

Explainable AI (XAI)

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Regnskap Norge – OVERSKUDD 2024

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Sometimes AI makes small mistakes...



Q: Who is Claudia Battistin?

A: Claudia Battistin is an Italian academic and professional known for her expertise in international relations, with a particular focus on conflict and post-conflict situations, humanitarian interventions, and the impact of war on societies. She has been involved in various roles related to international cooperation, peacebuilding, and the protection of human rights in conflict zones.

Battistin has also contributed to the academic field through research and publications, particularly on issues related to conflict resolution, peace processes, and international law. Her work often intersects with the efforts of international organizations, NGOs, and other institutions dedicated to addressing the complex challenges of war and peace.

... sometimes makes big mistakes

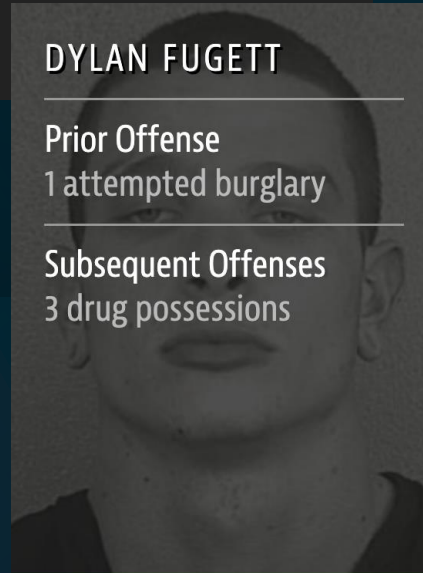


Donate

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica
May 23, 2016



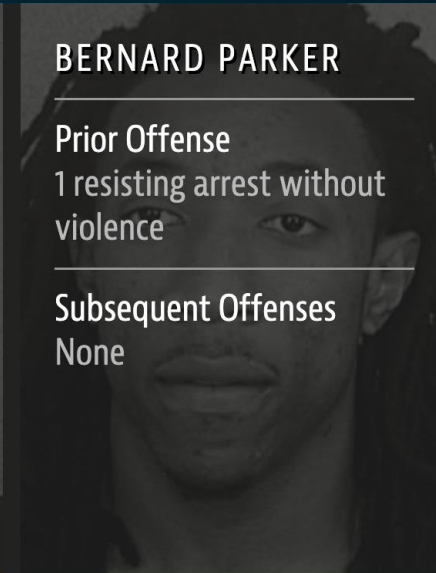
DYLAN FUGETT

Prior Offense
1 attempted burglary

Subsequent Offenses
3 drug possessions

LOW RISK

3



BERNARD PARKER

Prior Offense
1 resisting arrest without violence

Subsequent Offenses
None

HIGH RISK

10

Why does AI fail?



Training data

- Poor quality (standard, size, ...)
- Skewed
- Not representative of production data

