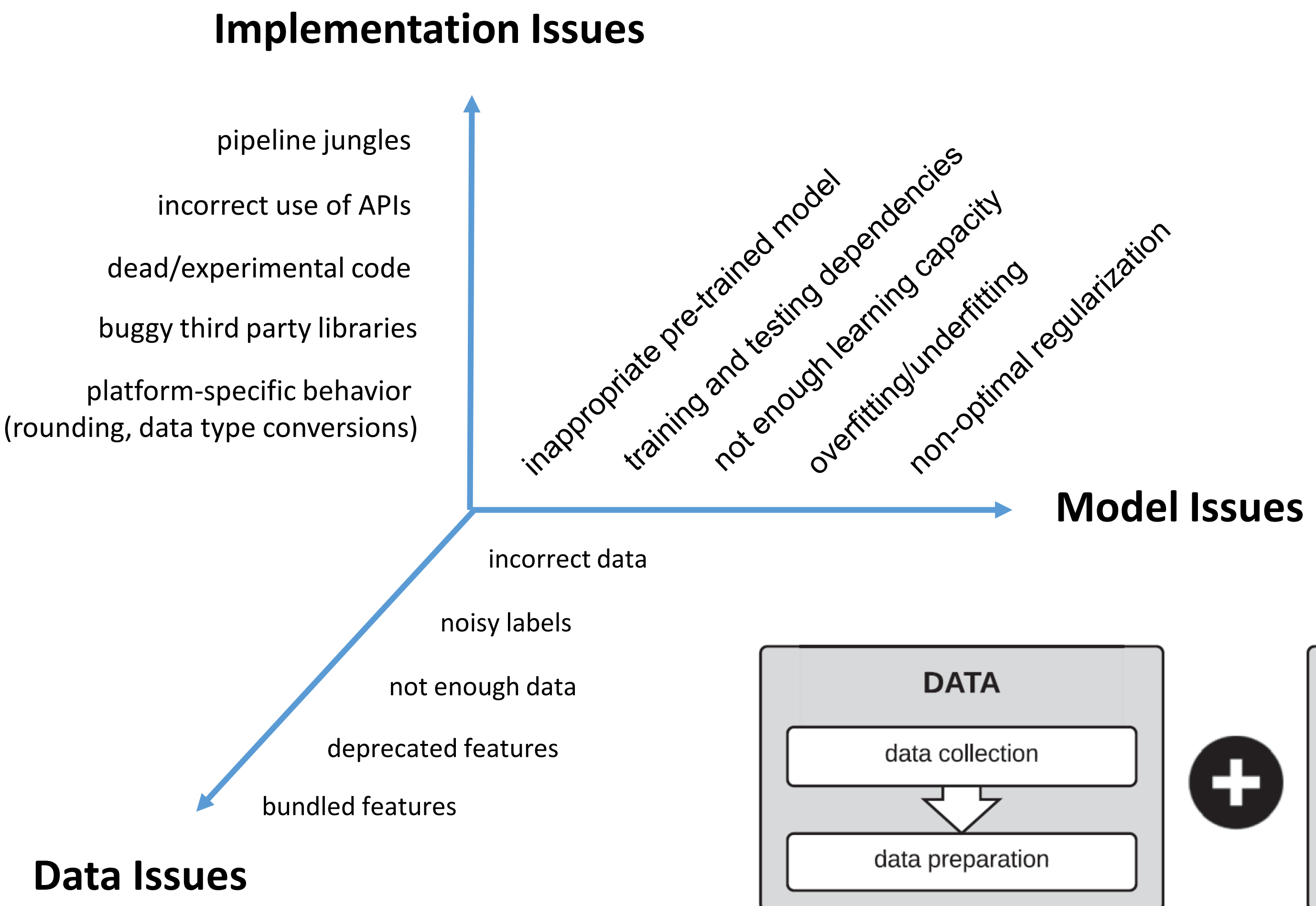
New Quality Properties: Trustworthiness of AI

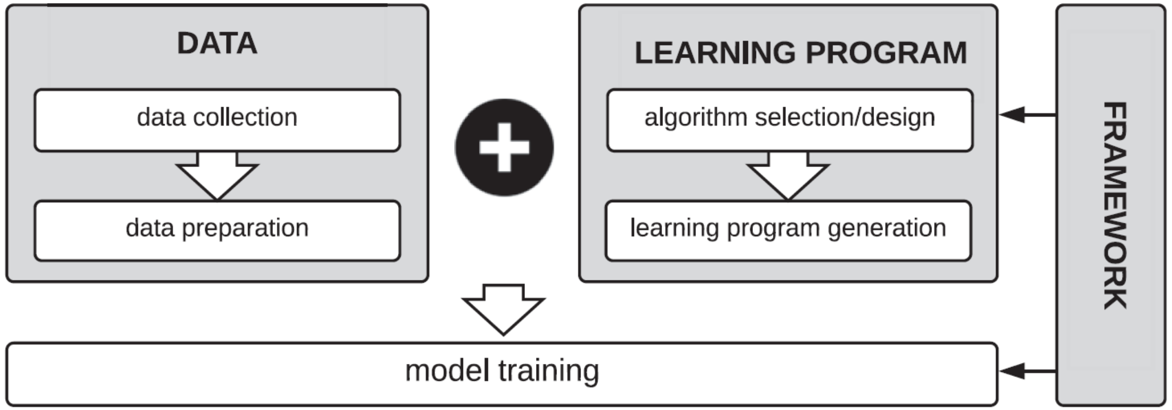
EU Ethics Guidelines for Trustworthy AI



Deloitte's Trustworthy AI Framework

Machine-Learning Systems as Software Systems





Zhang, Jie M., et al. *Machine learning testing: Survey, landscapes and horizons*. IEEE Transactions on Software Engineering, 2020

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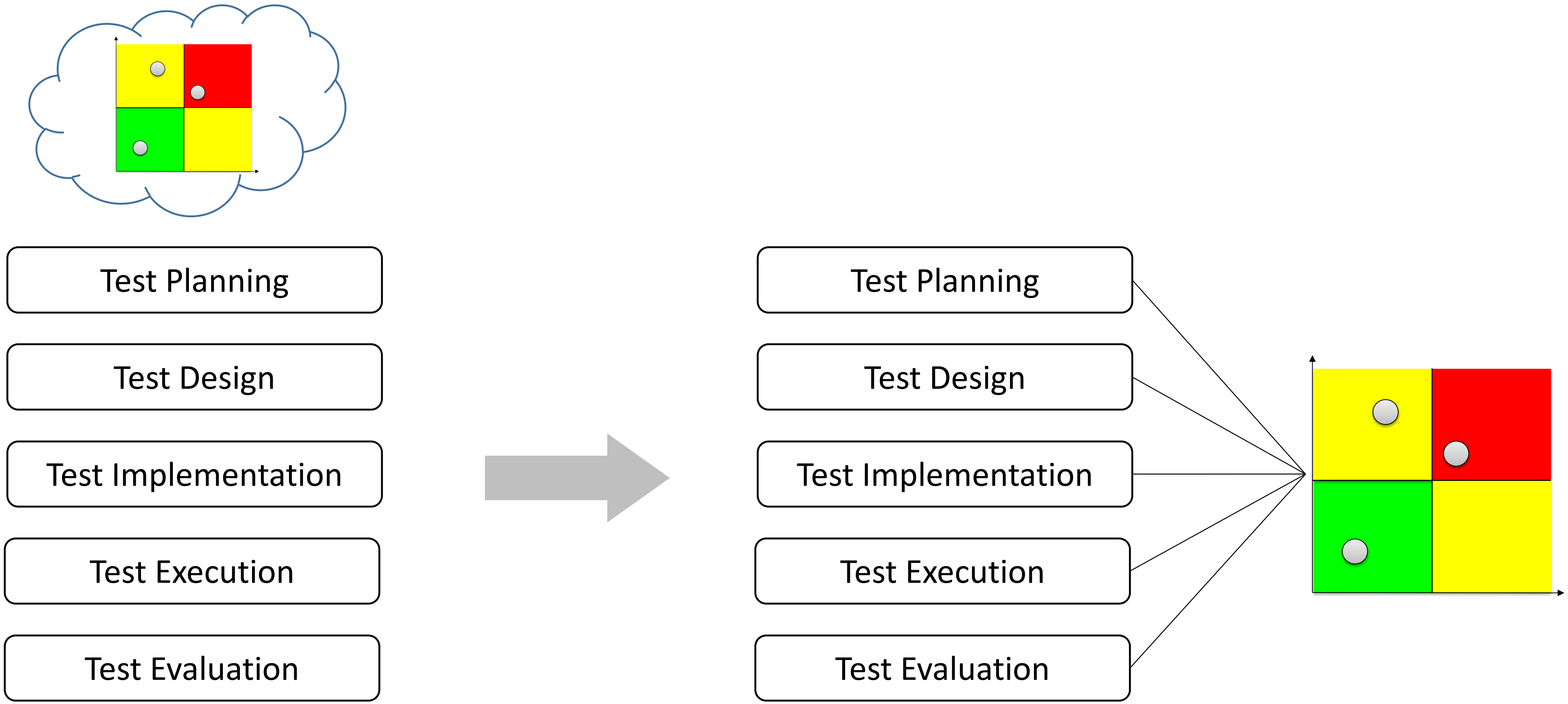
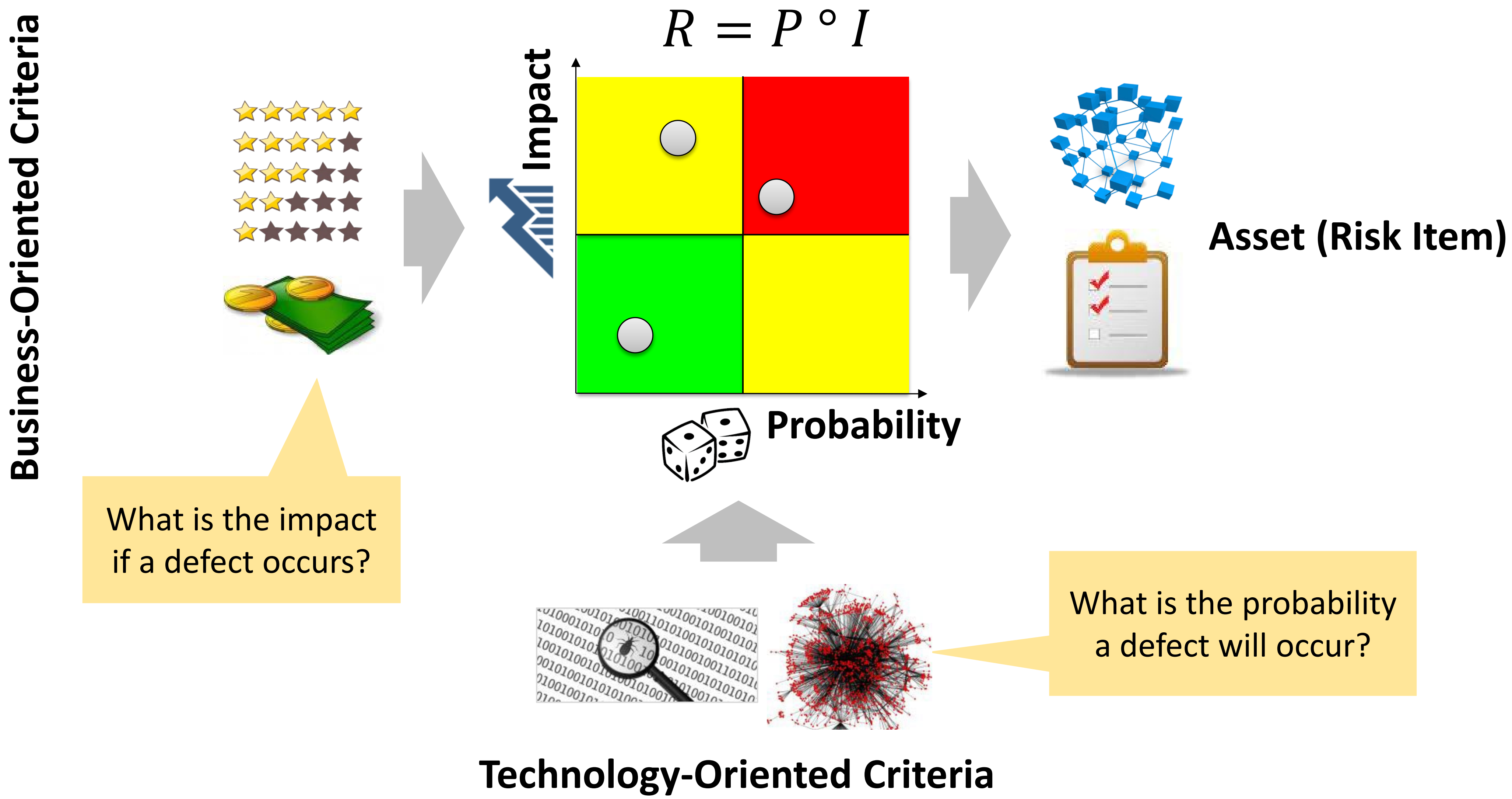
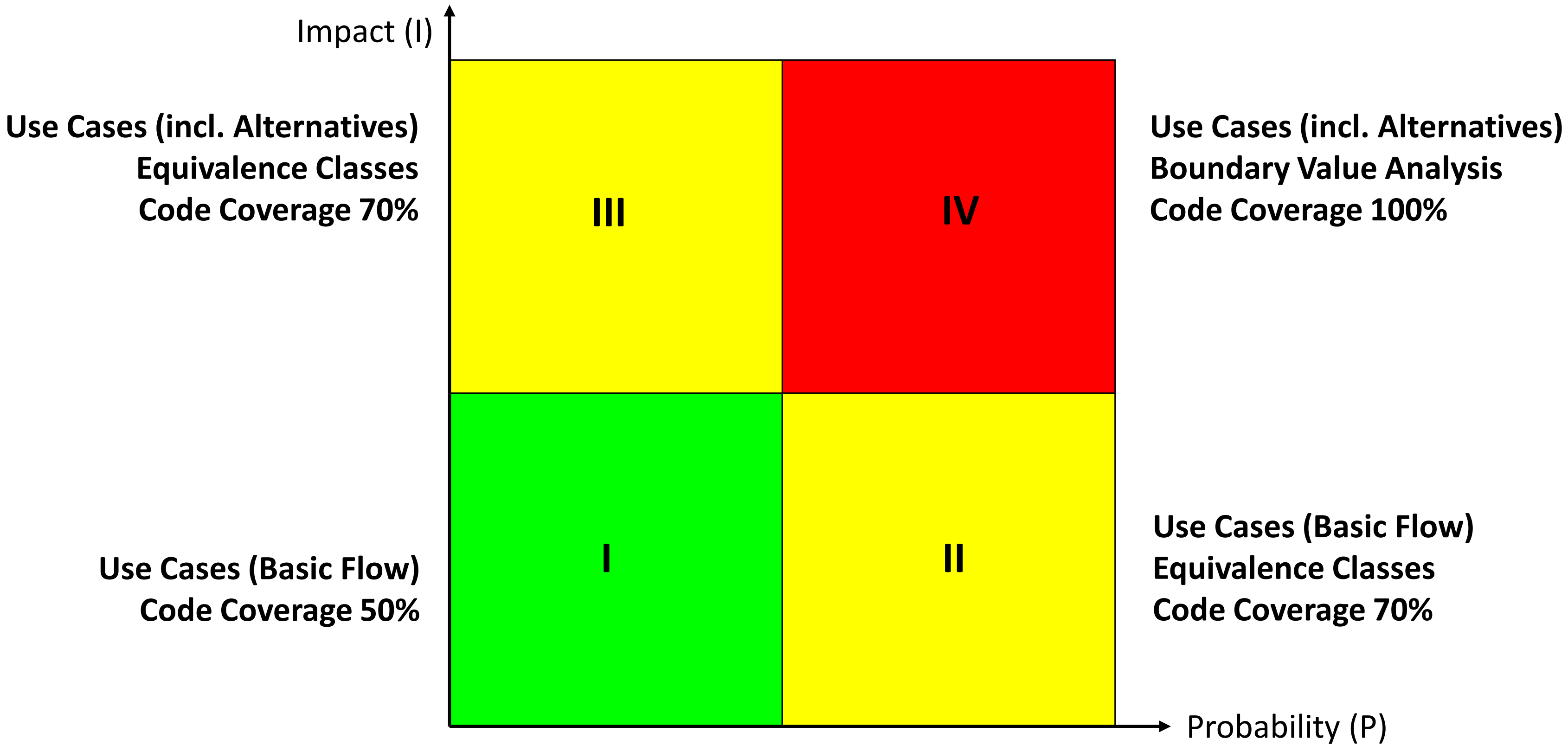
Risk-Based Testing (Risk-Based Quality Assurance)



