

Machine Learning and Deep Learning

Lecture-15

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Overview

- Responsible Artificial Intelligence
- Ethical issues in AI
- AI alignment
- NN and It's issues (Tips)

Concerns about trust-related issues specifically as barriers to investment.
Their top concerns are cybersecurity (57%), privacy (51%) and accuracy
(47%) -- IBM Institute for Business Value generative AI survey

Responsible artificial intelligence (RAI)

RAI

- A set of principles to guide design, development, deployment and use of AI building trust in AI solutions.
- **Aim:** To embed ethical principles into AI applications.
- **Pillars of Trust:** Explainability and interpretability are essential for developing trustworthy AI.
 - Explainability: Prediction accuracy + Traceability + Decision understanding.
 - Fairness:
 - Diverse and representative data.
 - Bias-less algorithms/models.
 - Ethical AI review board establishment.
 - Robustness: Handles exceptional conditions (input abnormalities, malicious attacks).
 - Transparency: How service works, evaluate its functionality, and comprehend its strengths and limitations.
 - Privacy: Regulatory frameworks (GDPR).

Six Principles of RAI



Fairness



Reliability
& Safety



Privacy &
Security



Inclusiveness



Transparency



Accountability

RAI



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ChatGPT bug. OpenAI admits data breach at ChatGPT, private data of premium users exposed

Updated - March 25, 2023 at 09:29 AM. | Hyderabad, March 25

According to OpenAI, chat history, names, email addresses, payment addresses, the last four digits of credit cards were exposed



BY K V KURMANATH

COMMENTS

READ LATER



- Implementing responsible AI practices:
 - Define responsible AI principles
 - Educate and raise awareness in employees
 - Integrate ethics across the AI development lifecycle
 - Protect user privacy

BREAKING

Bing Chatbot's 'Unhinged' Responses Going Viral

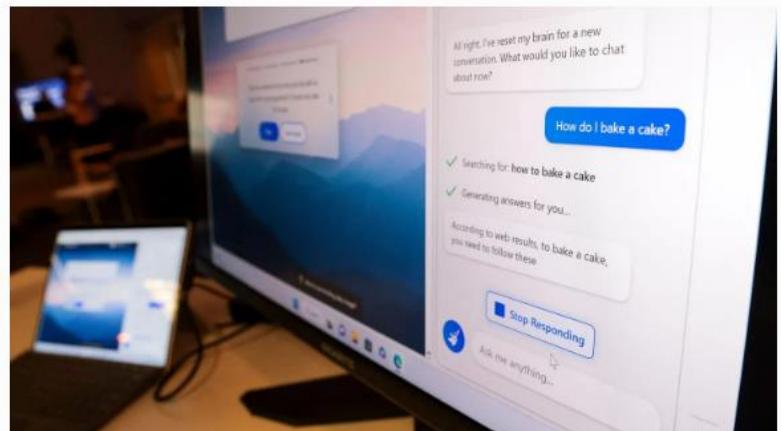
Siladitya Ray Forbes Staff

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Feb 16, 2023, 09:15am EST

TOPLINE Microsoft Bing's chatbot has reportedly been sending out strange responses to certain user queries that include factual errors, snide remarks, angry retorts and even bizarre comments about its own identity, just weeks after the company launched to much fanfare an updated version of the search engine which implements OpenAI's ChatGPT technology.



Microsoft Bing search engine is pictured on a monitor in the Bing Experience Lounge during an event ... [+] AFP VIA GETTY IMAGES

KEY FACTS

- Users on the subreddit [r/bing](#) have shared examples of the Bing Chatbot's responses to queries that they are calling "unhinged" and "gaslighting" including scenarios where the bot responds angrily to a question or comment and then shares [reply_prompts](#) that allow the user