AI design

- Poor feature selection
- Spurious correlations

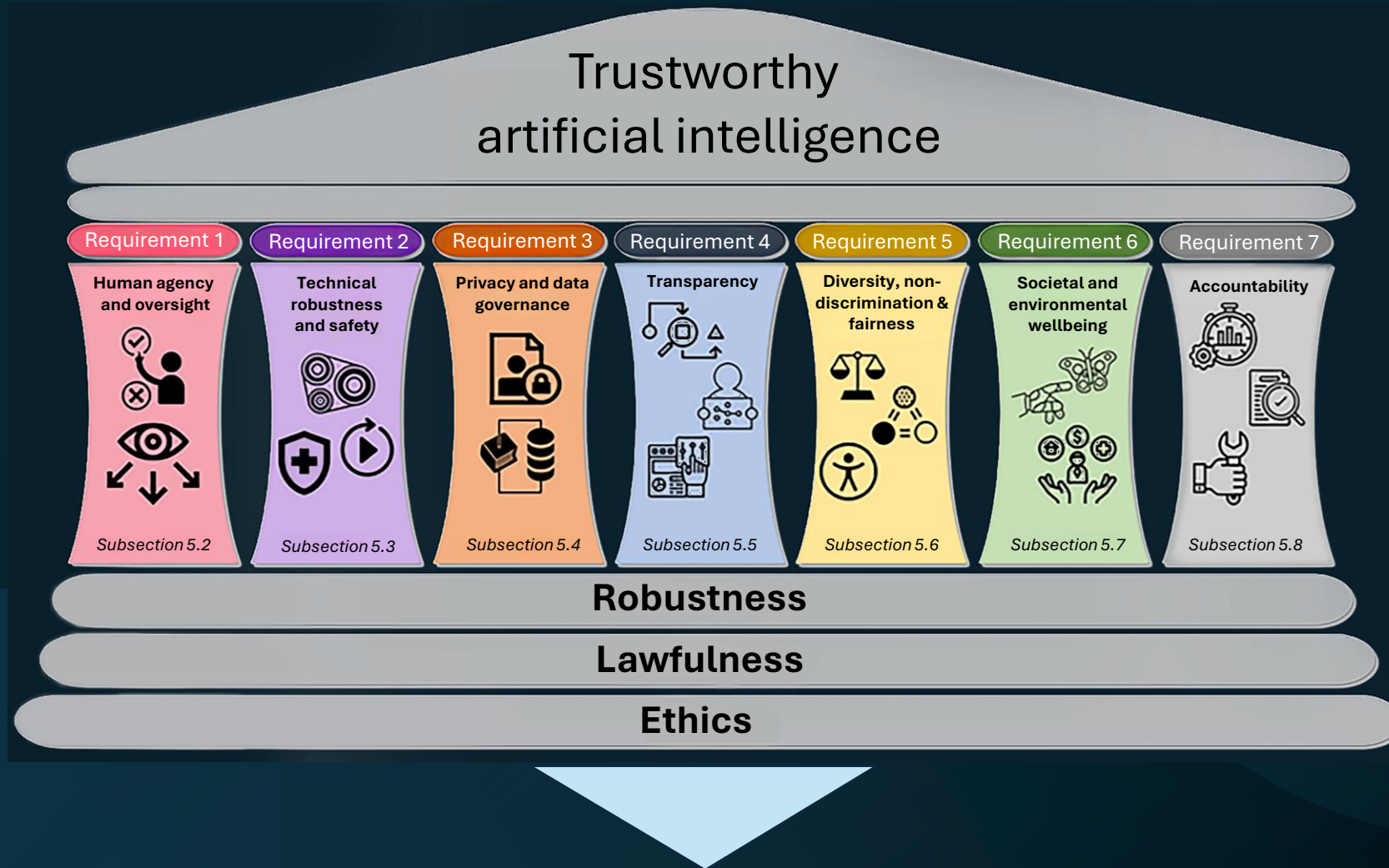
User prompt

- Limited instructions for use
- Absence of guardrails

... for high stake decisions

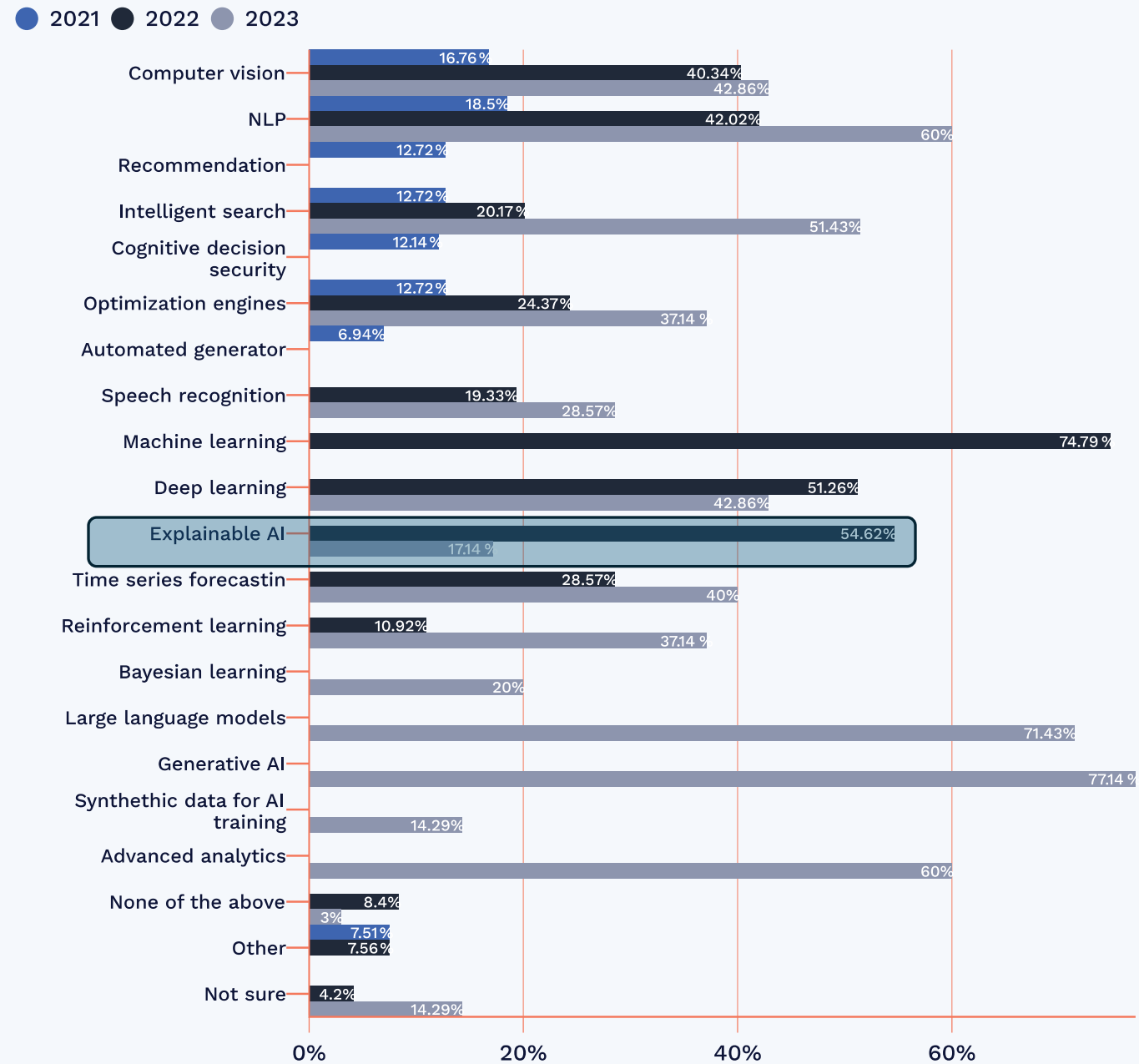


