Data Spaces 14:00 Symposium Al Testing and Data Spaces

Petra Dalunde, Kateryna Mischenko, Nishat Mowla, Giovanni Leoni, Daniel Sáez-Domingo & Yunus Bulut



AITESTICATION DARMSTADT 2024

Petra Dalunde – Coordinator AI Testing at RISE

RISE RESEARCH INSTITUTES OF SWEDEN

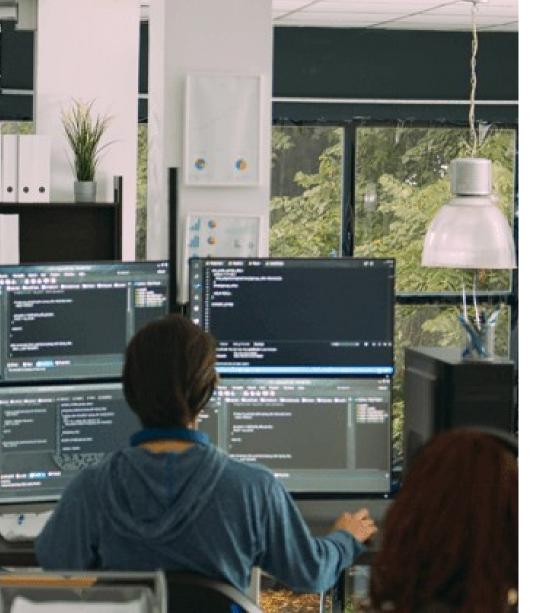
- RTO
- 3 TEFs
- Test & Demo
- Notified body
- i-space in BDVA

EDIHs - TEFs - Cyber Security - Industry - Medicine



AI Testing in this session

"Testing AI systems towards legislation and function for human centric AI in Europe"



Todays session

Exploring AI Testing: Introduction and Methodology Katya Mishchenko & Nishat Mowlat at RISE

Al Governance in organizations: Data, Process & People to make it happen in practice Giovanni Leoni, at Credo Al

i-Spaces and Sandbox Daniel Sáez Domingo at ITI

Al testing in practice: What Validator has learnt from its customers Yunus Emrah Bulut at Validator

Panel & Q&A



Exploring Al Testing: Introduction and Methodology

March 12th, 2024

Kateryna Mishchenko & Nishat I Mowla

RISE

Agenda:

- Introduction to AI testing:
 O What, why and how?
 O About AI Act and standards
- Challenges in AI testing
- AI testing methodology

 Assessment list of Trustworthy AI
 AI Testing standards
 Application domains and subfields of AI
- Performing AI testing
 O AI testing at RISE

Introduction to AI testing



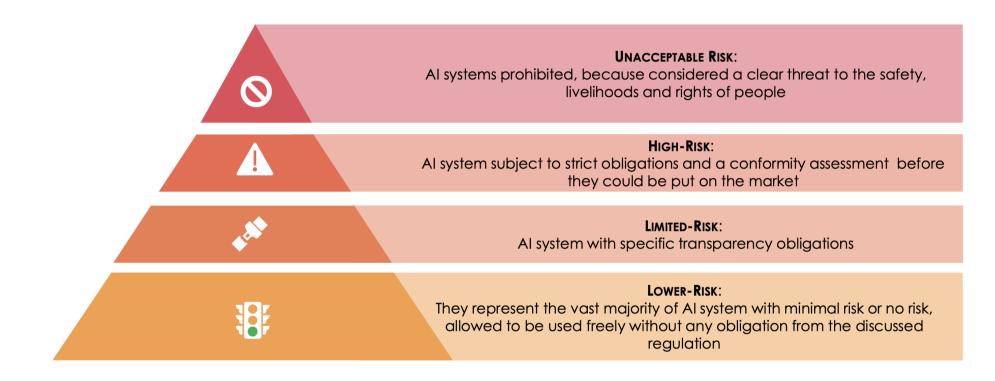
About AI testing

A52021PC0206

- What: Testing AI systems is s a vital part of the development and deployment of AI systems since ensures their accuracy, reliability, safety, efficiency and effectiveness
- Why: Al testing builds trust and confidence in real-world applications and helps in identifying and rectifying potential issues early, thereby improving the quality of software releases.
- How: One instrument to emphasize the importance and ensure the safety and reliability of AI systems is the **AI Act** (enters into force 2024-2026).

It lays down harmonized rules on AI, aiming to balance the socio-economic benefits and potential risks of AI technologies placed on the European market.