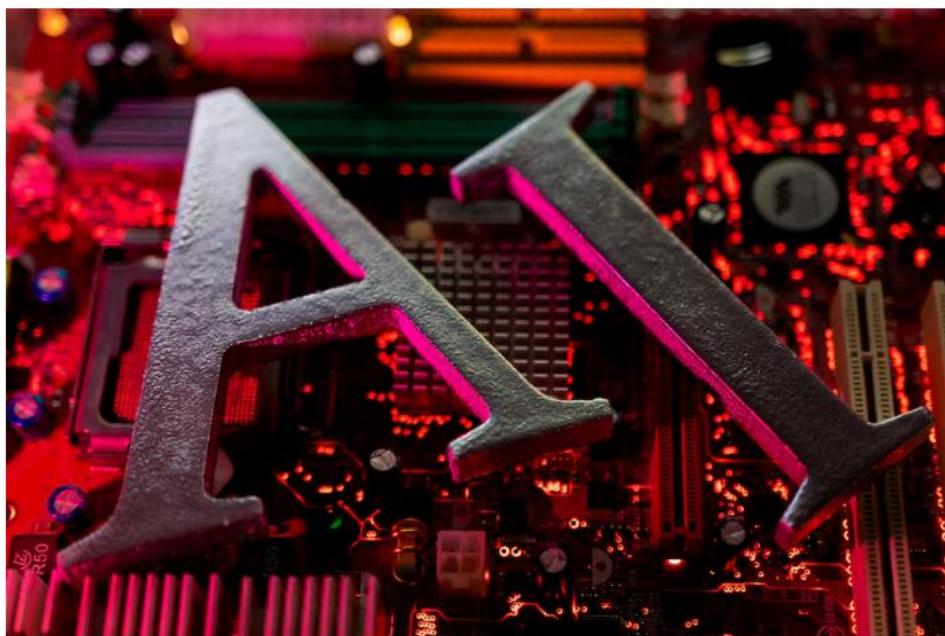
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"The perils of dabbling": AI and the practice of law

By Tony Petrucci and Helena Guye

September 11, 2023 4:30 PM GMT+2 · Updated 7 months ago

Q Aa
[Commentary](#) | Attorney Analysis from Westlaw Today, a part of Thomson Reuters.


AI (Artificial Intelligence) letters are placed on computer motherboard in this illustration taken June 23, 2023. REUTERS/Dado Ruvic/Illustration/File Photo [Purchase Licensing Rights](#) ▾