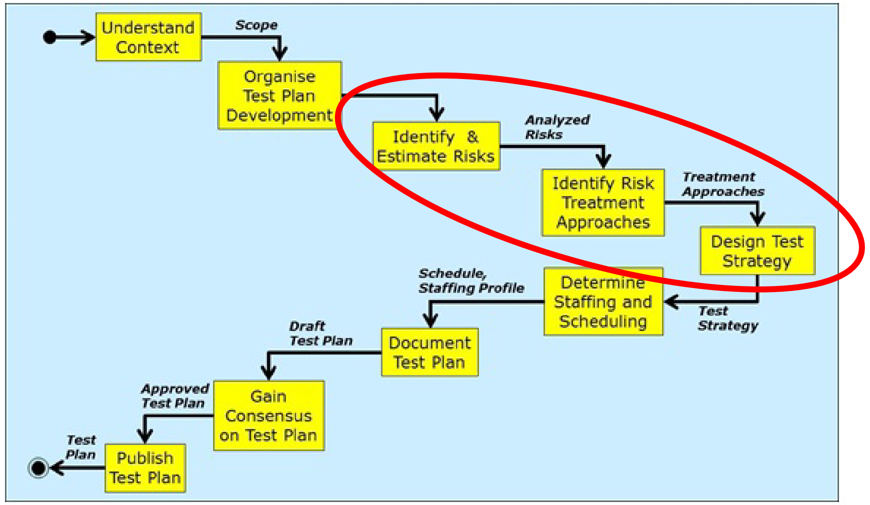
Risk Concept in Software Quality Engineering

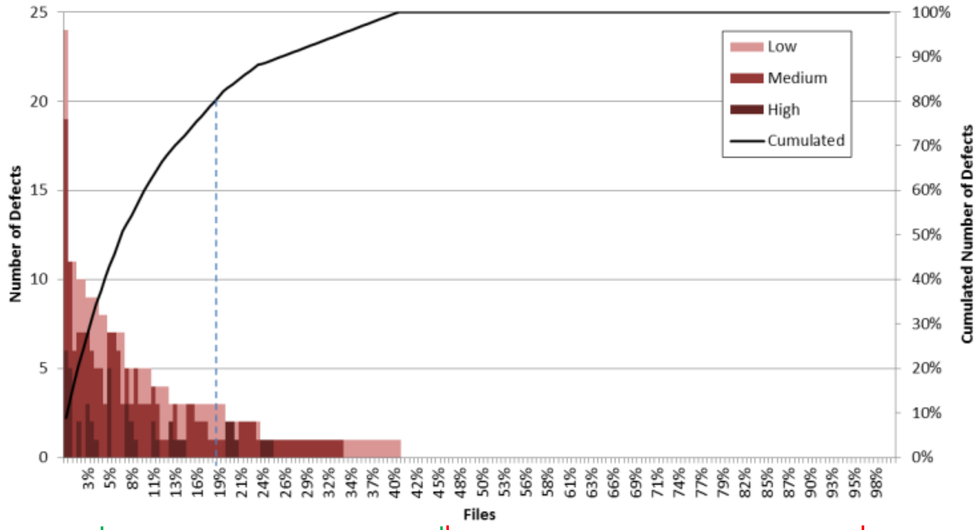


Risk-Based Test Strategy



Effectiveness and Efficiency of Risk-Based Testing





MORE **TEST** **LESS**

Compliance

- Aligned with standard
- Minimizing critical risks
- ...

Effectiveness

- Finding more defects
- Finding defects earlier
- Finding the critical defects
- ...

Efficiency

- Reduce time of testing
- Reduce cost of testing
- ...

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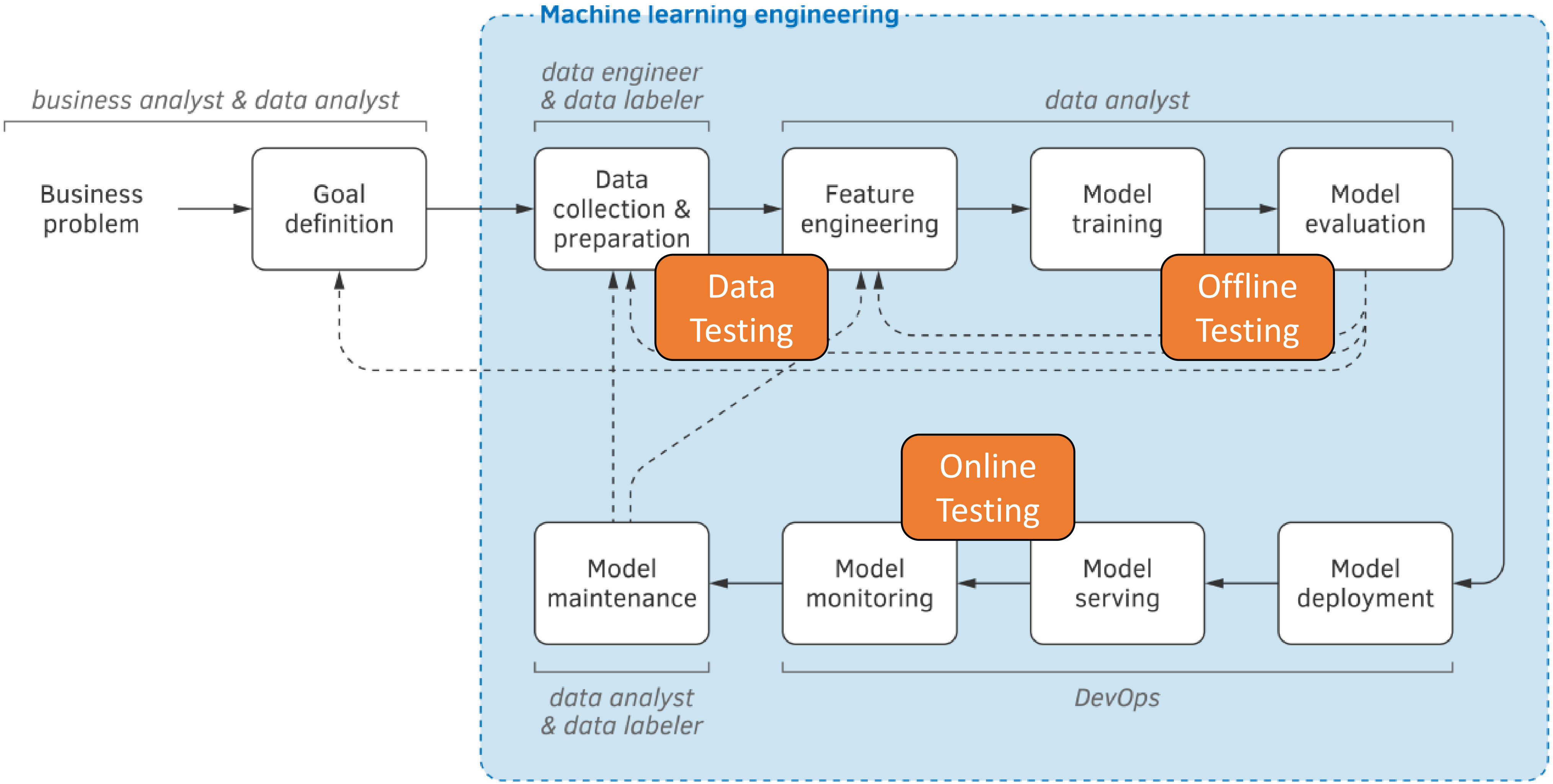
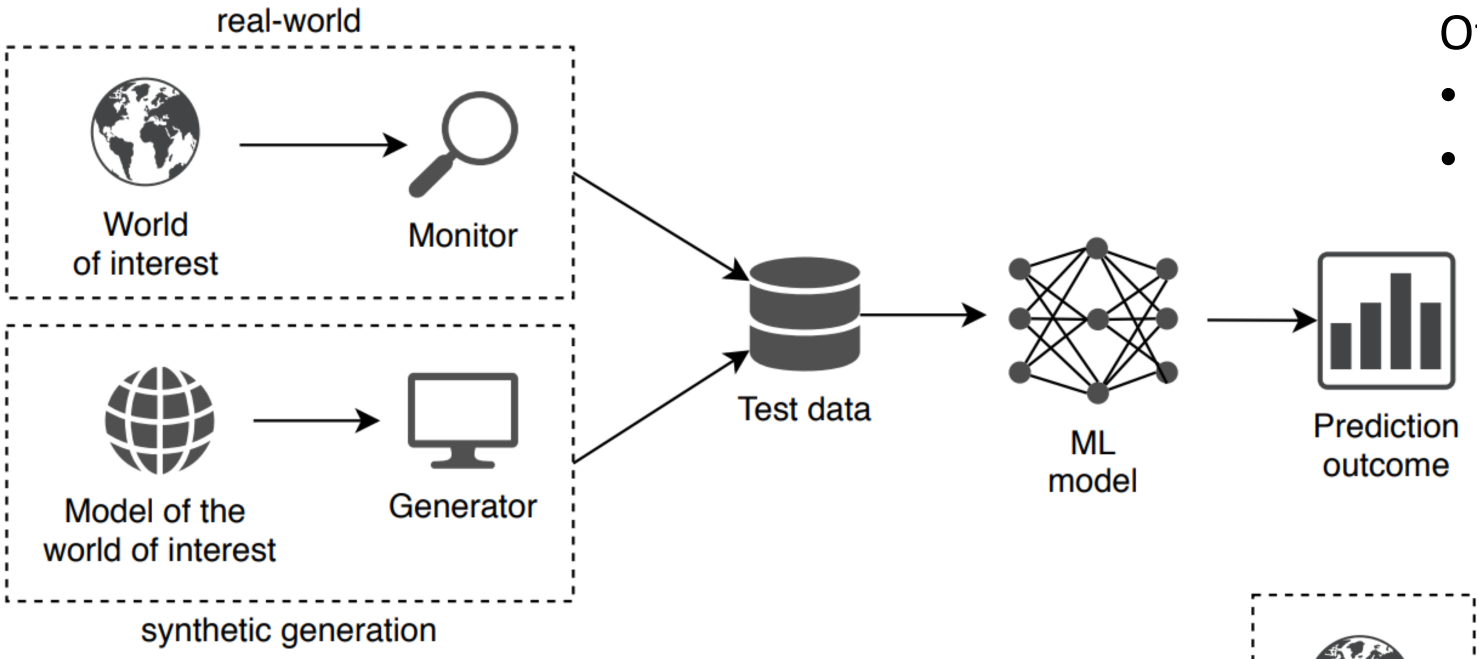
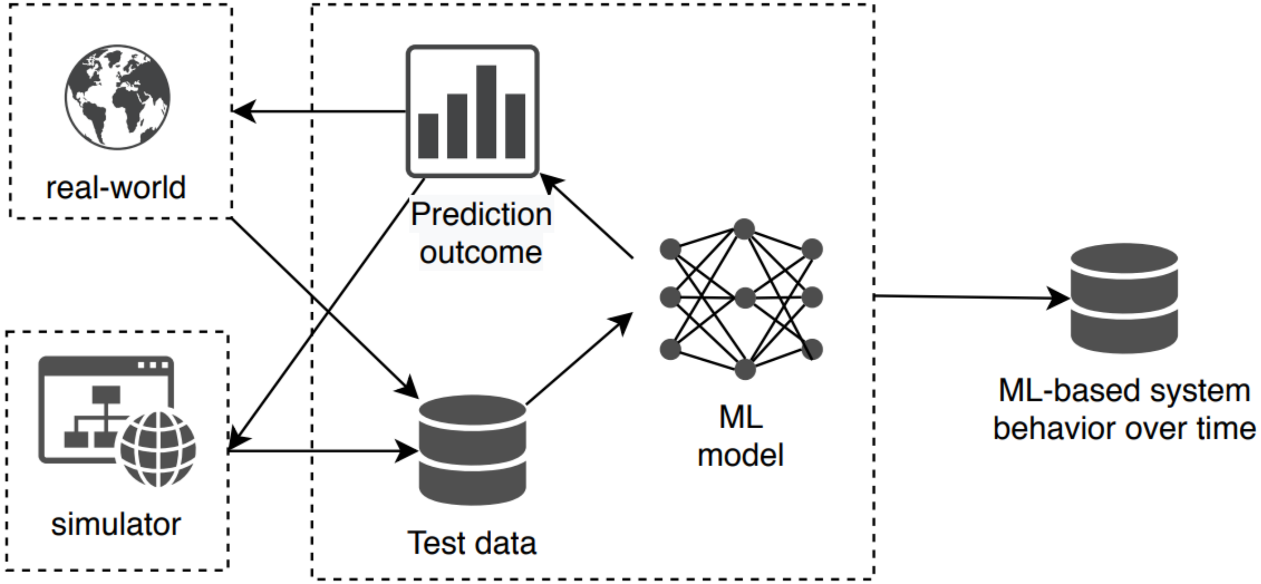
ML Engineering and Testing