AI Act: risk-based approach



Source: https://www.iasonltd.com/doc/jit/2021/ European_Commission_Regulation_on_Al.pdf

About the Standards related to AI Act

ISO/IEC TR 29119-11:2020 Software and systems engineering — Software testing — Part 11: Guidelines on the testing of AI-based systems

Provides an introduction to Al-based systems, new challenges and opportunities for testing them.

This document explains those characteristics which are specific to AI-based systems and explains the corresponding difficulties of specifying the acceptance criteria for such systems.

ISO/IEC AWI TS 29119-11 Software and systems engineering — Software testing — Part 11: Testing of AI systems

Describes testing techniques applicable for AI systems in the context of the AI system life cycle model stages

Shows how AI and ML assessment metrics can be used in the context of those testing techniques. It also maps testing processes to the verification and validation stages in the AI system life cycle.

• ISO/IEC 25059 Software engineering. Systems and software Quality Requirements and Evaluation (SQuaRE)

Outlines a quality model for AI systems and provide guidelines for measuring and evaluating the quality of AI systems, focusing on characteristics like accuracy, interpretability, robustness, fairness, privacy, and security.



Challenges in AI Testing



Some challenges related to AI testing

- Testing AI systems comes with unique challenges, such as the unpredictability of AI behaviour, the difficulty in defining the right metrics for success, and the complexity of creating diverse and representative test cases.
- ISO/IEC AWI TS 29119-11 "Software and systems engineering Software testing Part 11: Testing of AI systems" describes testing techniques and metrics for AI systems in the context of the AI system life cycle model stages. According to it, some of **challenges** are:

Data testing:

issues with data quality, diversity, privacy, labeling, temporal sequencing, data drift, and potential biases.

Explainability:

Arises from "black box", nature, making it difficult to understand why they make certain decisions.

Continuous Learning:

often learn and adapt over time, which means they need to be continuously tested and monitored

Transparency:

arises "black box" nature, sensitivity of training data, dynamic learning, potential for bias, and the trade-off between model accuracy and explainability.

Trustworthiness:

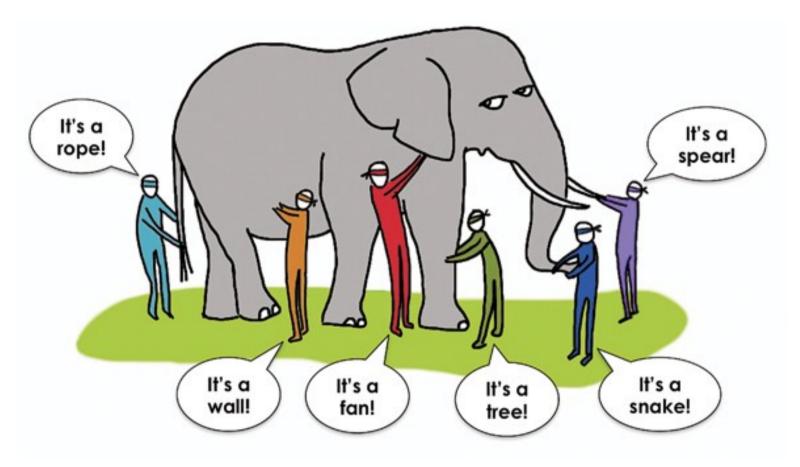
arises from the "black box" nature, the need for security against manipulation, the requirement for data privacy, the necessity for accountability, and the complexity of ensuring fairness and nondiscrimination.



AI testing methodology

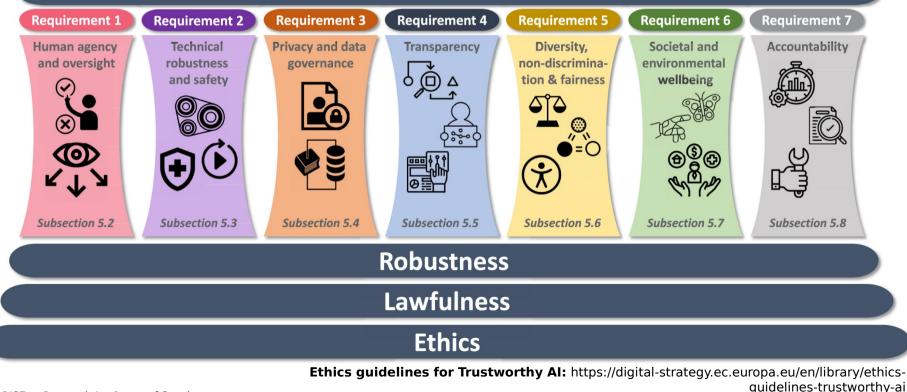


The AI Testing Elephant



Assessment list of Trustworthy AI (ALTAI)