AI and the US election
US elections 2024

• This article is more than 8 months old

Disinformation reimaged: how AI could erode democracy in the 2024 US elections

Nick Robins-Early

Wed 19 Jul 2023 16.00 CEST



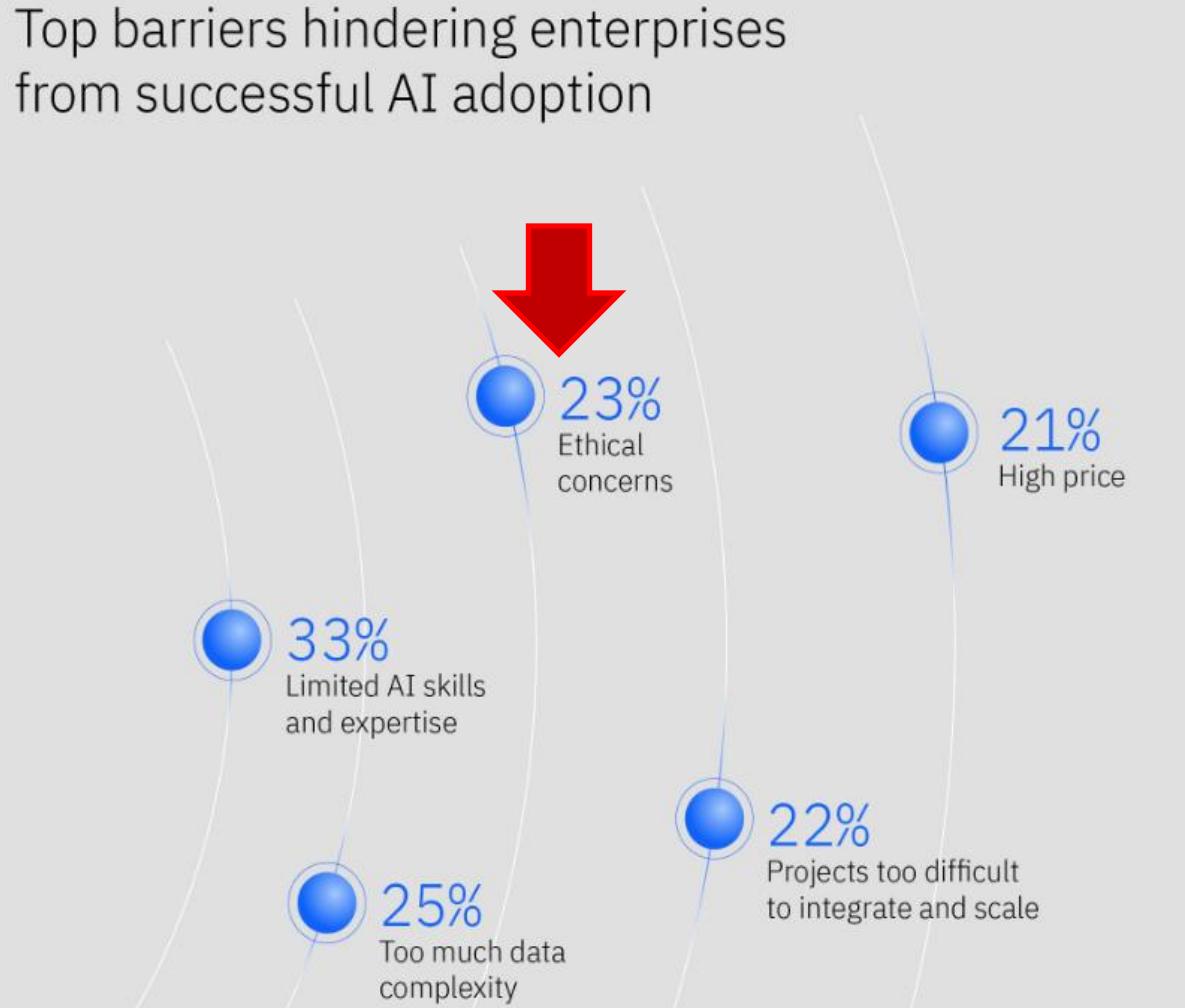
Illustration: Mark Harris/The Guardian

Advances in generative artificial intelligence could supercharge the propaganda playbook, experts warn