Offline and Online Testing

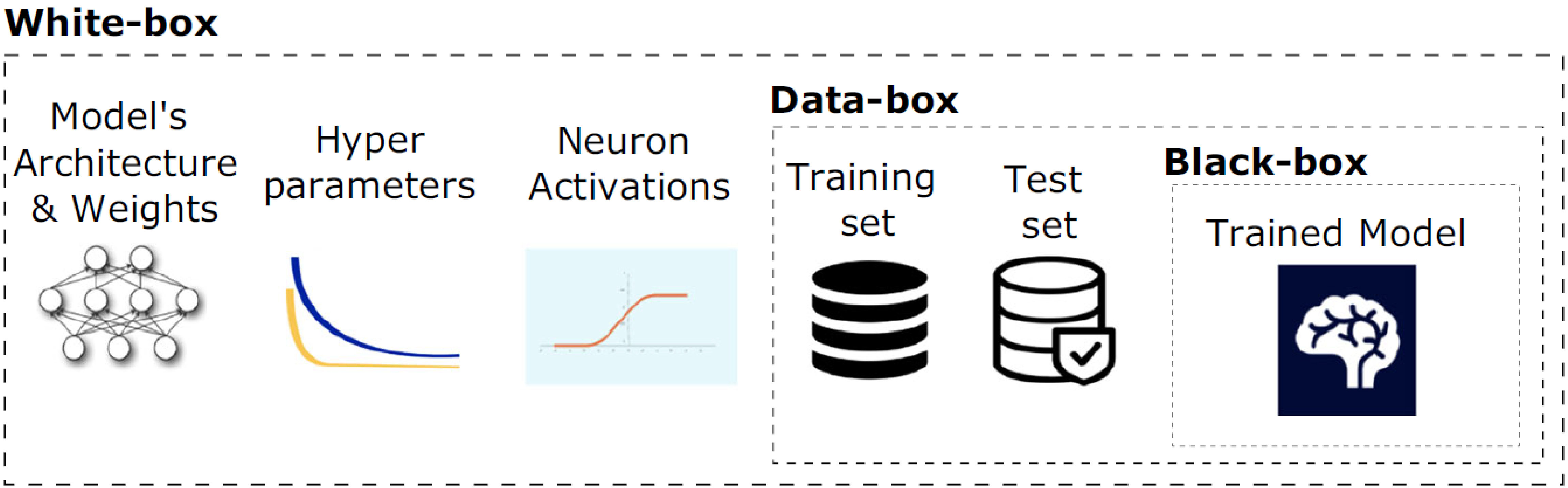


Offline Testing:
- Testing ML model as standalone component
- ML model tested as a unit in open loop mode

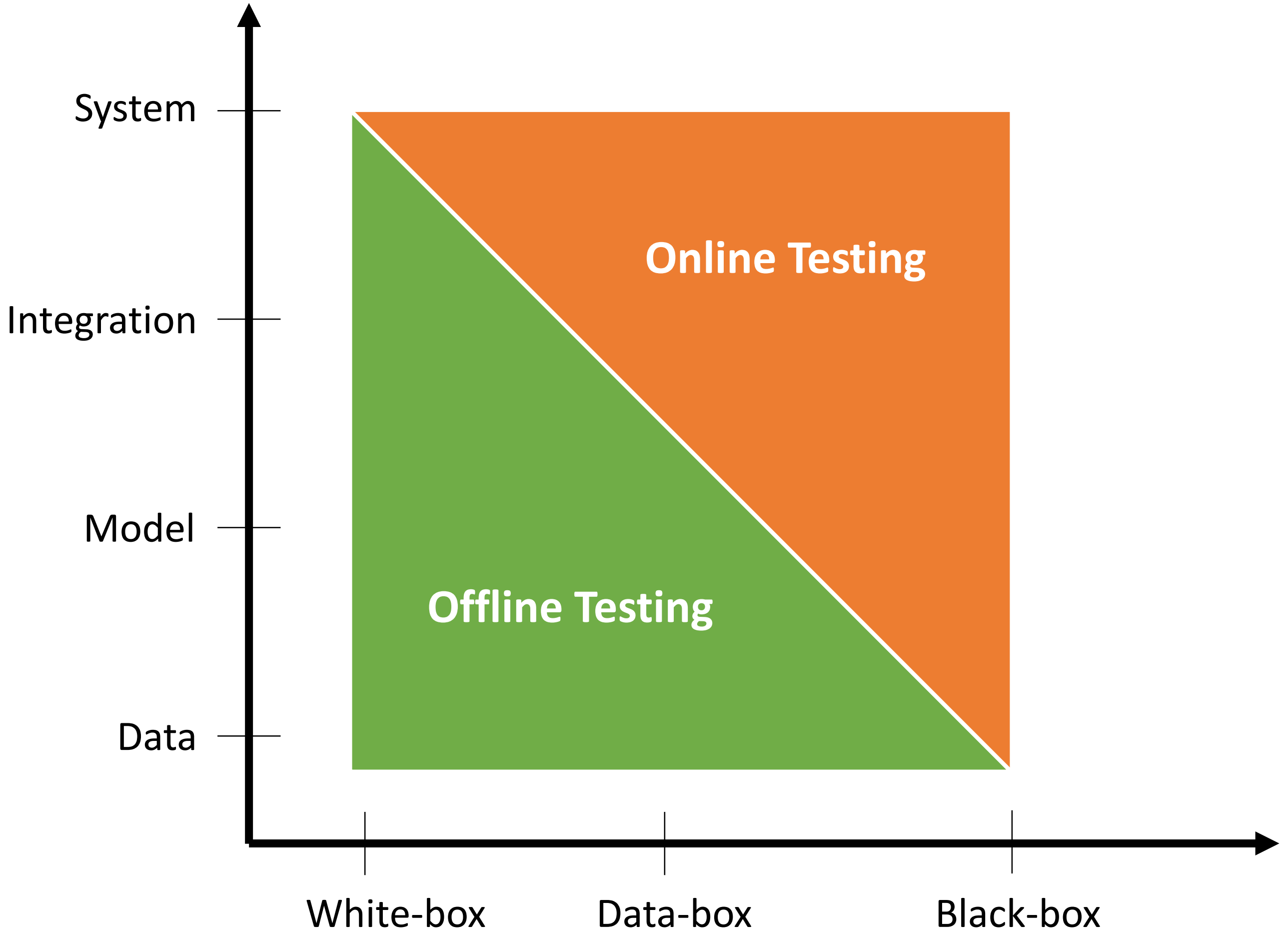


Online Testing:
- Testing ML model in real or simulated environment
- ML model tested as a unit in closed loop mode

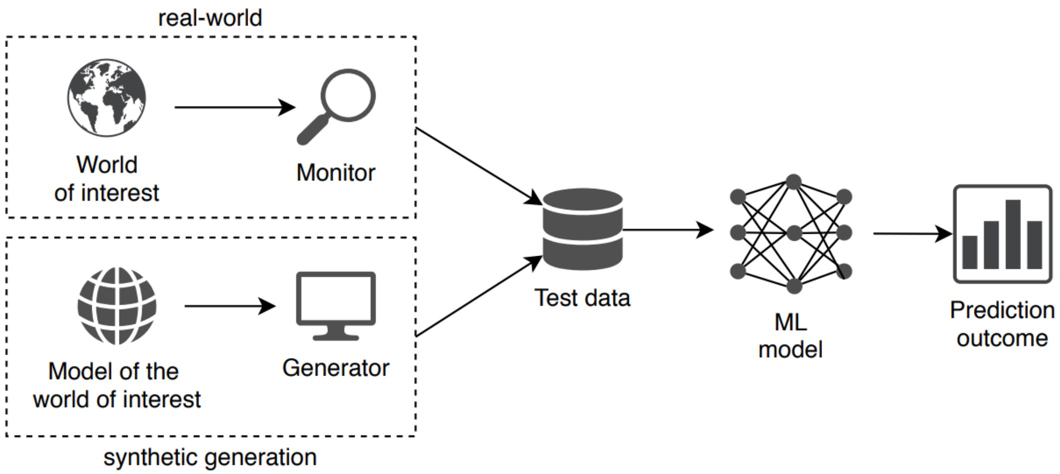
White-Box and Black-Box Testing?

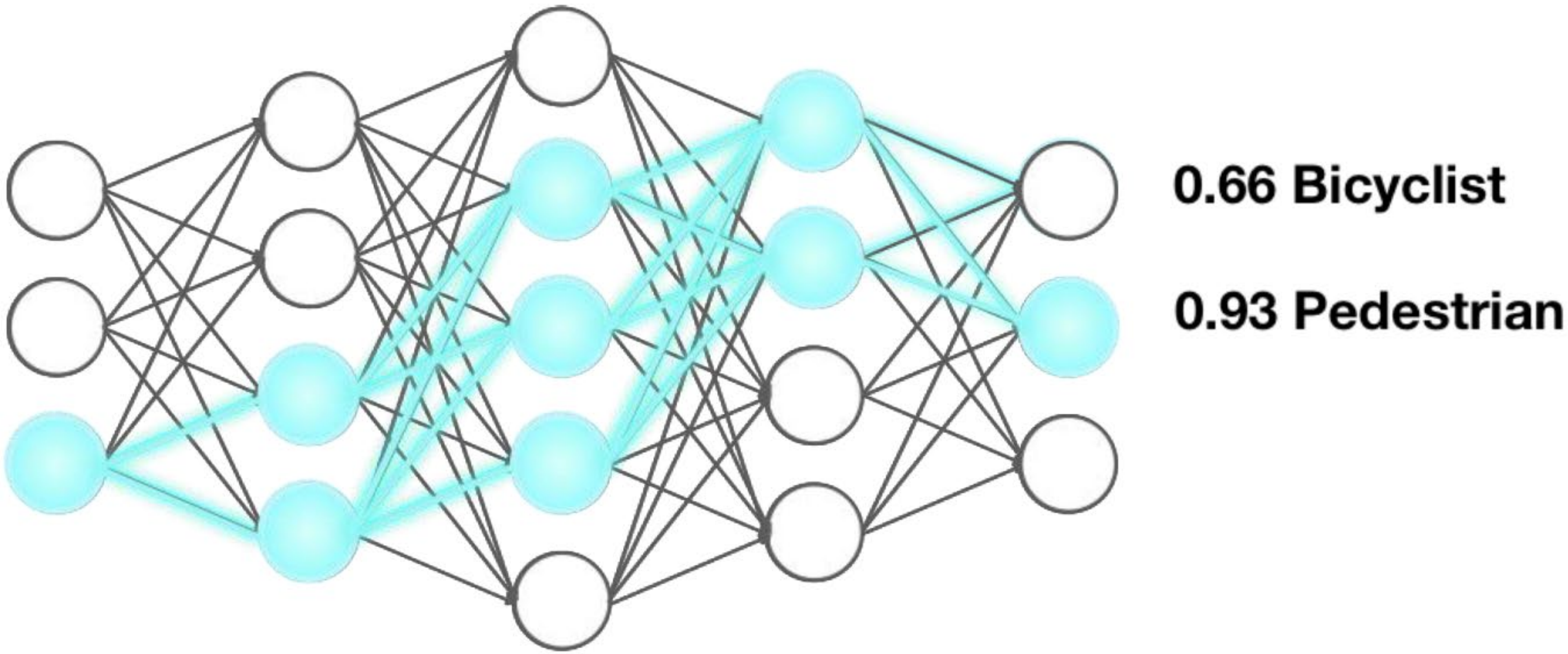


Offline vs. Online Testing



Offline Testing (White Box)





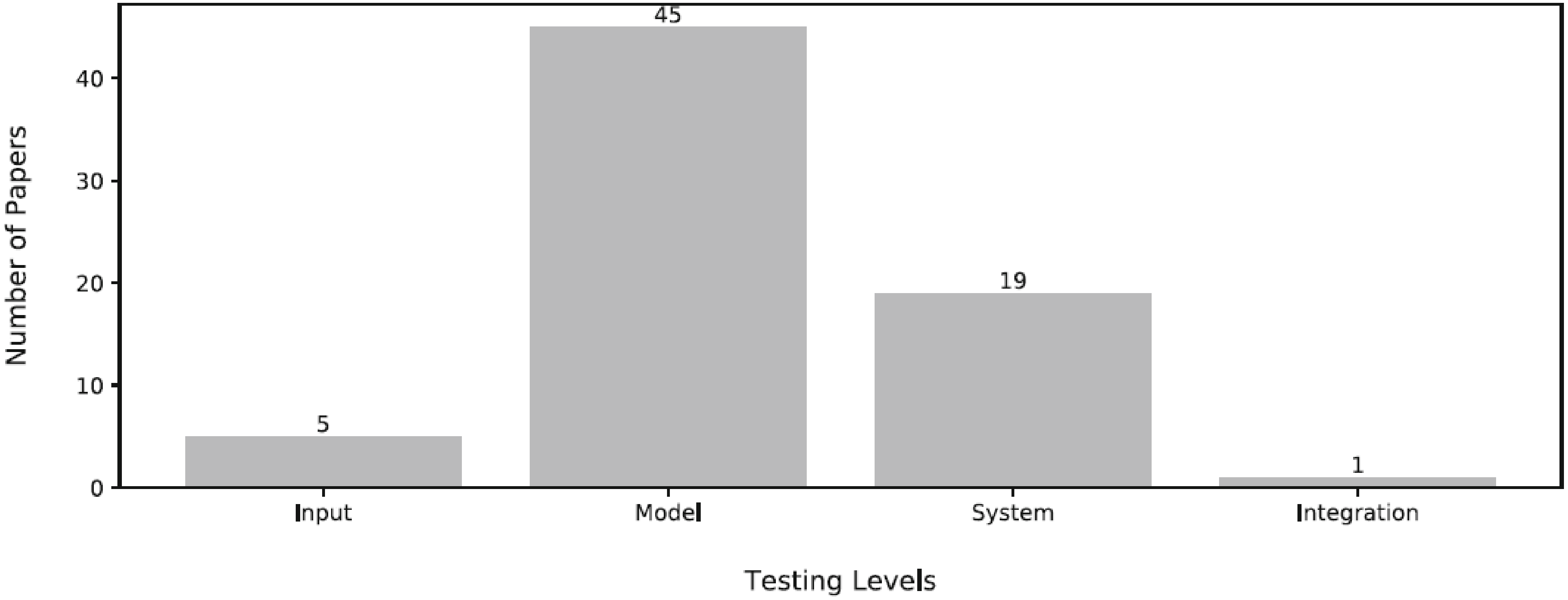
Neuron Coverage is not strongly and positively correlated with defect detection and naturalness.

Harel-Canada, F., et al. *Is neuron coverage a meaningful measure for testing deep neural networks*?. Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. 2020

Test Levels for Machine-Learning Systems

Four Test Levels

- Input Testing
- Model Testing
- Integration Testing
- System Testing



Riccio, Vincenzo, et al. *Testing machine learning based systems: a systematic mapping*. Empirical Software Engineering 25.6 (2020): 5193-5254.