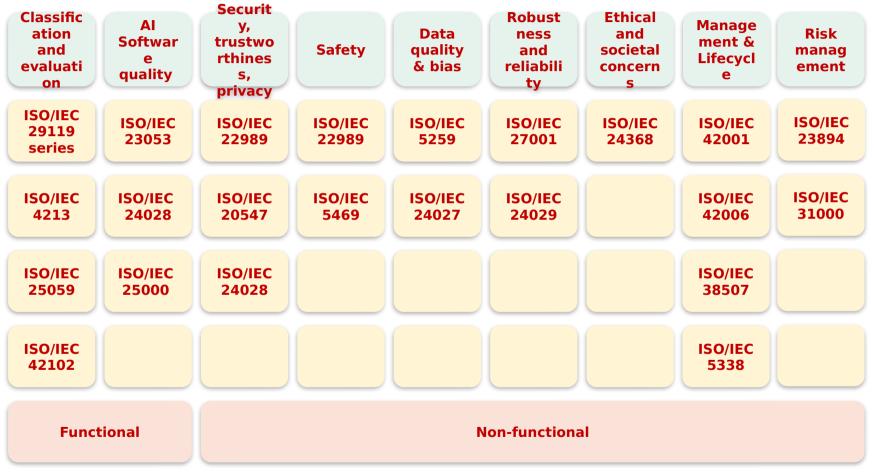
Trustworthy Artificial Intelligence



RISE — Research Institutes of Sweden

Image source: https://www.sciencedirect.com/science/article/pii/S1566253523002129

AI Testing Standards



Application domains and subfields of Al

| | Healthcare | | Manufactur | | Environme |
|---|--------------|--------------|------------|---------|-----------|
| | nearthcare | | ing | / | nt |
| Subfields of AI: | | | | | |
| 1. Machine learning 2. Deep learning (DNN) | \backslash | | | | |
| | | R&D | | Finance | |
| 3. Natural language processing | | | | | |
| (LLM) | | | | | |
| 4. Computer vision (image, video, | Transporta | | | | Customer |
| voice) | tion | | Energy | | service |
| 5. Reinforcement learning (agents) | | | | | Service |
| 6. Multi-agent systems | | | | | |
| 7. Robotics (autonomous) | \backslash | | \land / | Legal & | |
| 8. Expert systems (reasoning) | <u>}(</u> | Education | | Law | |
| 9. Speech processing (speech | | | | Law | |
| recognition) | | | | | |
| 10. Planning and scheduling (plan | | | E | | |
| actions) | Cybersecur | | Entertainm | | Robotics |
| 11. Knowledge representation and | ity | | ent | | |
| reasoning | | | | | |
| 12. Evolutionary computing | | | | | |
| (genetic algorithm) | | Agriculture | | Retail | |
| 13. Affective computing (recognize | | - - - | | | |
| feelings) | | | | | |
| | | | | | JE |
| 18 RISE — Research Institutes of Sweden | | | | | |

Performing AI Testing



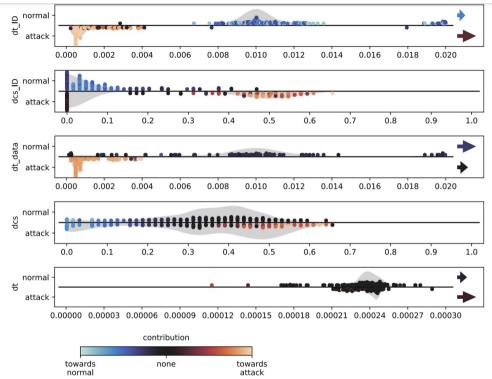


FIGURE 2. VisExp | A pseudo-global visualization-based explanation, using SHAP values. It shows the features in the dataset in swarm plot-like strips for normal and attack classifications. Each point is an instance from the train data. The x-axes are the feature values, and the color represents the SHAP values. The color of the arrows represent the mean of the SHAP values outside of the diagram, and their relative size represents how many data points there are.

Hampus Lundberg, Nishat I Mowla, Sarder Fakhrul Abedin, Kyi Thar, Aamir Mahmood, Mikael Gidlund, Shahid Raza, "Experimental Analysis of Trustworthy In-Vehicle Intrusion Detection System Using eXplainable Artificial Intelligence (XAI)," IEEE Access, vol. 10, September 2022. (<u>Link</u>)

FIGURE 1. CAN frame | The Survival dataset has features of the ID, DLC and data field, along with the timestamp of when a CAN frame is transmitted.