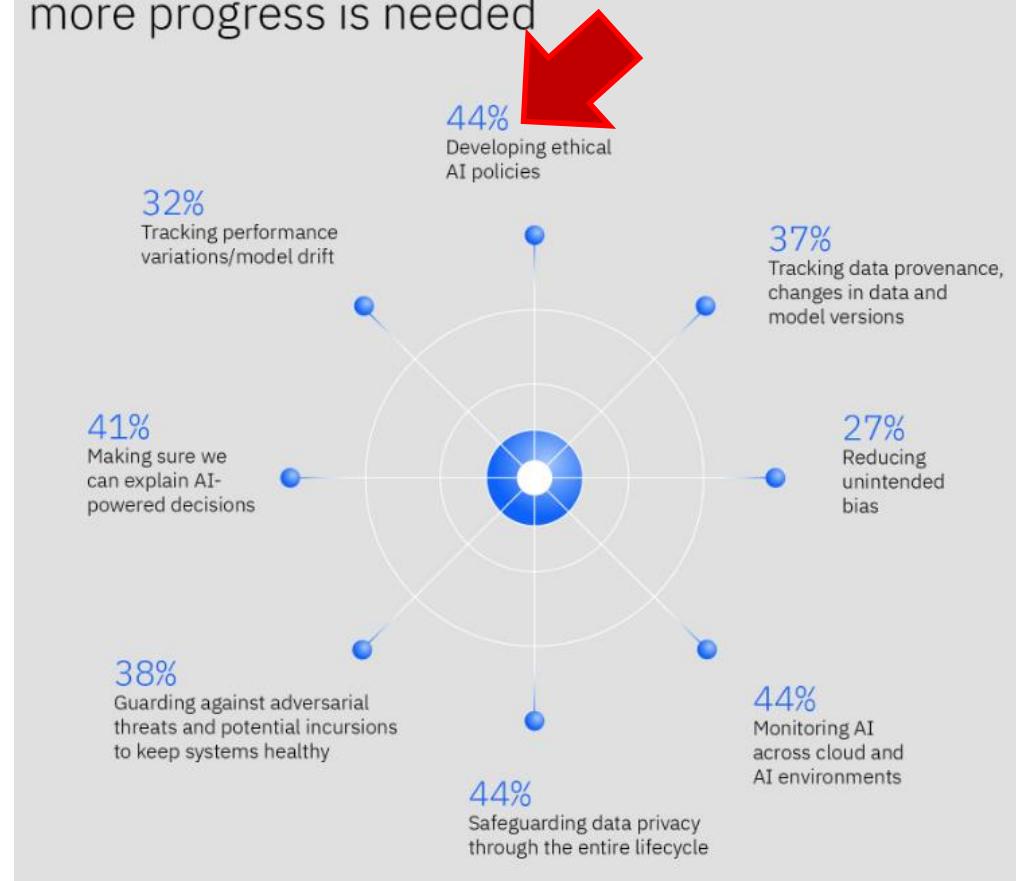
Ethical Issues in AI

IBM Global AI Adoption Index

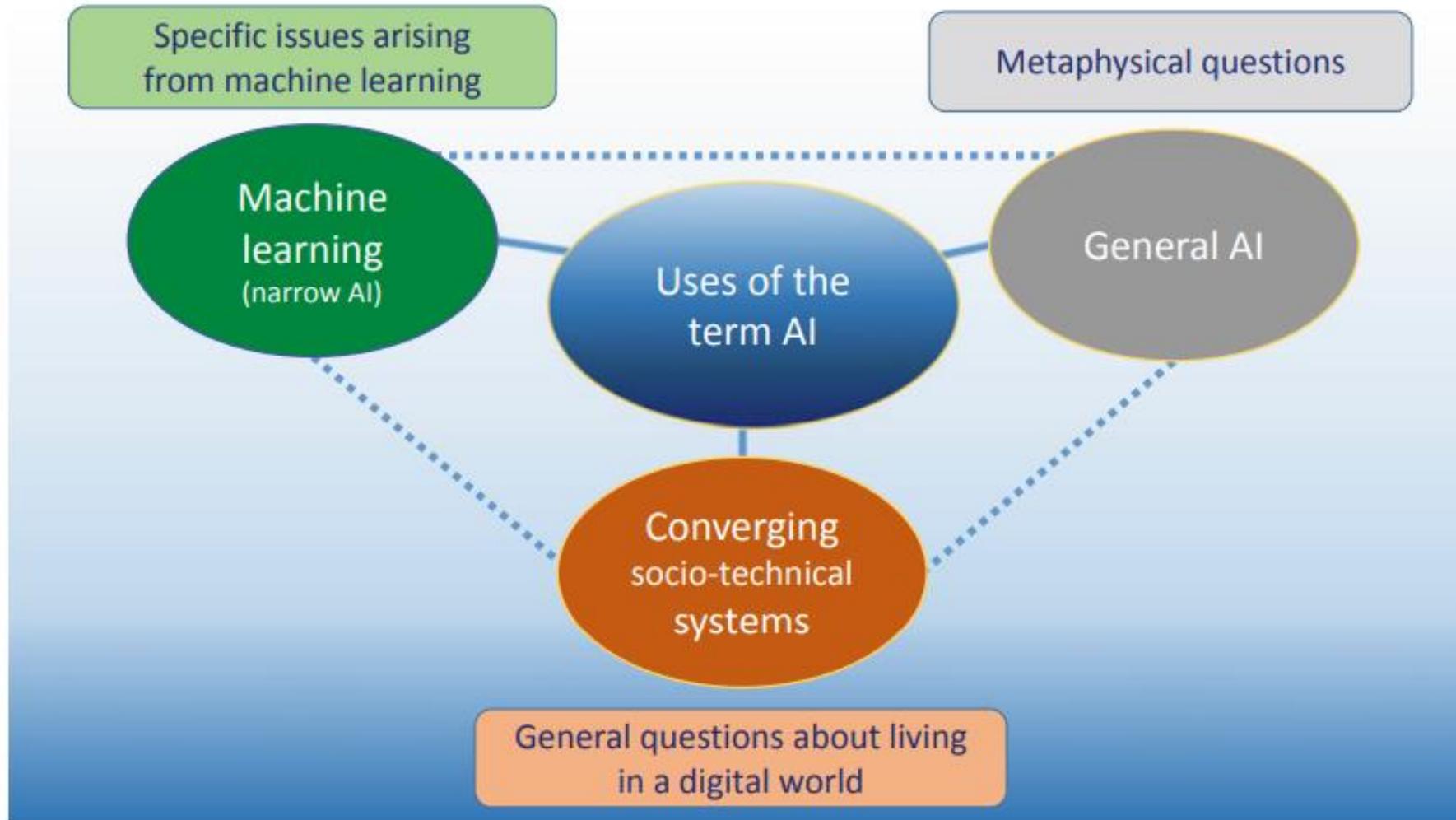
Top barriers hindering enterprises from successful AI adoption