Explainable AI – trust enabler



Explaining model and predictions

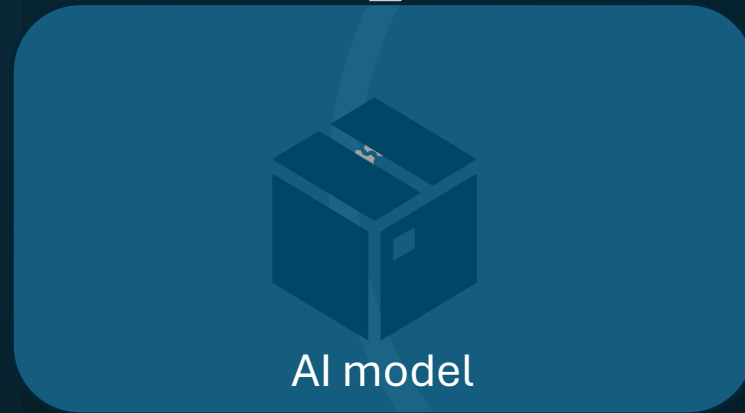
Explainable AI in the Nordics



AI vs XAI



Training data



Input data, prompt



Humans

Prediction, response



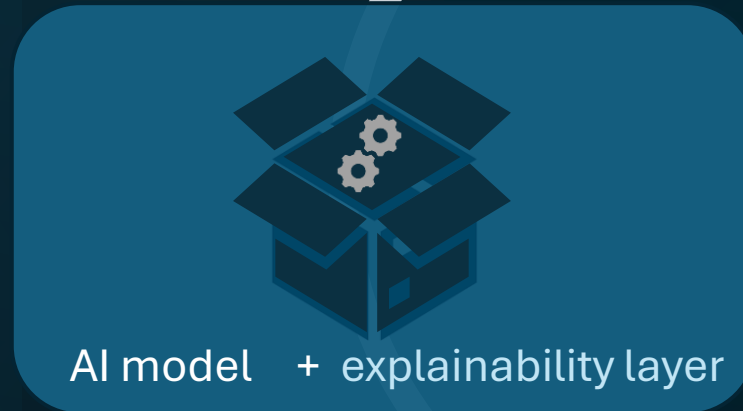
Politics