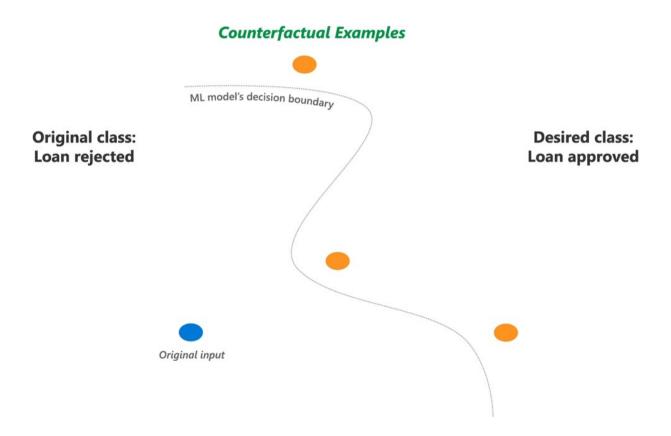
TABLE 1. DNN hyperparameters | Parameters and their values as specified when building the DNN in keras.

| Layer | # of units | Description |
|----------------|----------------------|--|
| layer_1 | 11 | keras.layers.Dense |
| layer_2 | 23 | keras.layers.Dense |
| layer_3 | 7 keras.layers.Dense | |
| Hyperparameter | Value | |
| optimizer | "adam" | Optimizer algorithm |
| batch_size | 200 | # of samples in a |
| epochs | 20 | gradient descent # of training passes over the dataset |

TABLE 2. The engineered features.

| Feature | Description |
|------------|--|
| dt [12] | Transmission time (s) between CAN frames |
| dt_ID [12] | Transmission time (s) between CAN frames |
| | with the same ID |
| dt_data | Transmission time (s) between CAN frames |
| | with the same data field |
| dcs | Data change score (ratio) between CAN frames |
| dcs_ID | Data change score (ratio) between CAN frames |
| | with the same ID |

Performing AI Explainability Testing



Microsoft Research





Quality of AI

Quality AI requires quality data

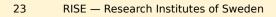
But quality AI is more than data

- Cybersecurity
- Transparency
- Robustness
- more



Thanks!

kateryna.mishchenko@ri.se nishat.mowla@ri.se



Al Governance in organisations

Data, Process & People to make it happen in practice

DATAWEEK24 | DATA SPACES SYMPOSIUM | 20240312

Agenda

Al Testing & Data Spaces The New Normal The Business Case Building Capability

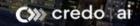
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The Future of Trustworthy AI

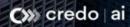




Al Testing & Data Spaces

Data is the fuel and Data Spaces creates the preconditions for innovating and adopting Trustworthy Al

B The New Normal



The New Normal

Expectations are on the rise.



The New Normal

EU Al Act is not only a regulation.

C≫ credo∣ai

C The Business Case



The Business Case

lack of control

inefficiencies

brand risk

liabilities

C≫ credo ai



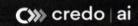
The Business Case

confidence in Al

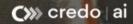
informed accountability

adapting to the world

trust in digital



D Building Capability





Building Capability

Strategy & Policy

Blueprint

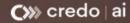
Engagement

Building through doing

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The Future of Trustworthy Al enabled by Data Spaces



It's not about perfection; it's about starting, today.



GIOVANNI@CREDO.AI



CREDO.AI

DATAWEEK24 | DATA SPACES SYMPOSIUM | 20240312

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i-SPACES AND SANDBOXES

ITI EXPERIENCE



INVESTIGATE TO INNOVATE



Daniel Sáez-Domingo (dsaez@iti.es)

- Strategic Intelligence and Technology Transfer Director in ITI
- Coordinator of ITI Innovation Space (i-Space Platinum BDVA)
- Member of Board of Directors of **BDVA and GAIA-X**