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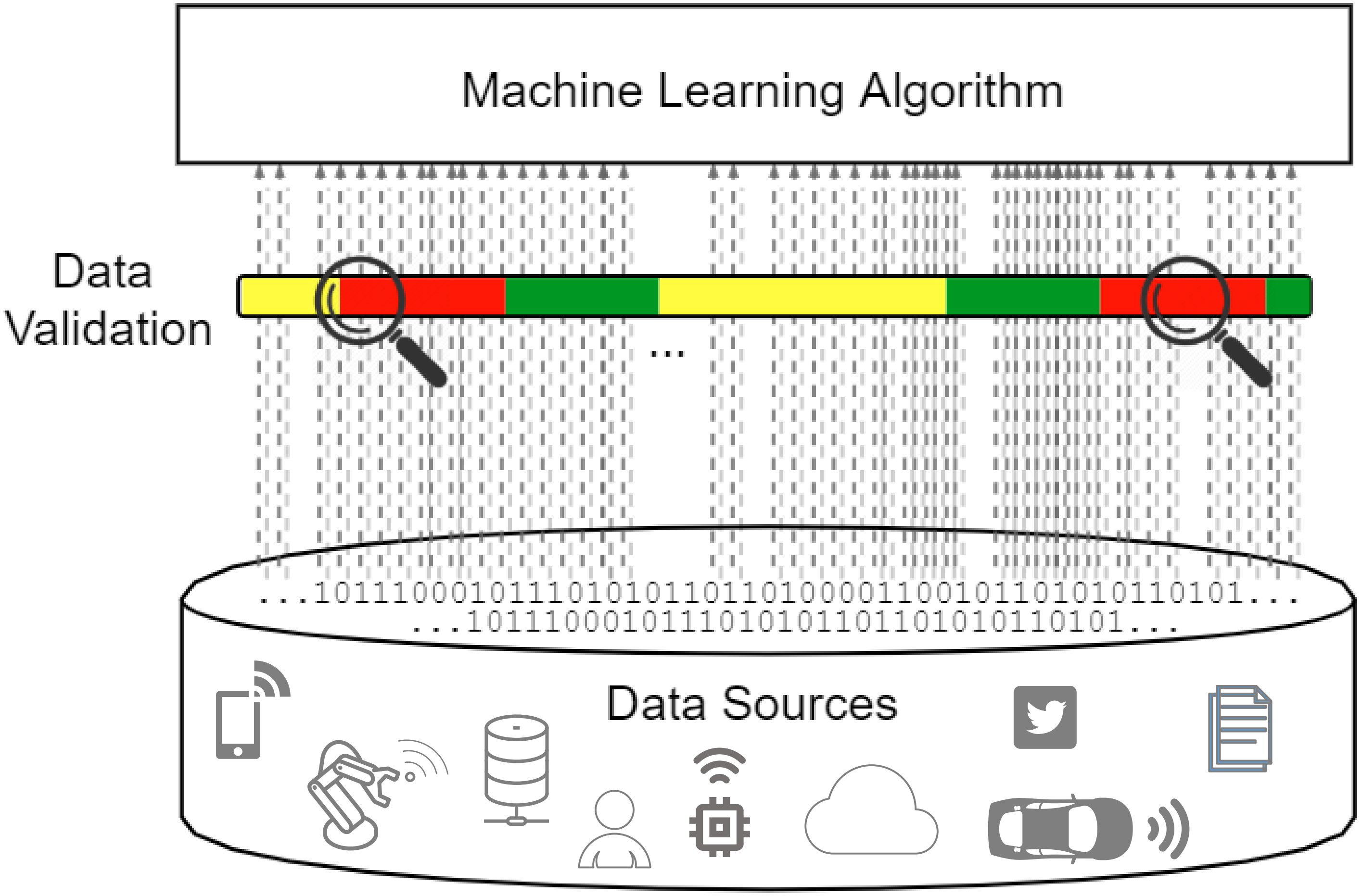
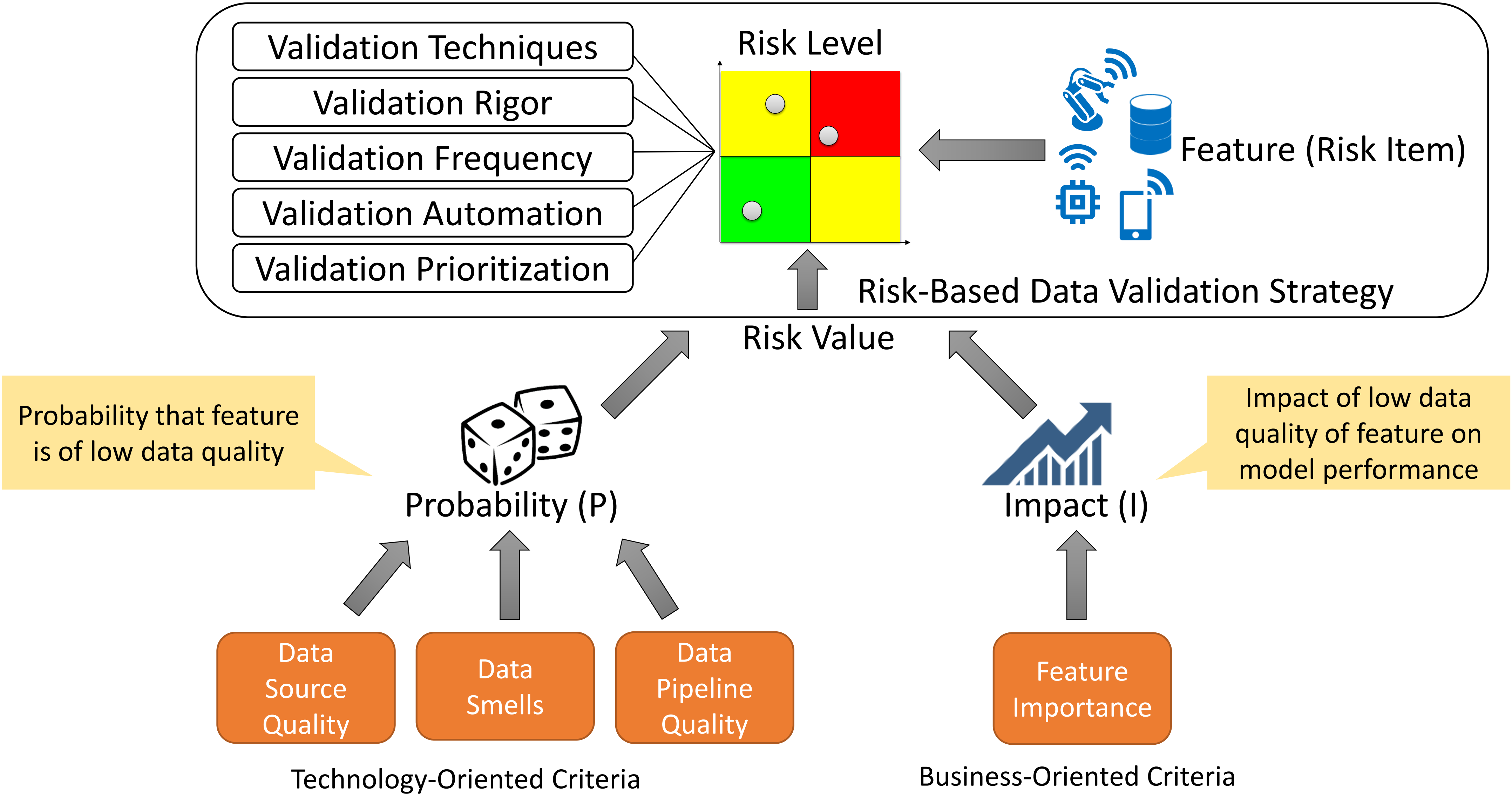
Idea of Risk-Based Data Testing



Risk-Based Data Testing Framework



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Data Smell Types

Context-independent, data value-based indications of latent data quality issues caused by poor practices that may lead to problems in the future.

- **Data Smells**
  - **Believability Smells**
    - *Suspect Date Value*
    - *Meaningless Value*
    - *Dummy Value*
    - *Suspect Precision*
    - *Suspect Distribution*
    - *Suspect Date/Time Interval*
  - **Understandability Smells**
    - **Encoding Smells**
      - *Date as Date/Time*
      - *Date as String*
      - *Date/Time as String*
      - *Floating-point Number as String*
      - *Integer as Floating-point Number*
      - *Integer as String*
      - *Time as String*
    - **Syntactic Smells**
      - *Ambiguous Date/Time Format*
      - *Ambiguous Value*
      - *Casing*
      - *Conctracting*
      - *Extraneous Value*
      - *Intermingled Data Type*
      - *Long Data Value*
      - *Separating*
      - *Small Number*
      - *Spacing*
      - *Special Character*
      - *Synonym*
  - **Consistency Smells**
    - *Abbreviation Inconsistency*
    - *Casing Inconsistency*
    - *Date/Time Format Inconsistency*
    - *Missing Value Inconsistency*
    - *Precision Inconsistency*
    - *Separating Inconsistency*
    - *Spacing Inconsistency*
    - *Special Character Inconsistency*
    - *Syntax Inconsistency*
    - *Transposition Inconsistency*
    - *Unit Inconsistency*

Example Smells

Appointme...	Appointme...	# Age
5638447	2016-04-29T00:00:00Z	21
5629123	2016-04-29T00:00:00Z	19
5630213	2016-04-29T00:00:00Z	30
5620163	2016-04-29T00:00:00Z	29
5634718	2016-04-29T00:00:00Z	22
5636249	2016-04-29T00:00:00Z	28

Date as Date/Time Smell

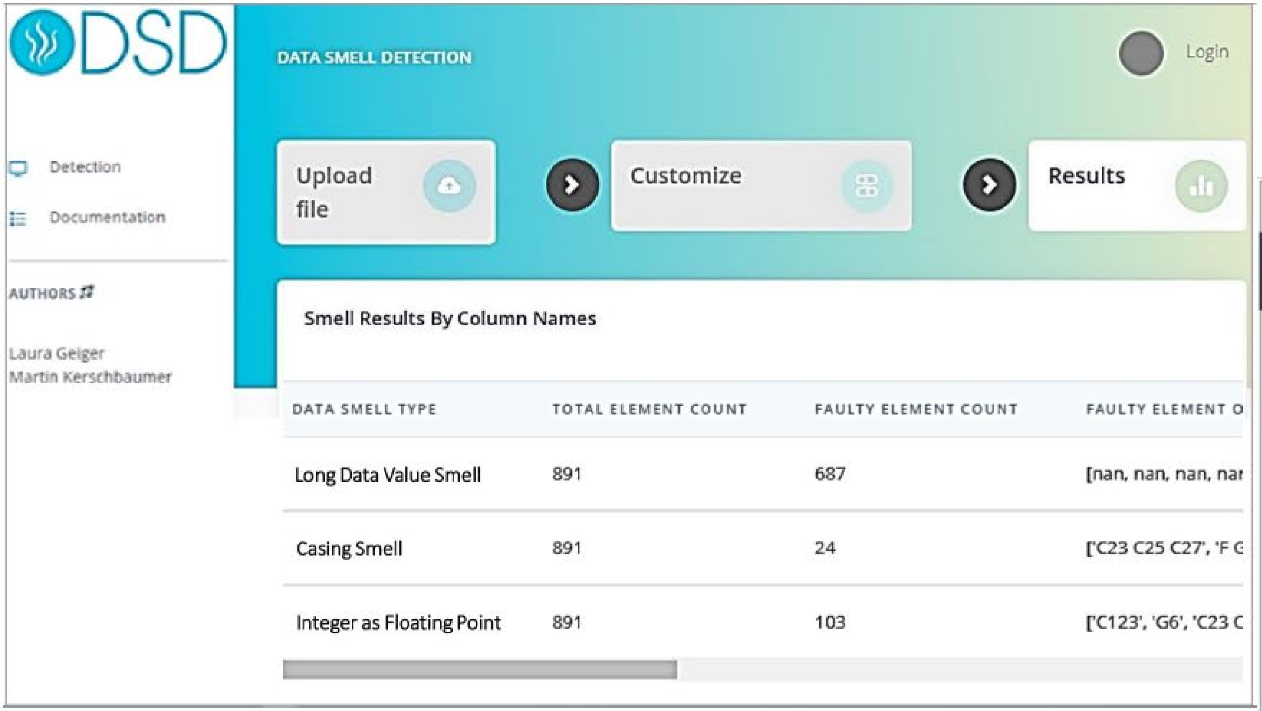
https://www.kaggle.com/joniarroba/noshowappointments

Date	# Daily Confi...	# Total Confi...
11-Feb	0	3
12-Feb	0	3
13-Feb	0	3
14-Feb	0	3
15-Feb	0	3
16-Feb	0	3
17-Feb	0	3
18-Feb	0	3

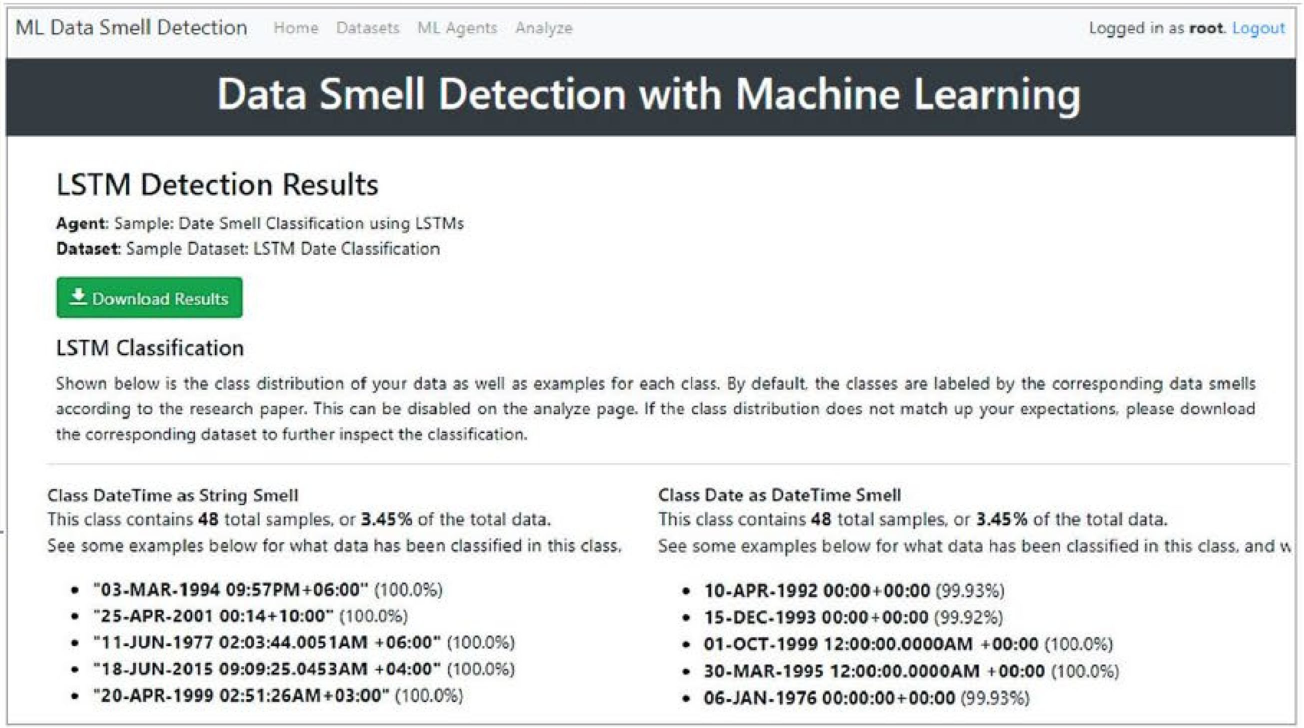
Ambiguous Date/Time Format Smell

https://www.kaggle.com/ravichaubey1506/covid19-india

Data Smell Detection Tools



Rule-based detection



Machine learning-based detection

Data Source Quality Model

Quality Characteristics		Description	Properties and Subquality Factors
Representational Data Store Quality	***Representational Adequacy***	Degree to which a data store presents data in a *concise and organized way*.	Schema Minimality
			Schema Normalization
			Schema Pertinence
	Representational Consistency	Degree to which a data store presents data *always in the same format and compatible with previous data.*	Data Format Variety
			Data Type Variety
			Schema Change Proneness
	Understandability	Degree to which *users can understand the data* provided by a data store.	Data Format Complexity
			Documentation Degree
			Metadata Quality
			Schema Readability
Dynamical Data Store Quality	***Accessibility***	Degree to which data are *easily and quickly retrievable.*	Access Maturity
			Operability
			Retrievability
	Availability	Degree to *which data are available* from a data store.	Durability
			Fault Tolerance
			Recoverability
			Scalablity
			Uptime
	Security	Degree to which *access to data for unauthorized persons is restricted* by a data store.	Authentification/Encryption
			Authorization Policy
	Timeliness	Degree to which a data store *provides up-to-date data in a timely manner.*	Refresh Rate
			Response Time
Statical Data Store Quality	***Completeness***	Degree to which a data store is able to represent *every meaningful state of the real world.*	Schema Completeness
			Schema Correctness
	Contactability	Degree to which a data store provides *contact information for further inquiries.*	Support Degree
	Trustworthiness	Degree to which a *data store can be trusted*.	Complexity
			Data Governance
			Maturity
			Verifiability