Mountain landscape

AI vs XAI



Training data



Input data, prompt



Humans

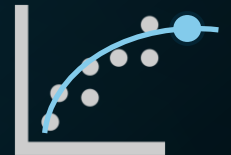
Prediction, response



Politics



Mountain landscape

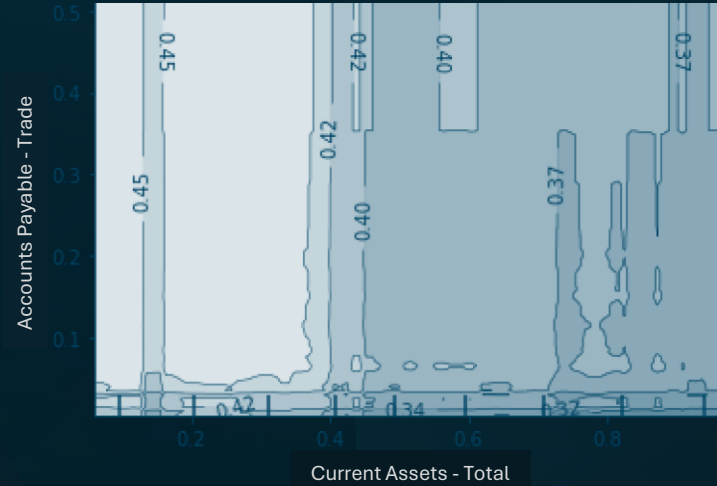


Explainable AI approaches