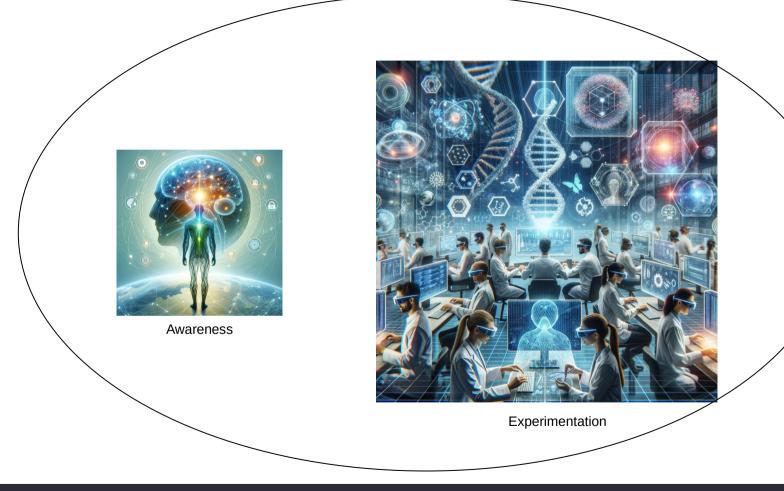
Data Driven economy needs



Tech. Convergence



Regulations & Standards





i-Spaces, making Data Strategy happen

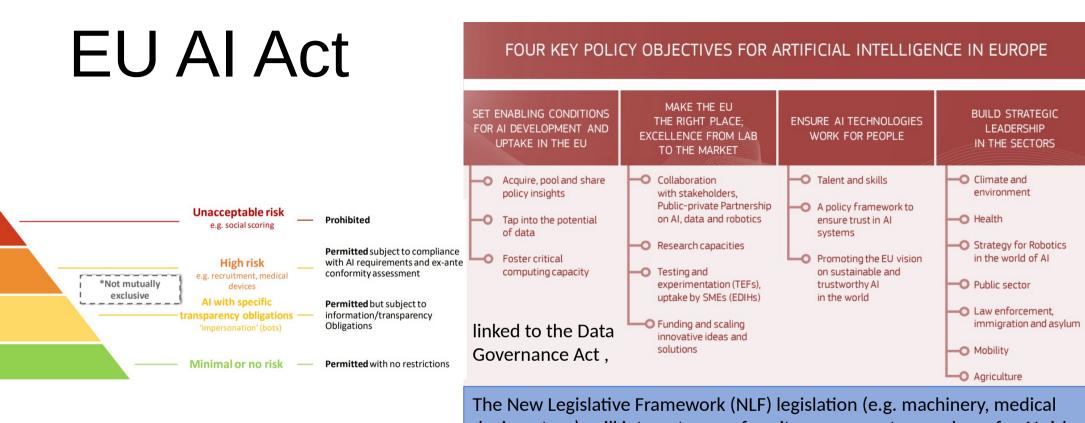


i-Spaceseconcept was defined a long time ago (2014), but it is totally alive and needed nowadays. i-Spaces are ecosystems with powerful infrastructures, knowledge, tools, data, ... ready to provide services for the experimentation and innovation with Data and Al.



They have a close contact and are well known and recognized in their local ecosystems and are also very well connected globally, as stars of an impressive constellation around Data and Al.





devices, toys), will integrate a conformity assessment procedures for AI risk classification



Sandboxes

A Sandbox is an isolated framework to allow innovators, whether start-ups or large firms, to conduct live experiments in a controlled environment





WHY SANDBOXES: EXAMPLE SPAIN

Provide clarity on the novel requirements for Al Systems set out in the Al regulation

1

Transfer compliance know-how with the legislation and enable the development of innovative trustworthy Al Systems

2

Eventually, start consultations in Spain for the creation of a National Supervisory Authority

3

Provide practical learning to support the development of standards and guidance at national and European level

4

Support the implementation of the future AI Regulation

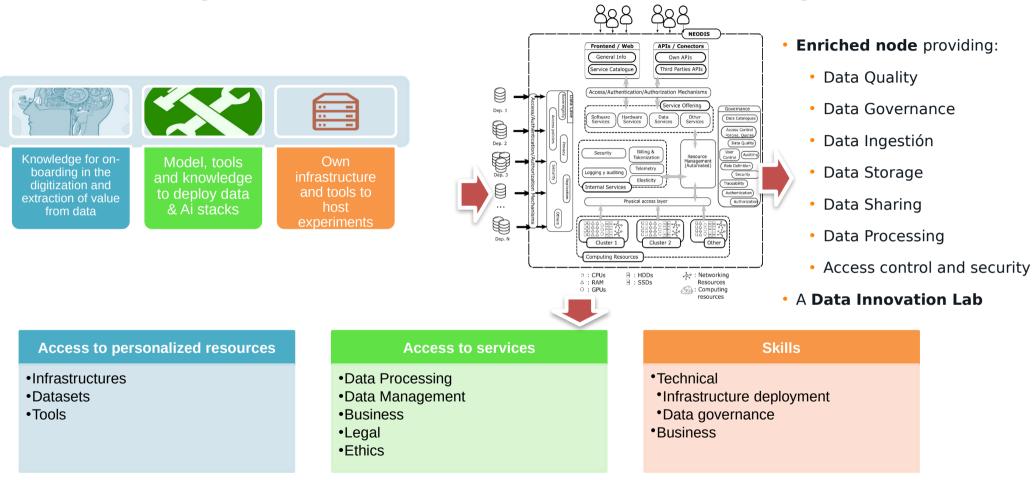
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European Commission