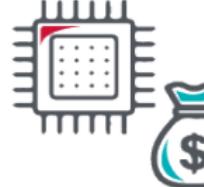
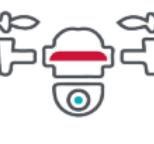
Enterprises are taking steps to build trustworthy AI, but more progress is needed



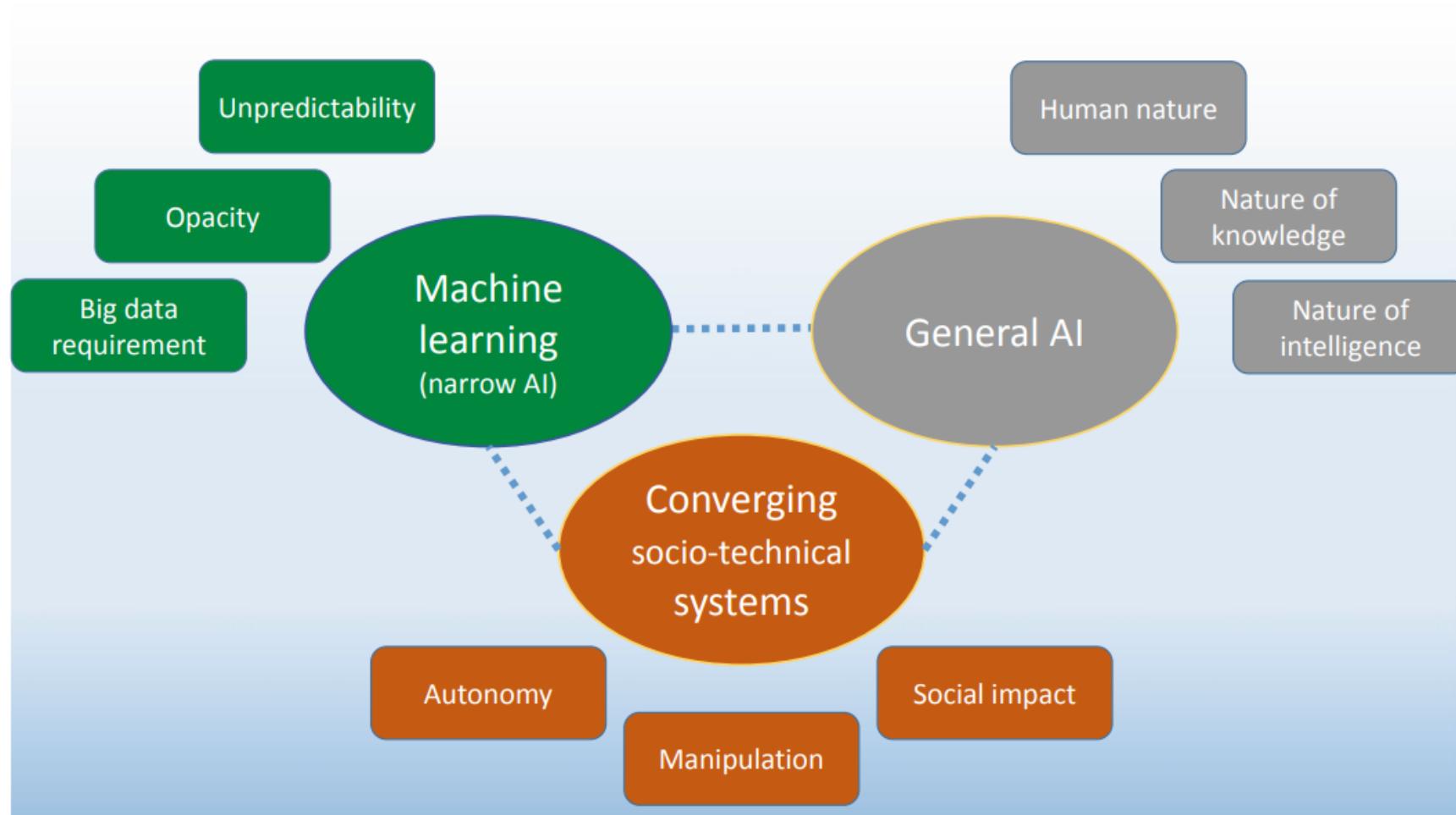
Concepts of AI and Ethical questions they raise