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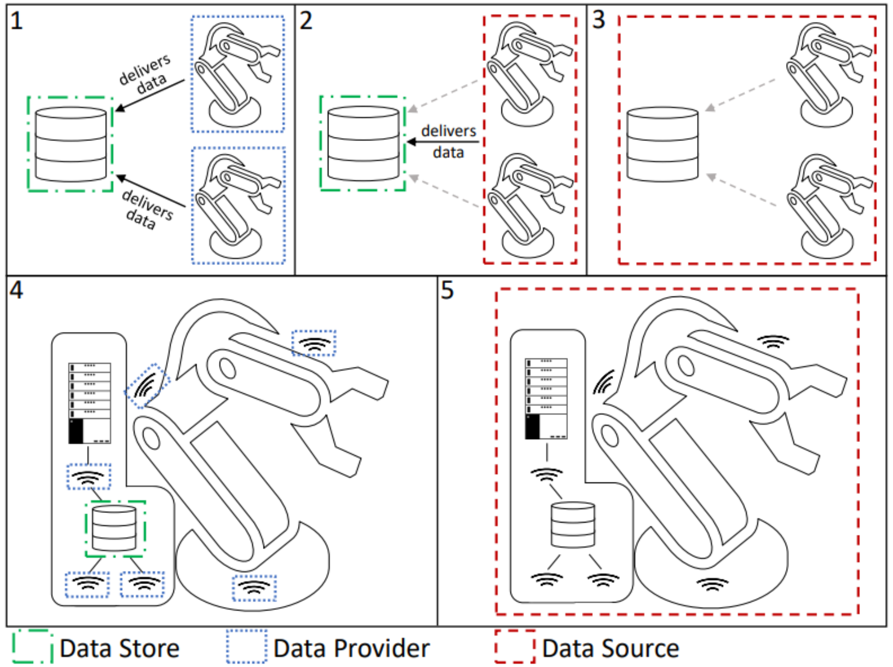
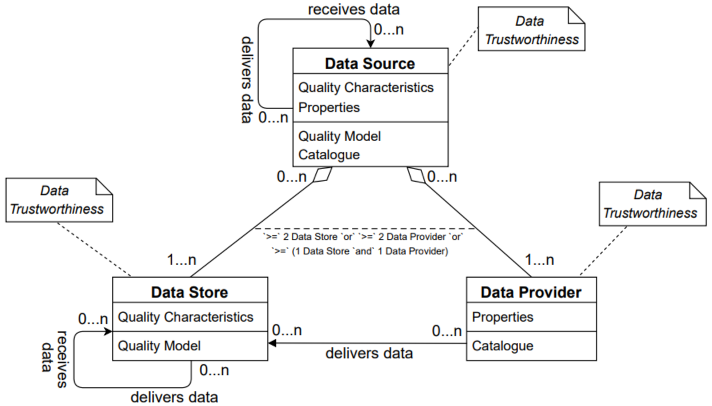
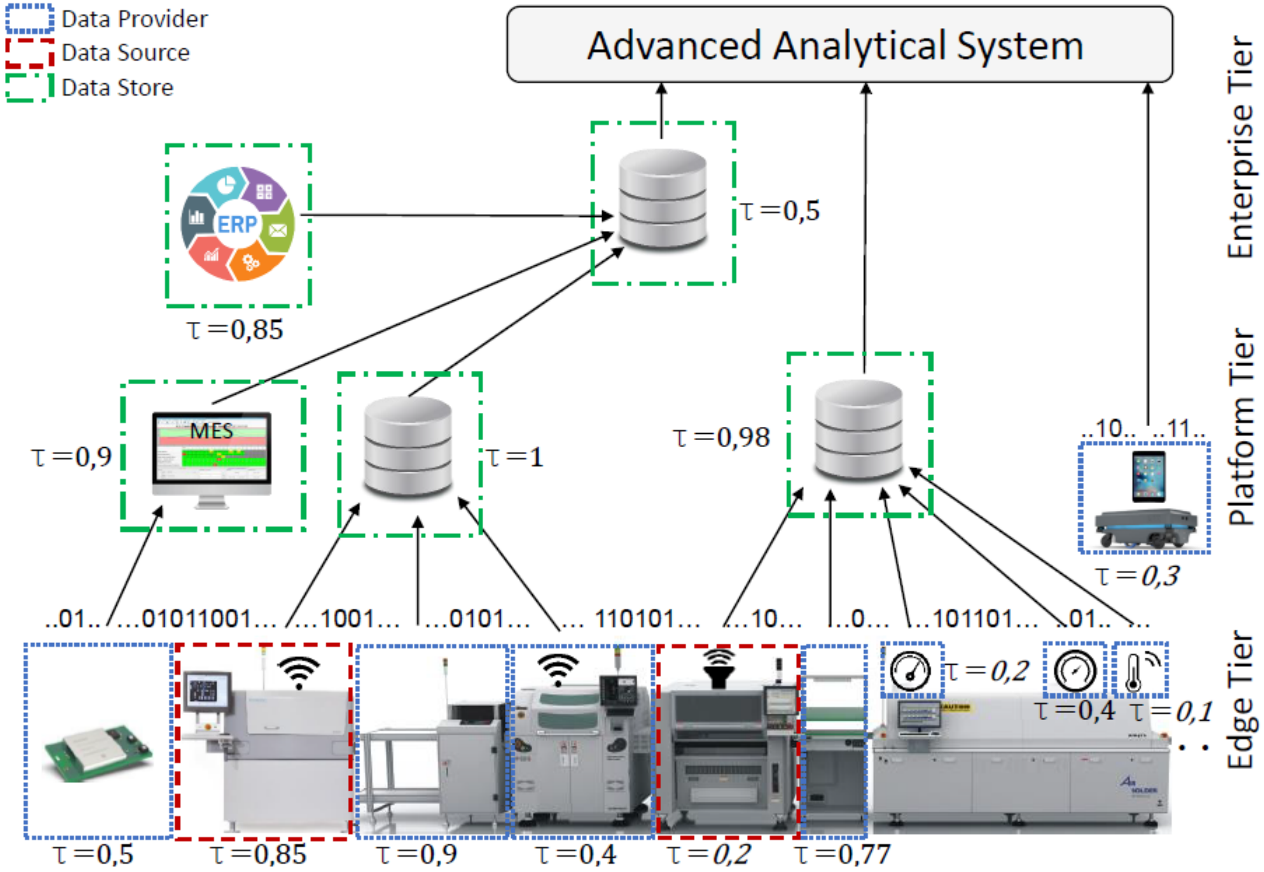
Data Source, Provider, and Store







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Data Pipeline Quality

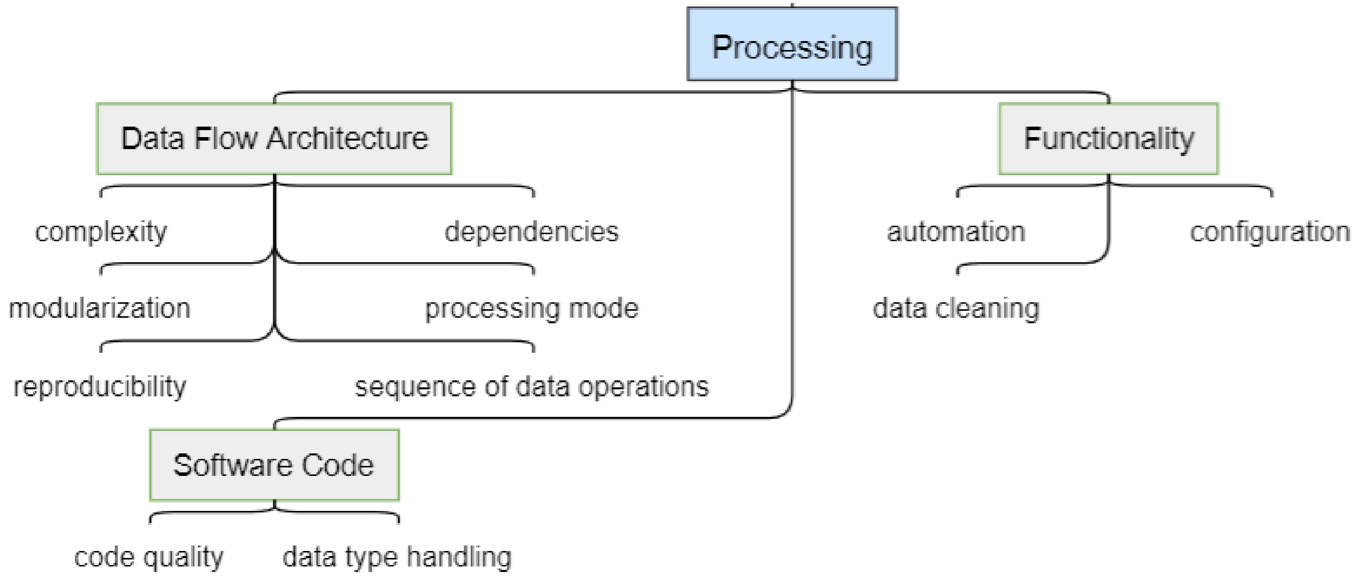
Issues of the implemented data pipeline that can affect the quality of the processed data

Code smells

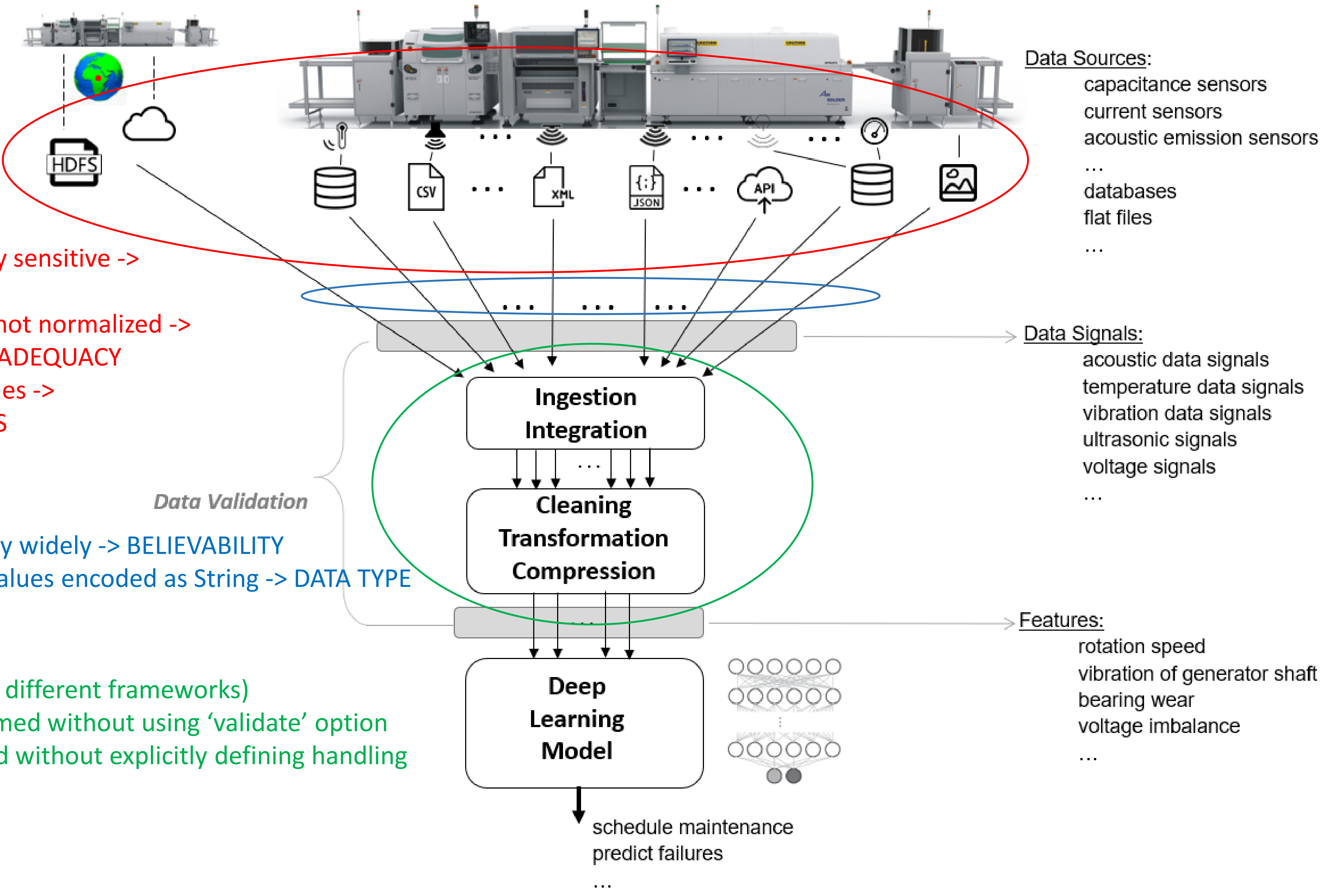
- libraries Pandas vs. Numpy handling missing values differently by default (e.g. pandas.DataFrame.max vs. numpy.amax)

```
DataFrame.max(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
```

skipna : *bool, default True*
Exclude NA/null values when computing the result.