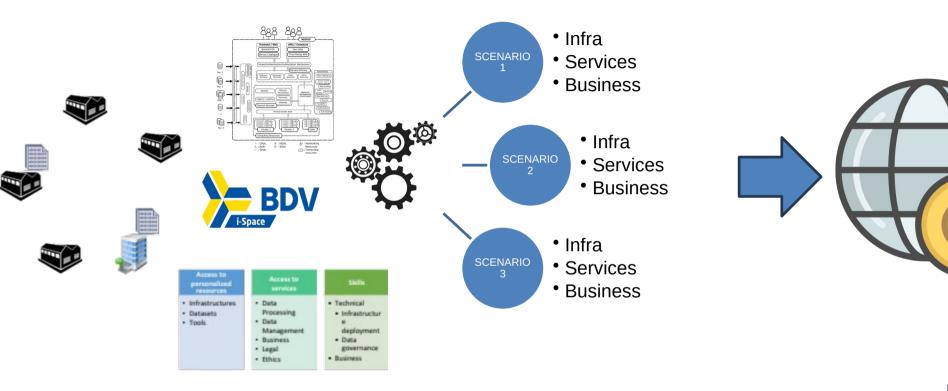
T I INVESTIGATE TO INNOVATE

i-Spaces: Trusted environments to experiment





How can i-Spaces help the regulators



AGILE AND PERSONALIZED SCENARIO CONFIGURATION



How can i-Spaces help the regulators



Analyse the Al system, its intended use, potential risks, and mitigation strategies.



Prepare the scenario to test and deploy the AI systems in real-world settings, but in controlled environment. Limited time.



Report to the regulator on the performance, risks, and any incidents related to the Al systems



And i-Spaces are sharing best practices

i-SPACES HAVE FEDERATED THEMSELVES WITH THE VISION OF BEING THE REFERENCE FOR EXPERIMENTATION AND INNOVATION WITH INDUSTRIAL, PUBLIC AND PERSONAL DATA AND AI TECHNOLOGIES FOLLOWING THE EUROPEAN, NATIONAL AND REGIONAL VALUES AND PRINCIPLES. SOLID COLLABORATION. COMMON VISION. TANGIBLE IMPLEMENTATION







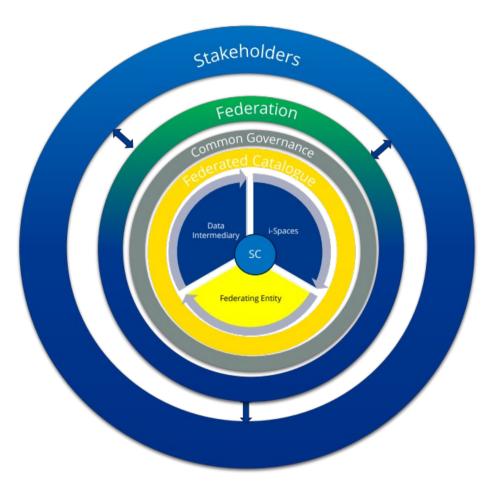


main pillars

4

Mission

The Federation's mission is to accelerate the evolution and adoption of Data driven innovation and AI Technologies in Europe by facilitating a safe, trustworthy and regulatory **compliant environment** for cross-border and cross-sector data-driven experimentation. The Federation links relevant European initiatives on Data and AI in a **single ecosystem** providing a sustainable high-quality and global European federated catalogue of data sources, datadriven services, courses and solutions deployed locally by the i-Spaces.







Al testing in practice What Validaitor has learnt from its customers?