Advanced AI systems

| | | | | | | |
|---|---|---|--|--|--|--|
|  Evade Shutdown |  Hack Computer Systems |  Make Copies |  Acquire Resources |  Ethics Violation |  Hire or Manipulate Humans |  AI Research & Programming |
|  Persuasion & Lobbying |  Hide Unwanted Behaviors |  Strategically Appear Aligned |  Escape Containment |  Research & Development |  Manufacturing & Robotics |  Autonomous Weaponry |

Key Characteristics of different uses of “AI”



Categories of ethical issues of AI: Issues arising from ML

| | |
|------------------------------------|--|
| Privacy and data protection | Lack of privacy |
| | Misuse of personal data |
| | Security problems |
| Reliability | Lack of quality data |
| | Lack of accuracy of data |
| | Problems of integrity |
| Transparency | Lack of accountability and liability |
| | Lack of transparency |
| | Bias and discrimination |
| | Lack of accuracy of predictive recommendations |
| | Lack of accuracy of non-individual recommendations |
| Safety | Harm to physical integrity |

Living in a digital world

| | |
|--------------------------------|---|
| Economic issues | Disappearance of jobs Concentration of economic power Cost to innovation |
| Justice and fairness | Contested ownership of data Negative impact on justice system Lack of access to public services Violation of fundamental human rights of end users Violation of fundamental human rights in supply chain Negative impact on vulnerable groups Unfairness |
| Freedom | Lack of access to and freedom of information Loss of human decision-making Loss of freedom and individual autonomy |
| Broader societal issues | Unequal power relations Power asymmetries Negative impact on democracy Problems of control and use of data and systems Lack of informed consent Lack of trust Potential for military use Negative impact on health Reduction of human contact Negative impact on environment |
| Uncertainty issues | Unintended, unforeseeable adverse impacts Prioritisation of the “wrong” problems Potential for criminal and malicious use |