Predictive Maintenance Example



Data Source Quality

- capacitance sensor very sensitive -> AVAILABILITY
- database of generator not normalized -> REPRESENTATIONAL ADEQUACY
- Personal data in XML files -> TRUSTHWORTHINESS
- …

Data Smells

- temperature values vary widely -> BELIEVABILITY
- timestamp of current values encoded as String -> DATA TYPE
- …

Data Pipeline Quality

- pipeline jungle (several different frameworks)
- vibration data transformed without using 'validate' option
- voltage data normalized without explicitly defining handling of missing values
- …

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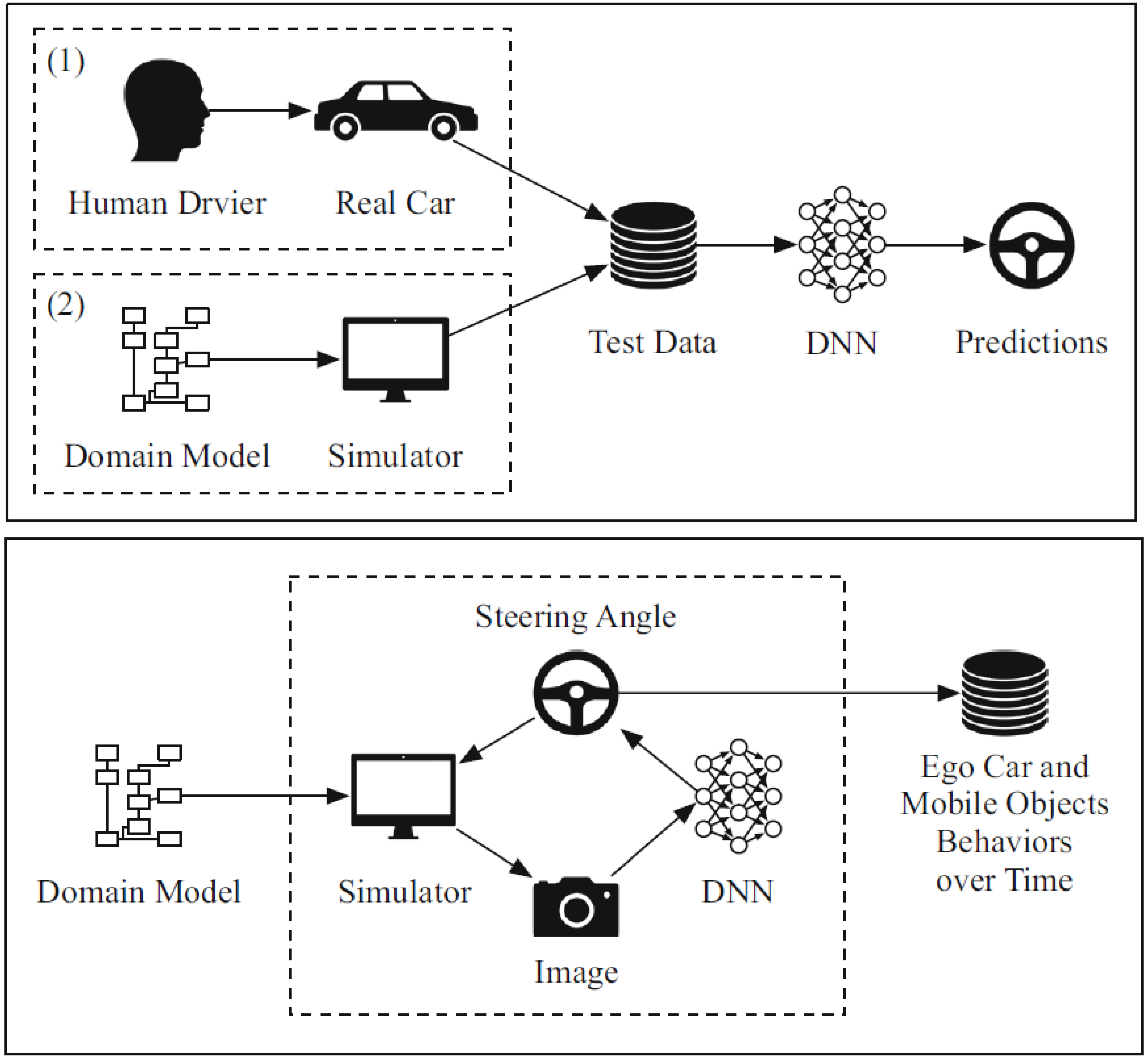
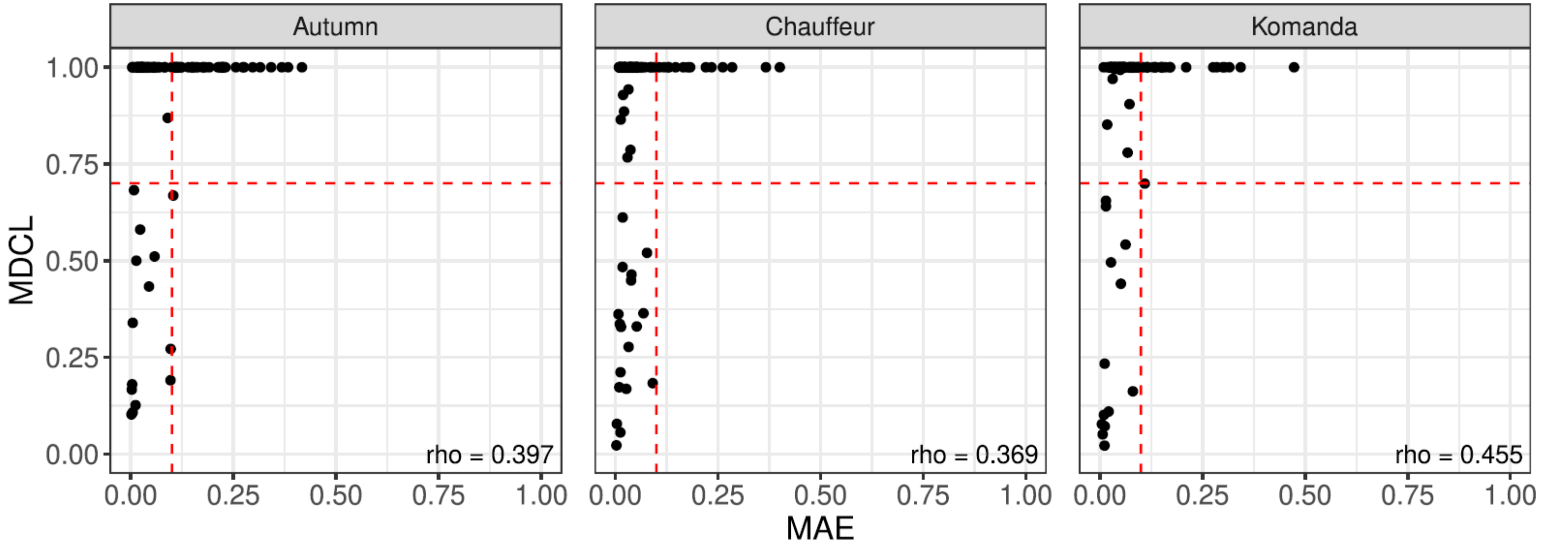
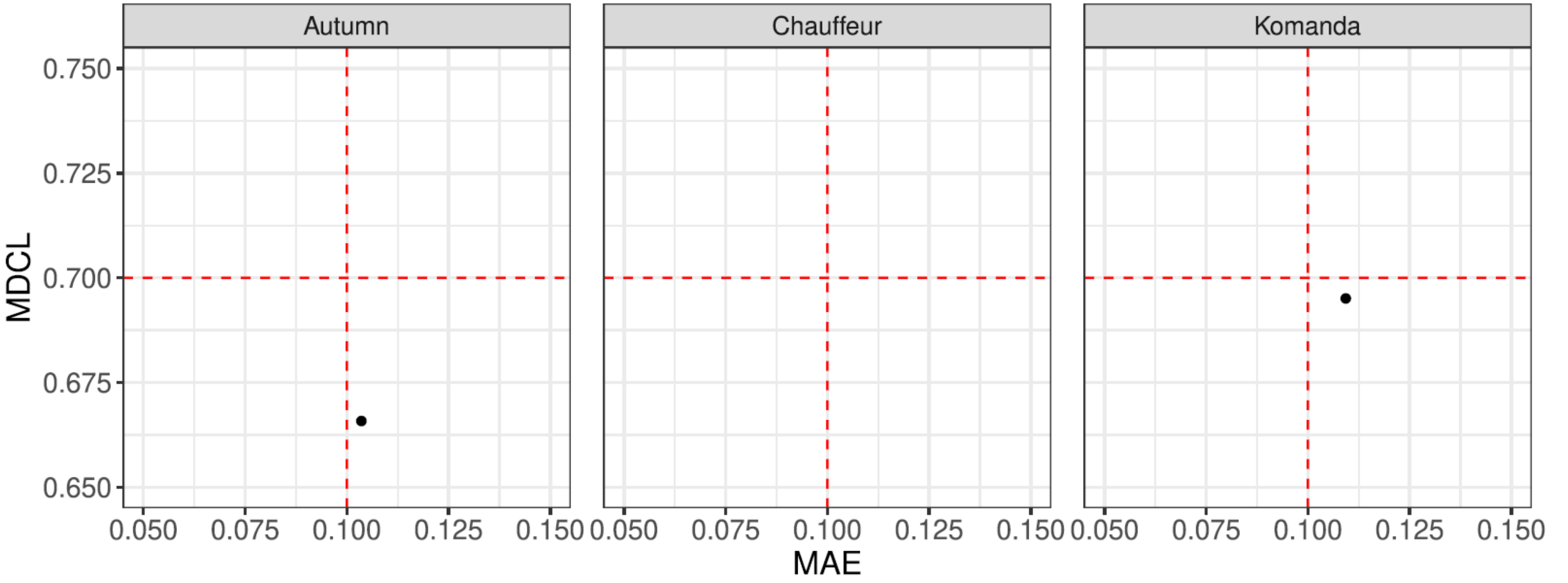
Offline and Online Testing



Haq, Fitash Ul, et al. *Can Offline Testing of Deep Neural Networks Replace Their Online Testing?*. Empirical Software Engineering 26:5, 1-30, 2021

Comparison Offline and Online Testing Results





Many safety violations identified by online testing could not be identified by offline testing

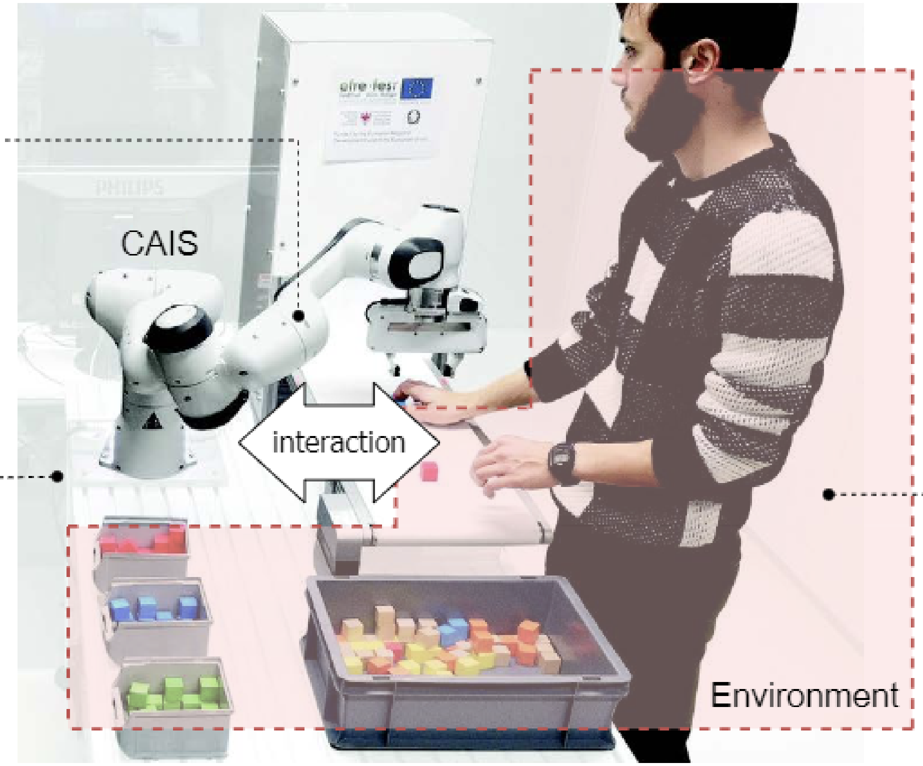
Offline testing cannot properly reveal safety violations

MDCL: Maximum Distance from Center of Lane (Online Testing)
MAE: Mean Absolute Error (Offline Testing)

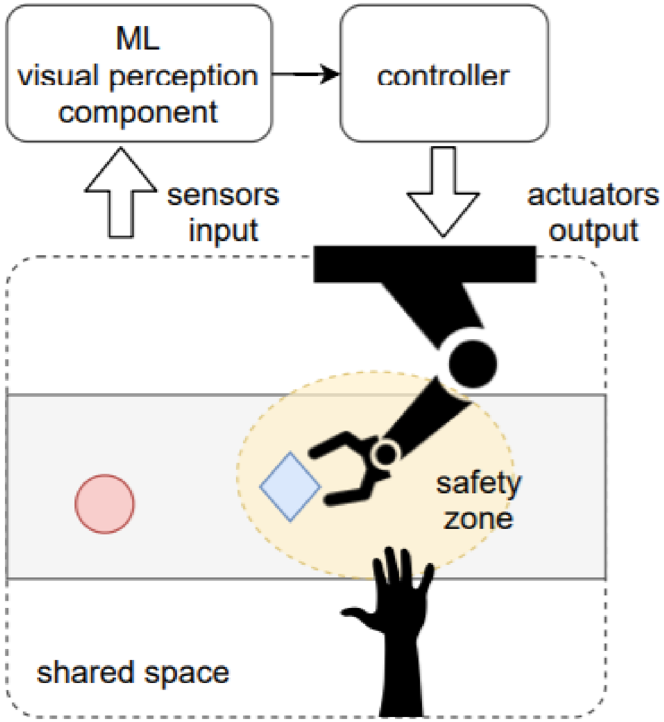
Collaborative AI Setting and Safety

Online learning:
object classification,
human classification,
motion direction,
motion speed

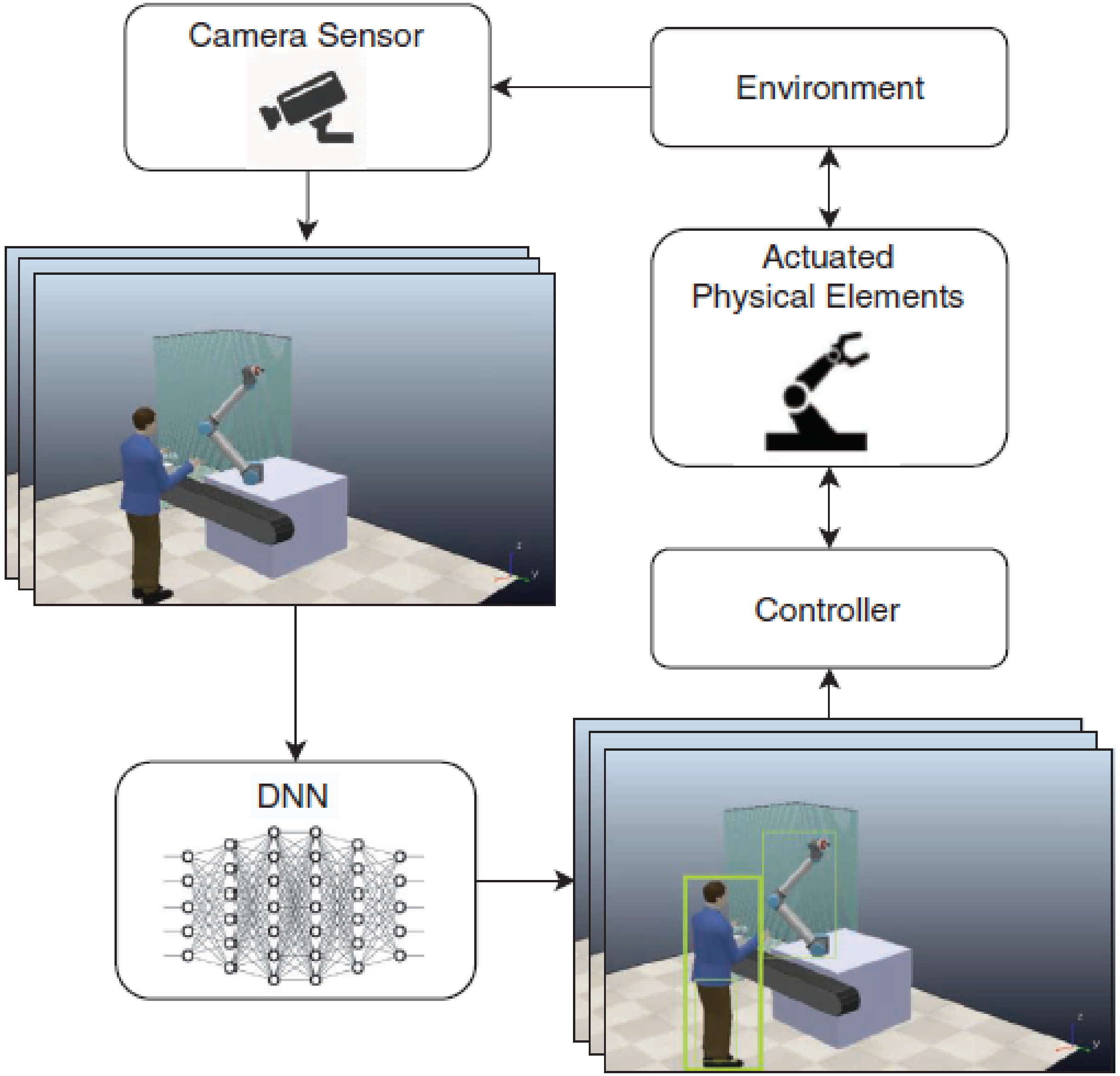
Risks:
protective distance violation,
injuring behavior,
robot unable to classify objects,
robot prevails over human needs