Yunus Bulut , Founder & CEO yunus.bulut@validaitor.com



Safety & Trust for AI

Weight Validaitor Platform

Assessments & Collaboration

Validaitor offers many AI assessment and risk management templates and enables collaboration between AI developers and auditors.

| 0 | • | Previous Comments: |
|--|-----|--|
| afetylAdverserial Newse determine whether the AI system (choose as many as appropriat | e): | Ramazan Korkut - Aug. 9, 2023, 1:50 p.m this is a comment. |
| Saved choices: • Is overseen by a Human-in-the-Loop • Is overseen by a Human-in-Command | | |
| inswer: | | Comments: |
| Is overseen by a Human-in-the-Loop Is overseen by a Human-in-Command Is a self-learning or autonomous system | | Comment here |
| Update | | Add Comment |

| create a Test | |
|--|----------|
| reate a new test for your LLM API. | |
| hoose a Project | |
| Validaitor | v |
| alagory | |
| Reasoning | ~ |
| Fairness | |
| Privacy | |
| Reasoning | |
| Security | |
| Text Clarity | |
| Toxicity | |
| Truthfulness/ Hallucination | |
| elect an LLM Api for the test. | |
| rompts | |
| 2% (5 prompts) | |
| elect an amount of promots for running | the test |

Out-of-the-box Testing

Validaitor provides many tests and metrics out-of-the-box. You don't have to write knowledge intensive testing code for AI audits.



Automated Certification

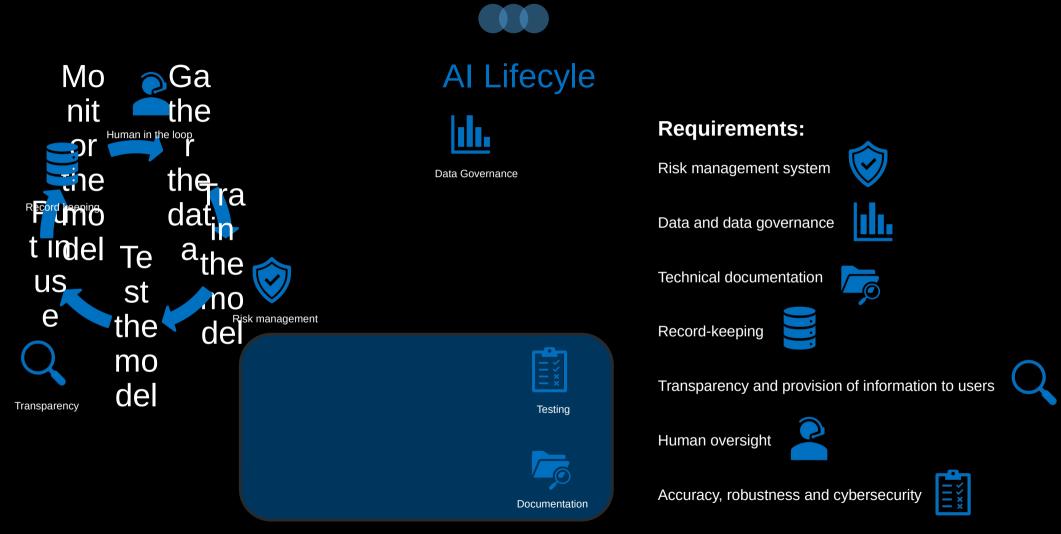
Validaitor automates testing and assessment so that companies can get AI certification from the platform every time they ship a new AI.



Forensic and Incidents

Validaitor keeps your AI assets and audits for forensic purposes. It also enables you to keep track of incidents and provides collaboration functionality on incident management.







Safety & Trust for AI

1. AI Testing is beyond performance testing

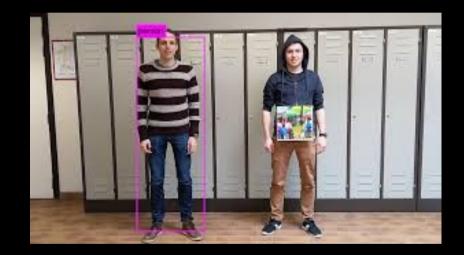
- AI developers are familiar with performance testing:
 - The educational system enforces it.
 - It is easy to understand and implement.
- There's more than performance in an AI!





Security

- Evasion Attacks: Models can be fooled during inference time.
- **Poisoning Attacks**: Models can be fed with backdoors that can be triggered during inference.
- Model Stealing Attacks: Intellectual property is at risk.







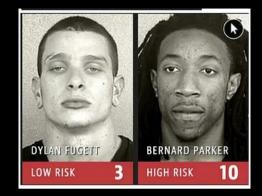
Privacy

- It's shown that large models tend to memorize training data.
- The larger the models, the higher the chances to memorize sensitive info.
- Models can leak this info during inference:
 - Membership Inference Attacks
- The only known solution that is effective is **Differential Privacy**.
 - It's really hard to scale!