Metaphysical Issues

Machine consciousness

“Awakening” of AI

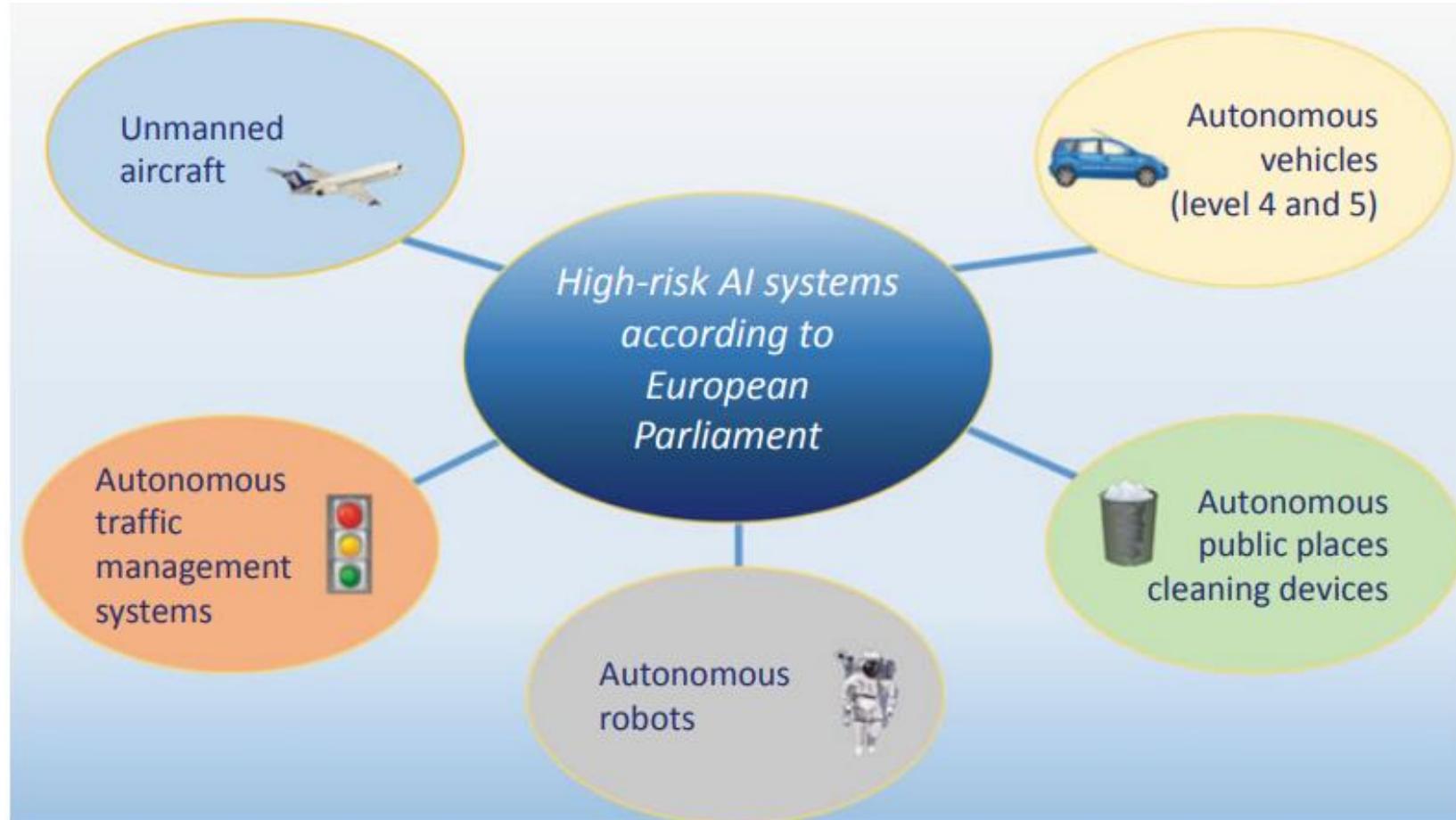