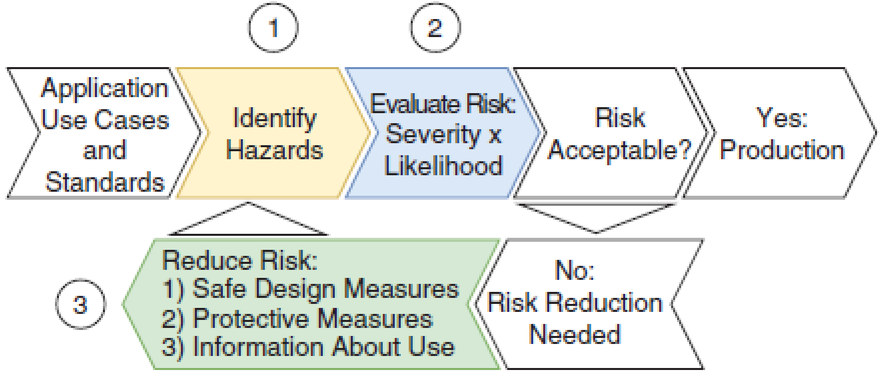
Uncertainties:
human position,
human motion speed,
human-background contrast,
luminance,
shape/color of objects

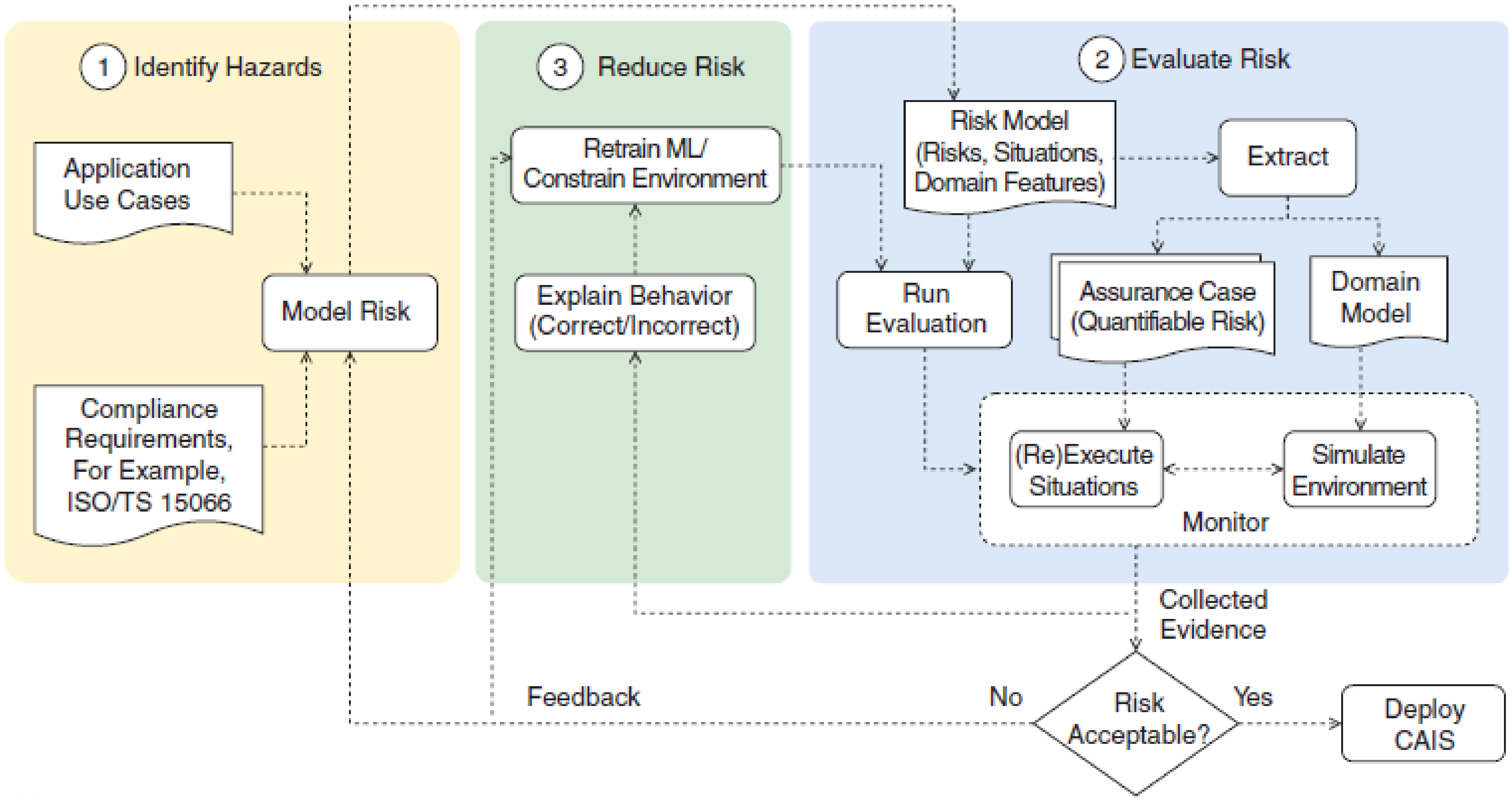


Setting for Online Testing

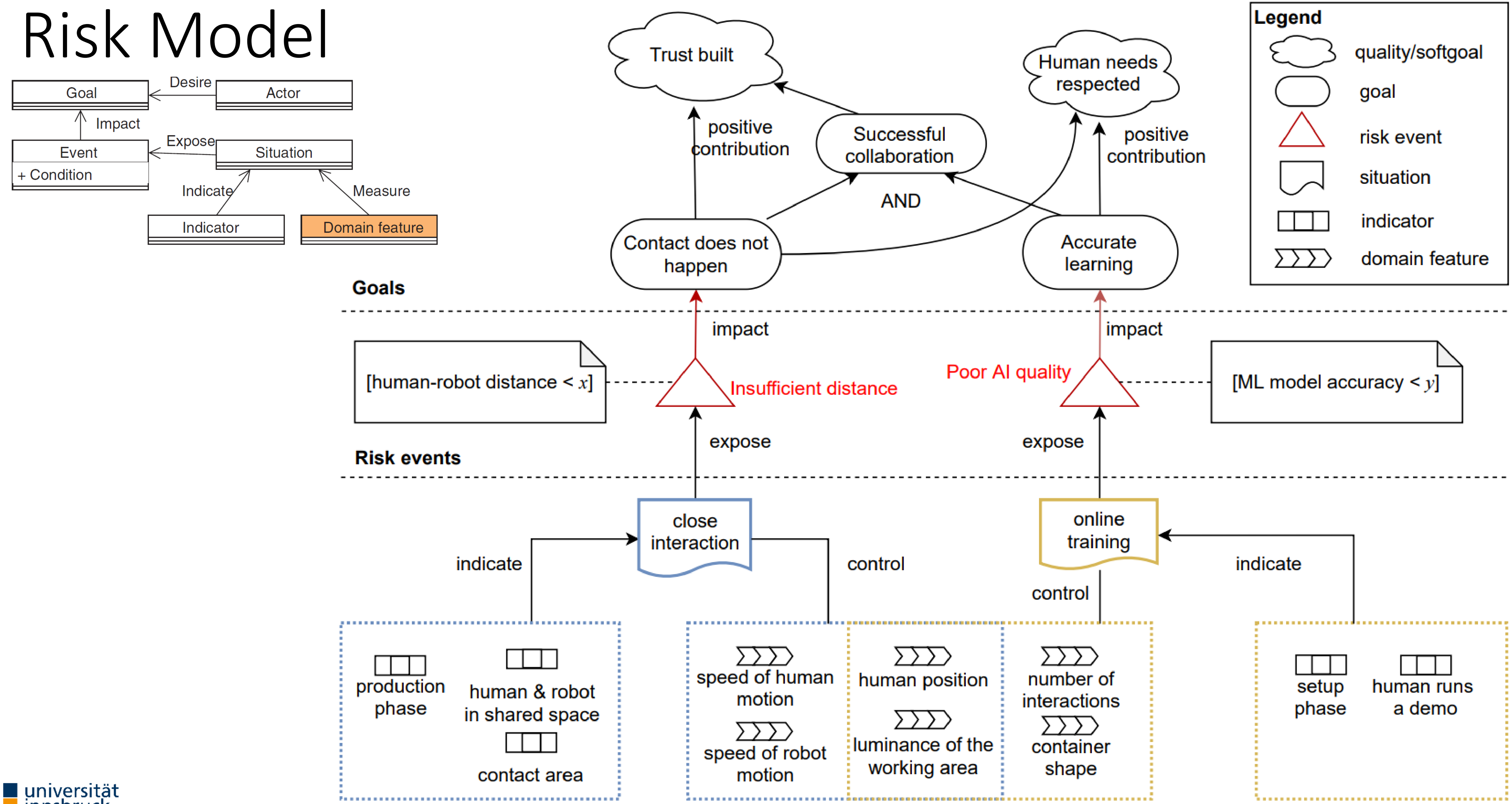


Risk-Driven Assurance Process





Risk Model


Goal
Desire
Actor
Impact
Event
+ Condition
Expose
Situation
Indicate
Measure
Indicator
Domain feature
Trust built
Human needs respected
positive contribution
Successful collaboration
positive contribution
AND
Contact does not happen
Accurate learning
Legend
quality/softgoal
goal
risk event
situation
indicator
domain feature
Goals
impact
impact
[human-robot distance < x]
Insufficient distance
Poor AI quality
[ML model accuracy < y]
expose
expose
Risk events
close interaction
online training
indicate
control
control
indicate
production phase
human & robot in shared space
contact area
speed of human motion
speed of robot motion
human position
luminance of the working area
number of interactions
container shape
setup phase
human runs a demo

Search Space Exploration and Risk Evaluation

1. [Start] Initialize simulator variables for path e.g., Given initial system states (s_0, n, U) and "m" number of runs such that:

s_0 = robot arm coordinates *(R [x, y, z]), human* position *(H [x, y, z]),*

$n = 0 : 0, 1, 2 \ldots n \subseteq m$

$U = []$

2. [Input space] "p" population of *key simulator features* (suitable solutions for the problem) which is the expected output:

$F' \leq F$ *(e.g., environment lighting (L [h, s, l]))*

Path trace during its execution $(v = (v_1, \ldots, v_p))$*, implicitly determined within simulator*

3. [Fitness] Determine fitness function *f(x)* of each arrangement in the population that satisifies a value ϕ along the path *v,* e.g.,

$d(R, H) \leq \phi$

4.[Update] The simulation rewards those path functions where an unsafe state is reached for instance with a "1" or otherwise "0", returns:

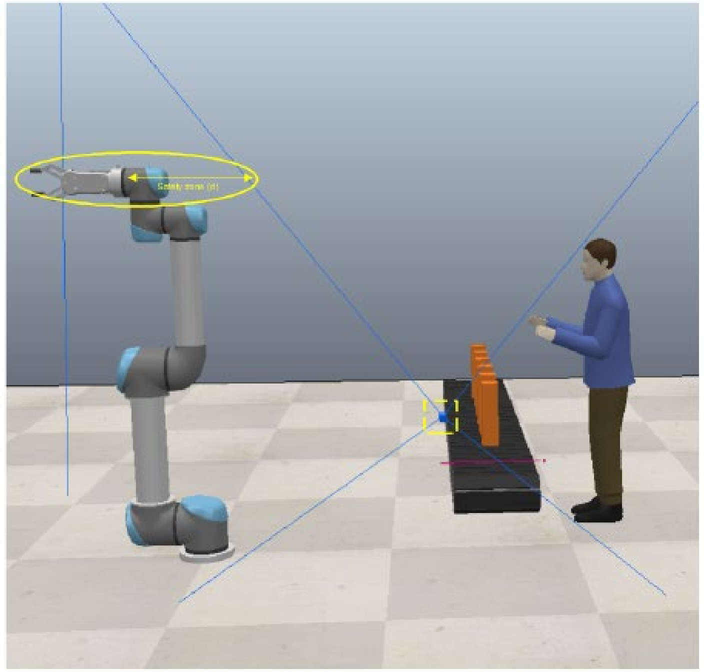
feature $F' \subseteq U$

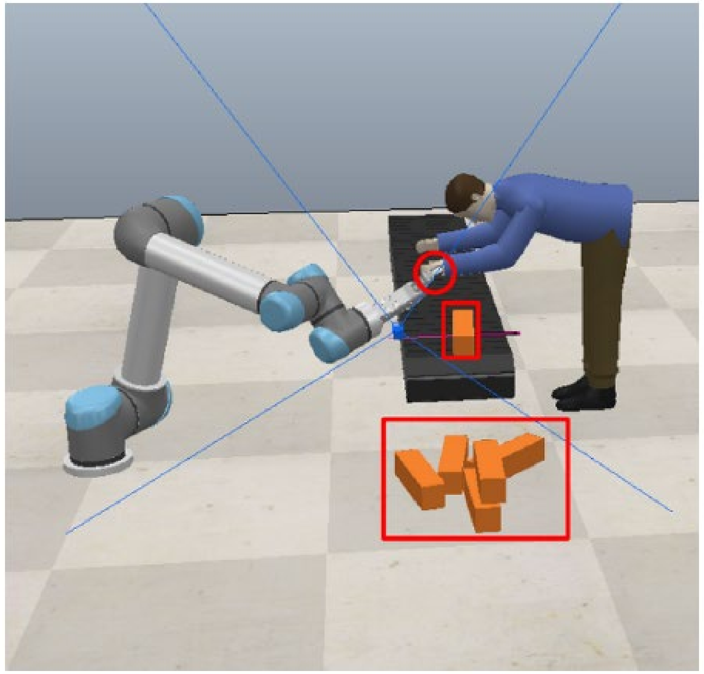
$$Ur = \begin{cases} 1, & dvi(R,H) \leq \phi \\ 0, & otherwise \end{cases}$$