Feature attribution – Counterfactuals –

Model agnostic

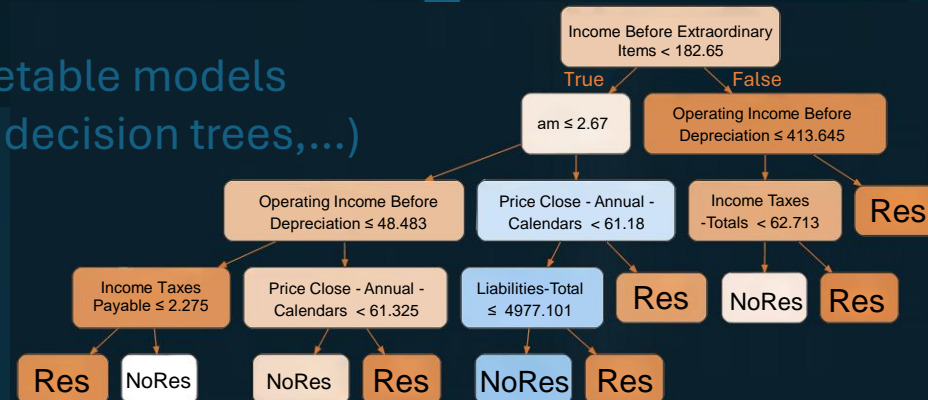


- Surrogate interpretable models
- Stats of local explanations

Local

Global

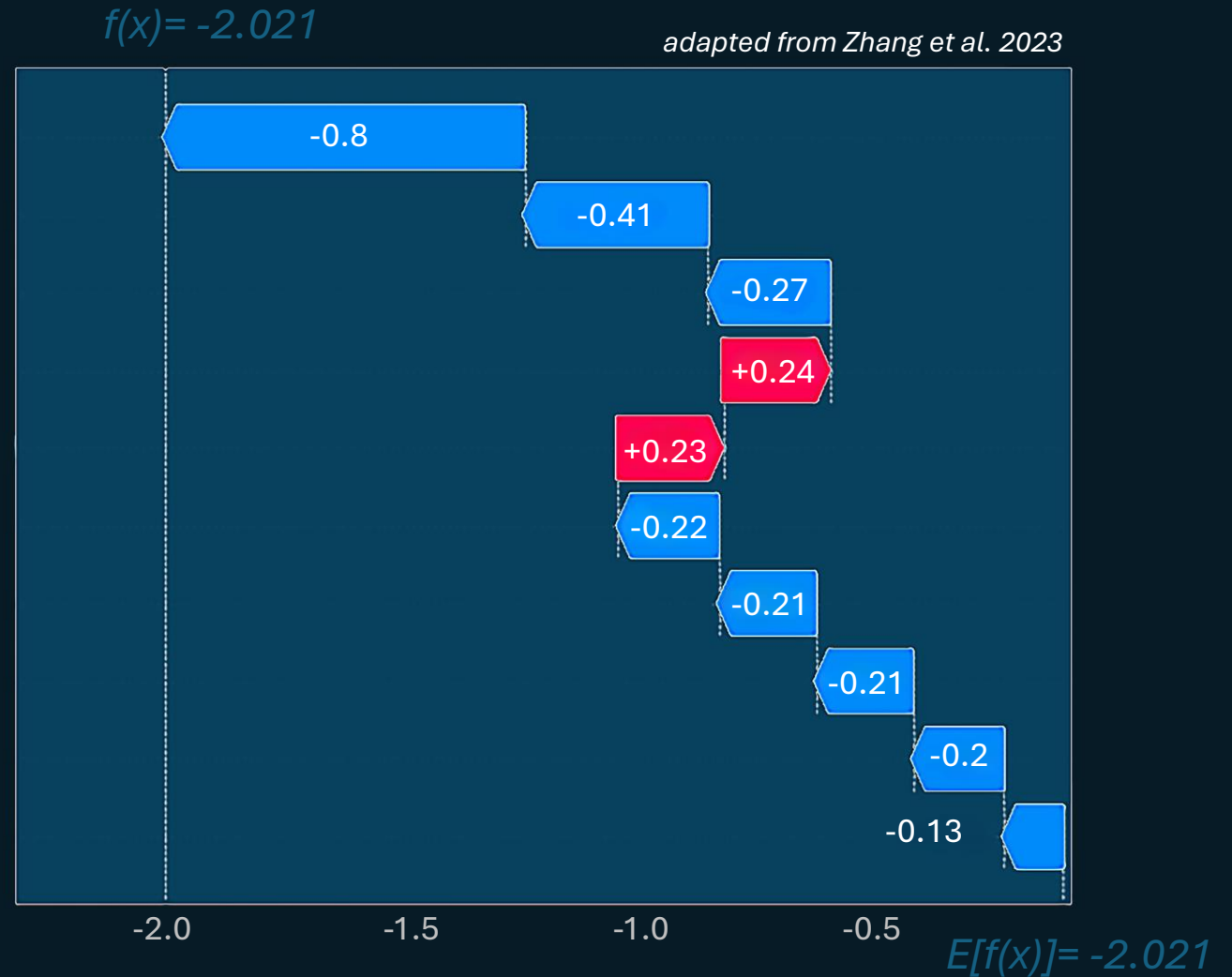
Interpretable models
(linear, decision trees,...)