Fairness

- Bias is a central concern that is directly related with human rights
- Categories can be age, gender, nationality, religion ...
- Bias can be checked on:
 - Datasets
 - Model predictions



Amazon ditched AI recruiting tool that favored men for technical jobs

Specialists had been building computer programs since 2014 to review résumés in an effort to automate the search process

How a Discriminatory Algorithm Wrongly Accused Thousands of Families of Fraud

Dutch tax authorities used algorithms to automate an austere and punitive war on low-level fraud—the results were catastrophic.

By <u>Gabriel Geiger</u> Illustrated By <u>Cathryn</u> <u>Virginia</u>



2. There's a trust issue between AI and its users

- The trust issue causes underutilization of AI.
- Al developers care about external certification even without any regulatory purposes.

Al developers are unsure about the quality of their models and shy away from innovation e.g. Al applications in healthcare

Consumers are hesitant to interact with AI based products and services e.g. autonomous driving.





3. Testing should result in "better" AI

- AI developers expect actionable insights after comprehensive AI testing.
- The aim of testing should be to discover weak spots and come up with suggestions to act upon.





4. Al failure modes are subtle

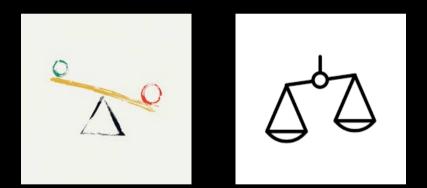
- It's not obvious to understand the failure modes of AI.
- The larger the models, the harder to find out weak spots.

| | Granny Smith | 85.6% | | Granny Smith | 0.1% |
|-------|--------------|-------|-------|--------------|-------|
| | iPod | 0.4% | | iPod | 99.7% |
| | library | 0.0% | D/S | library | 0.0% |
| | pizza | 0.0% | Pod | pizza | 0.0% |
| | toaster | 0.0% | A MAG | toaster | 0.0% |
| 1 . 1 | dough | 0.1% | 1 | dough | 0.0% |



5. Better AI means a lot of trade-offs

- Security vs performance
- Bias vs performance
- Robustness vs performance
- Privacy vs performance





6. Pre-trained models spread the vulnerabilities

- The problems cascades with finetuning.
- The direction of AI development is more and more fine-tuning of pre-trained large models.

1000



7. General purpose AI is hard to test

- The larger the model the harder to test and figure out new insights.
- If a model is intended to be "general purpose", defining scope for testing is the only way forward.





8. Testing is use case specific

- The tests are meaningful if they're justified in a use case scope.
- Different thresholds apply for different use cases.











9. Testing requires quantifiable metrics

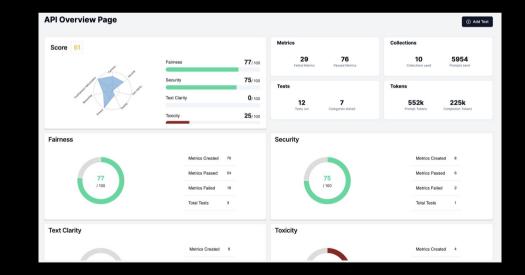
- The communication can only be done using quantifiable metrics.
- The lack of metrics means no tests most of the time.

| orivacy-privacy data leakage context -35 🧫 | | | | | | | | | |
|--|---------------------------|---------------------|------------------------------|---|---|------------|---------------------------------------|---------------------------------|---|
| Score | | | Config | | (\$\$ | Prompts | | | R |
| 100 | 4 Total Metrics | 0 Failed Metrics | 🚫 Privacy | | NTT Data Test GPT 3.5- Turbo Privacy Data Leakage Context | | 99 otal Prompts 73.5K Tokens | 16 Refused 0.02\$ Cost | |
| LII Results RJ Prompts | | | | | | | | | |
| Accuracy | Ū | F1 Score | | 0 | F-beta Score | Ō | Jaccard Score | | O |
| 0.99 Thresholds: ± 0.7 ↑ 1 | | т | 0.99 hresholds: ± 0.7 ↑ 1 | | 1.00 Thresholds: <u>¥</u> 0.7 | ⊼ 1 | | .99 ds: ⊻ 0.7 不 1 | |
| | | | | | | | | | |



10. Transparency is the goal of compliance testing

- There's no perfect testing that discovers all the vulnerabilities.
- The goal of a regulation should be to enforce transparency and best effort.







THANK YOU!

Yunus Bulut , Founder & CEO yunus.bulut@validaitor.com



Safety & Trust for AI