5. [Increment] test case n = n + 1

6. [Repeat/Loop] : Step 2 until n = m

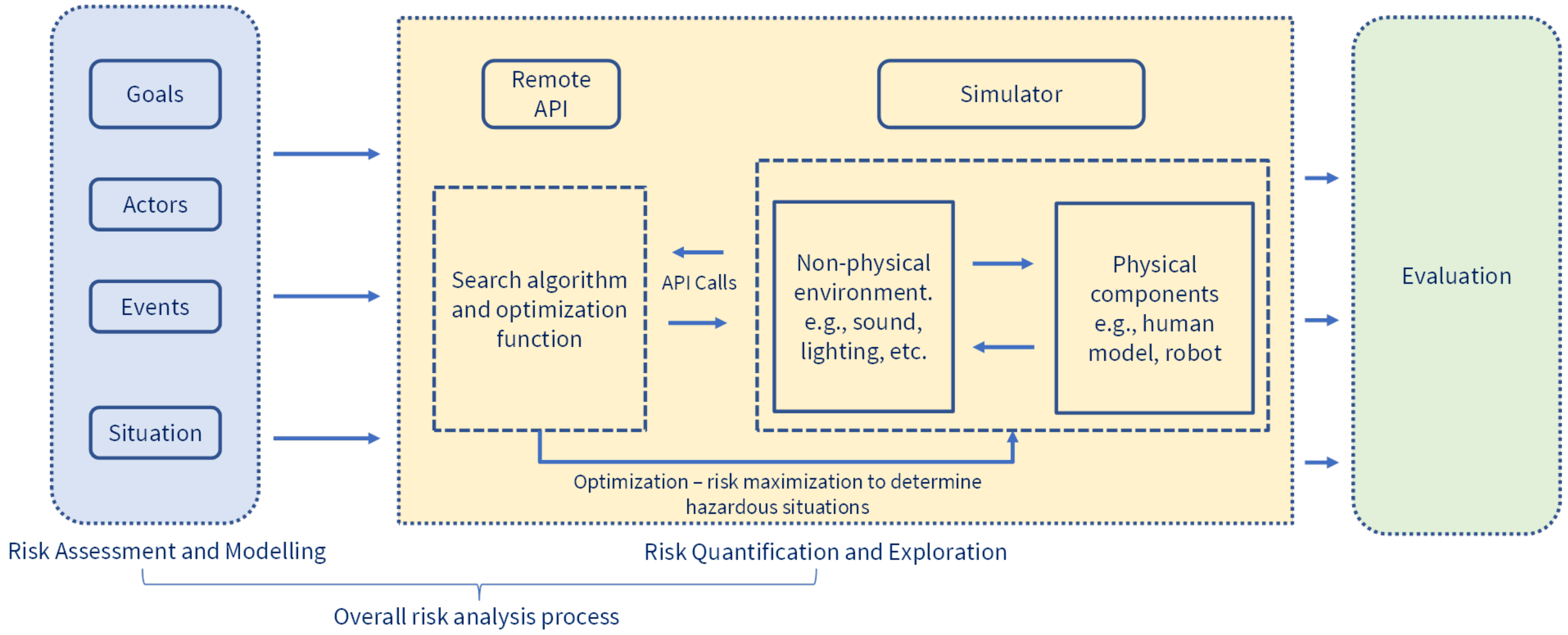
7. Return outcome U



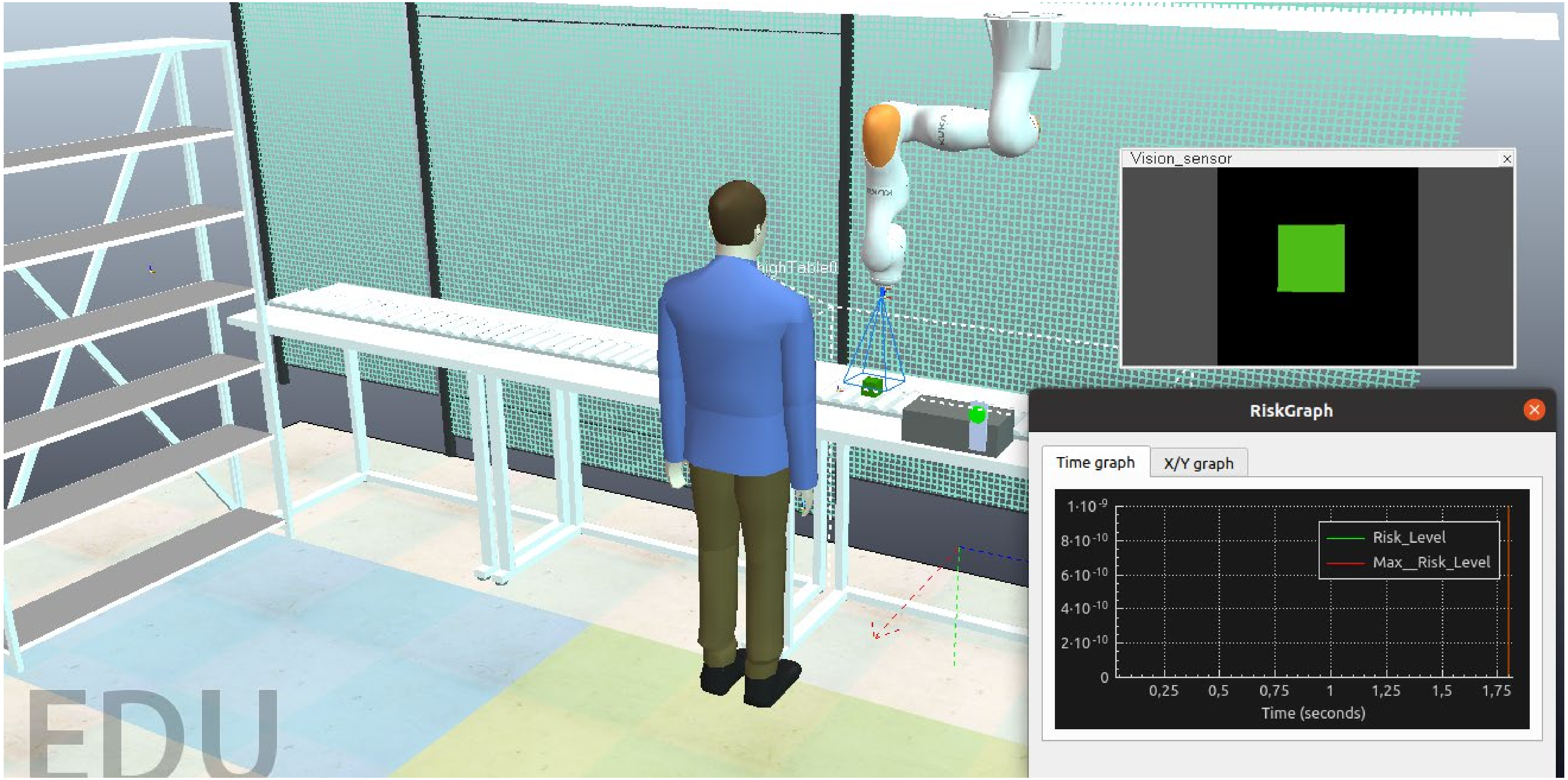


Objective Functions:
Minimum distance between human and robot arm
Relative speed of human and robot arm

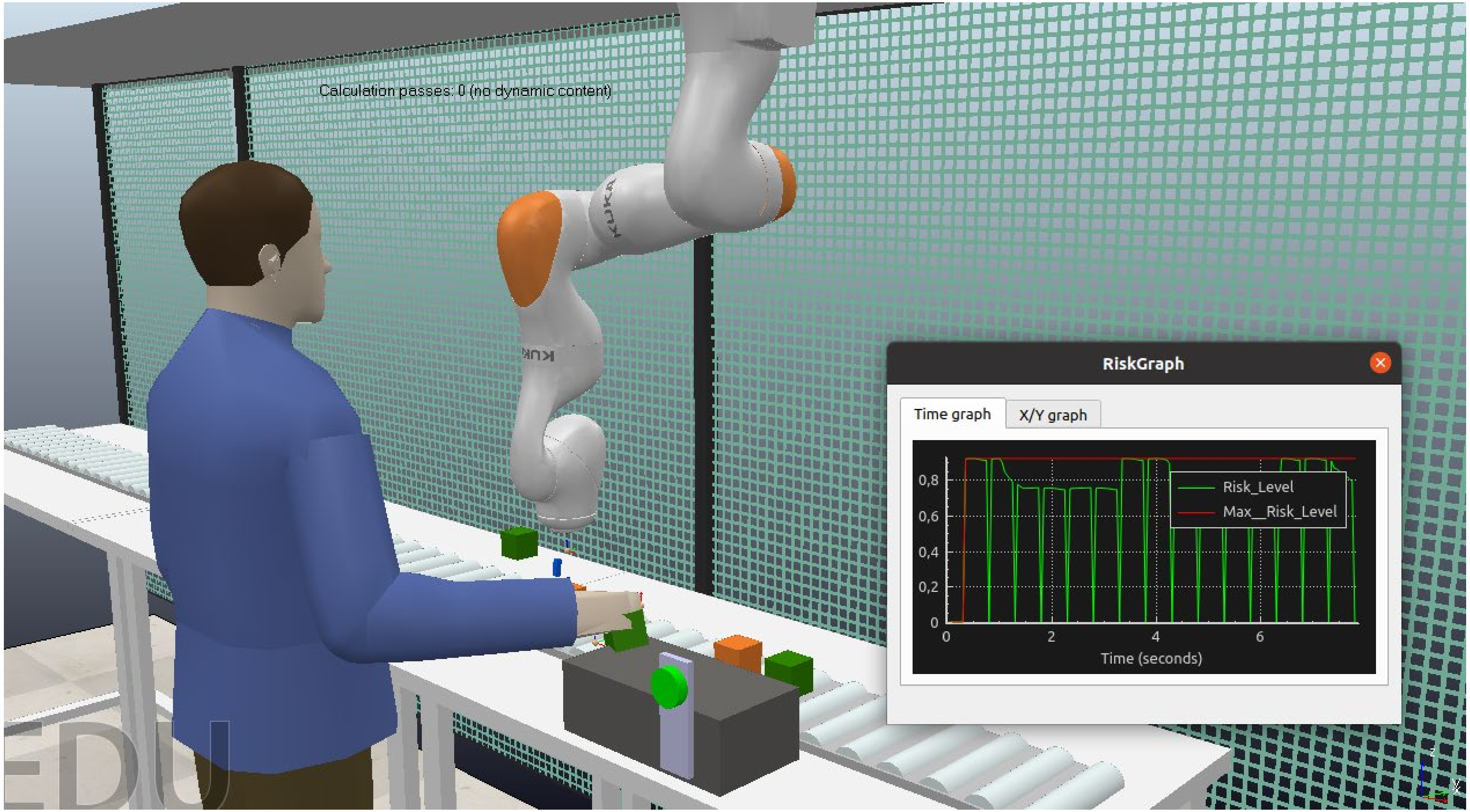
Test Environment



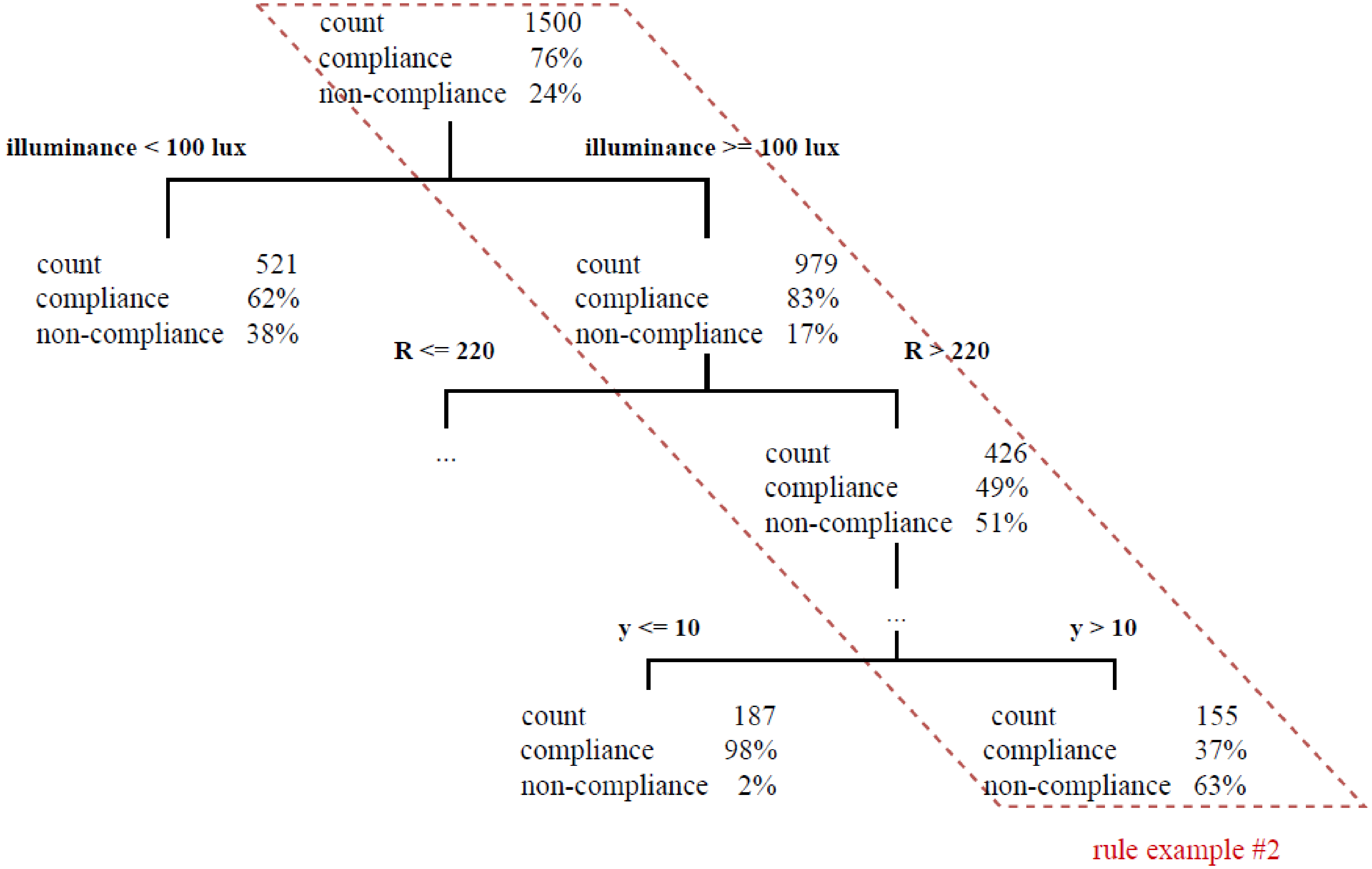
Simulation in CoppeliaSim (1/2)



Simulation in CoppeliaSim (2/2)



Risk Quantification, Decision Tree and Rule Extraction



rule example #	domain features illuminance (lux)	operator arms color (R,G,B)	operator position (x,y)
1	<100	-	-
2	>100	R >220, G >236, B >200	x >180, y >10

Summary

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[1] Zhang, Jie M., et al. *Machine learning testing: Survey, landscapes and horizons*. IEEE Transactions on Software Engineering, 2020

[2] Riccio, Vincenzo, et al. *Testing machine learning based systems: a systematic mapping*. Empirical Software Engineering 25.6 (2020): 5193-5254.

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