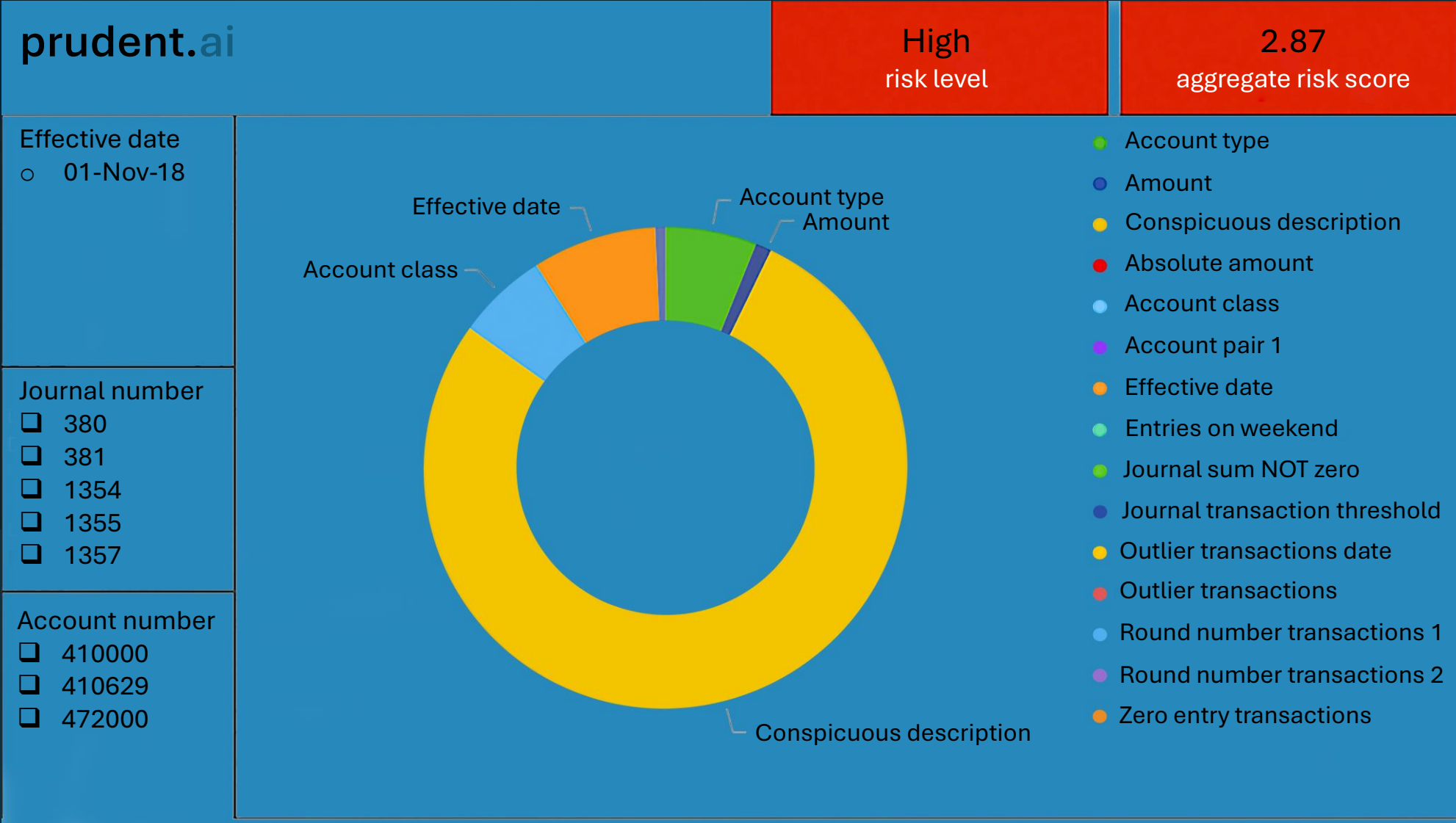
Model specific

Probability of material restatement

- 0.01 = earnings to prices
- 0.203 = lag_Return
- 0.002 = change in return of assets
- 0.324 = Soft Assets
- 0.027 = change in cash margin
- 0.002 = performance matched discretionary accruals
- 0.179 = lag_mean adjusted absolute DD residual
- 0.041 = deferred tax expense
- 0.014 = change in cash sales
- 12 other features

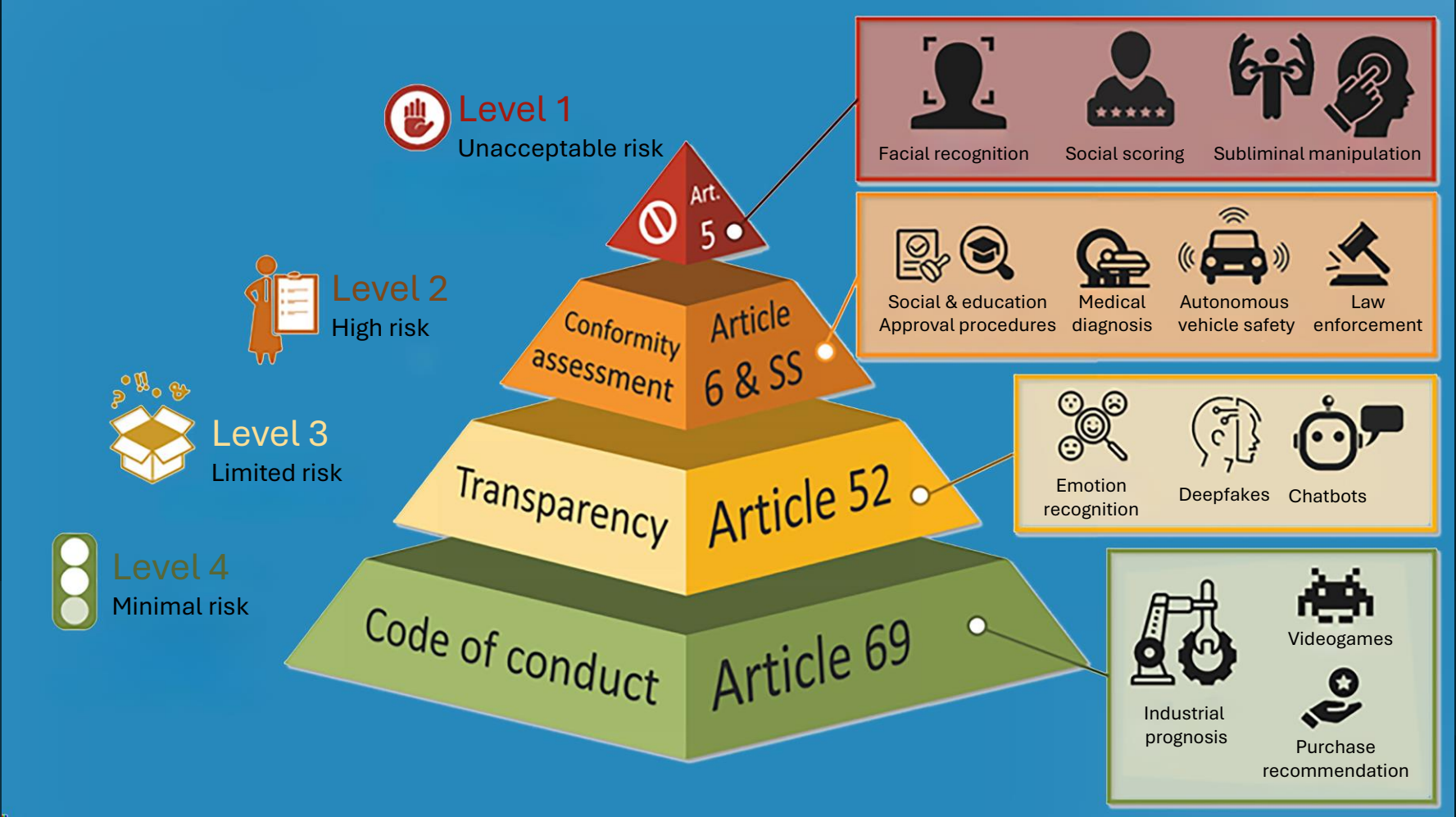


Risk of transaction



adapted from Vaidyanathan, ACCA

Explainable AI – EU AI Act



Transparency

- ❖ Documentation
- ❖ Instruction to users (scope, limitations, error rate, **GLOBAL EXPLANATIONS**, ...)
- ❖ Watermarking

Human oversight (LOCAL EXPLANATIONS?)

adapted from Díaz-Rodríguez et al. 2023

Explainable AI – GDPR

Recital 71 (not binding) – LOCAL EXPLANATIONS

The data subject should have the right [...] to obtain an explanation of the decision [solely on automated processing] reached after such assessment and to challenge the decision.

Right to explanation

Article 13(2)(f) – GLOBAL EXPLANATIONS

In the event a controller relies on automated decision-making, [...] the controller is under the duty to provide the data subject with "meaningful information about the logic involved" [...] of such forms of processing.

Why explainable AI in accountancy?



Understand
AI
predictions



Professional
skepticism



Foster AI
Innovation



Thanks