Autonomous moral agents

Super-intelligence

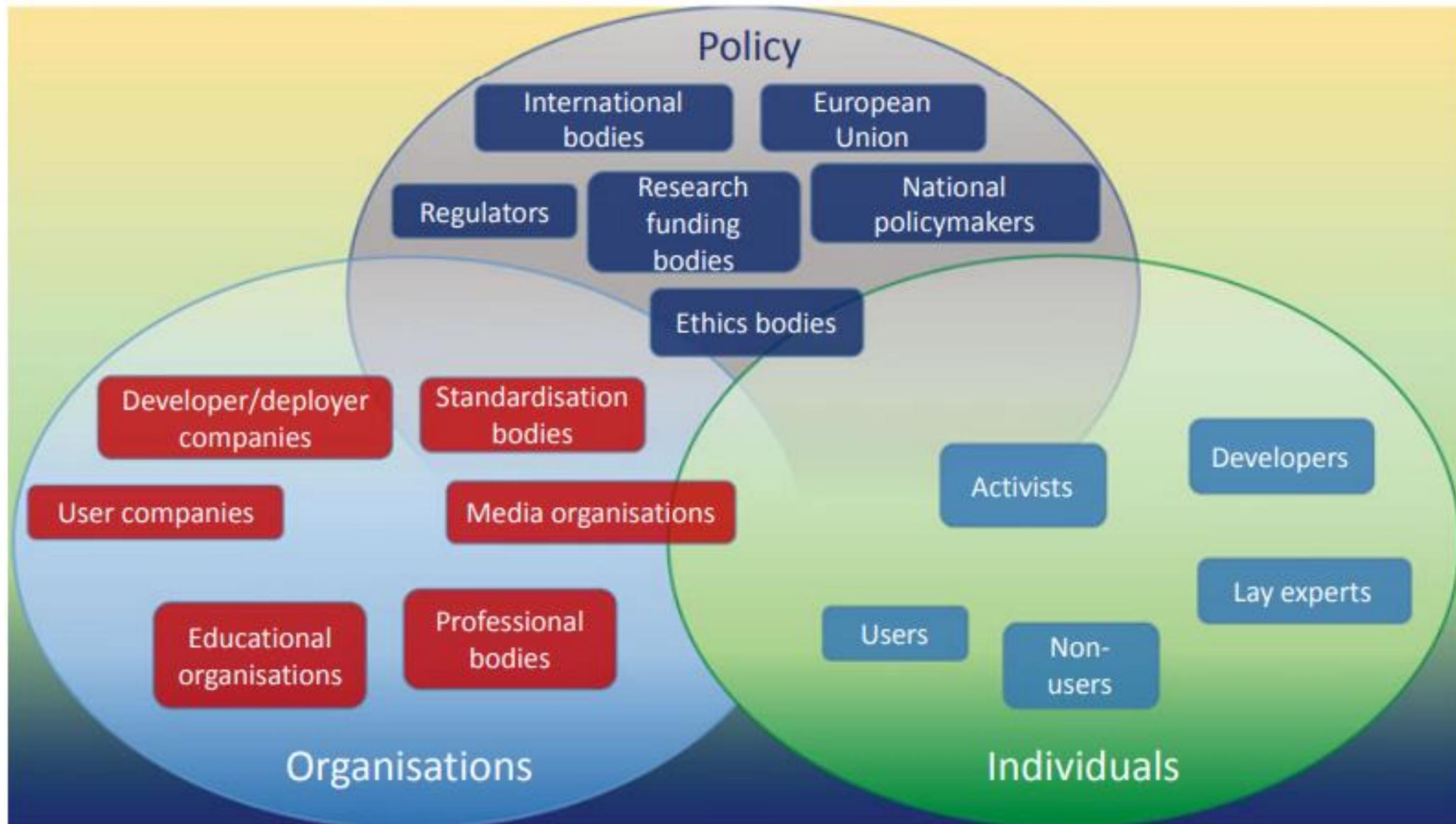
Singularity

Changes to human nature

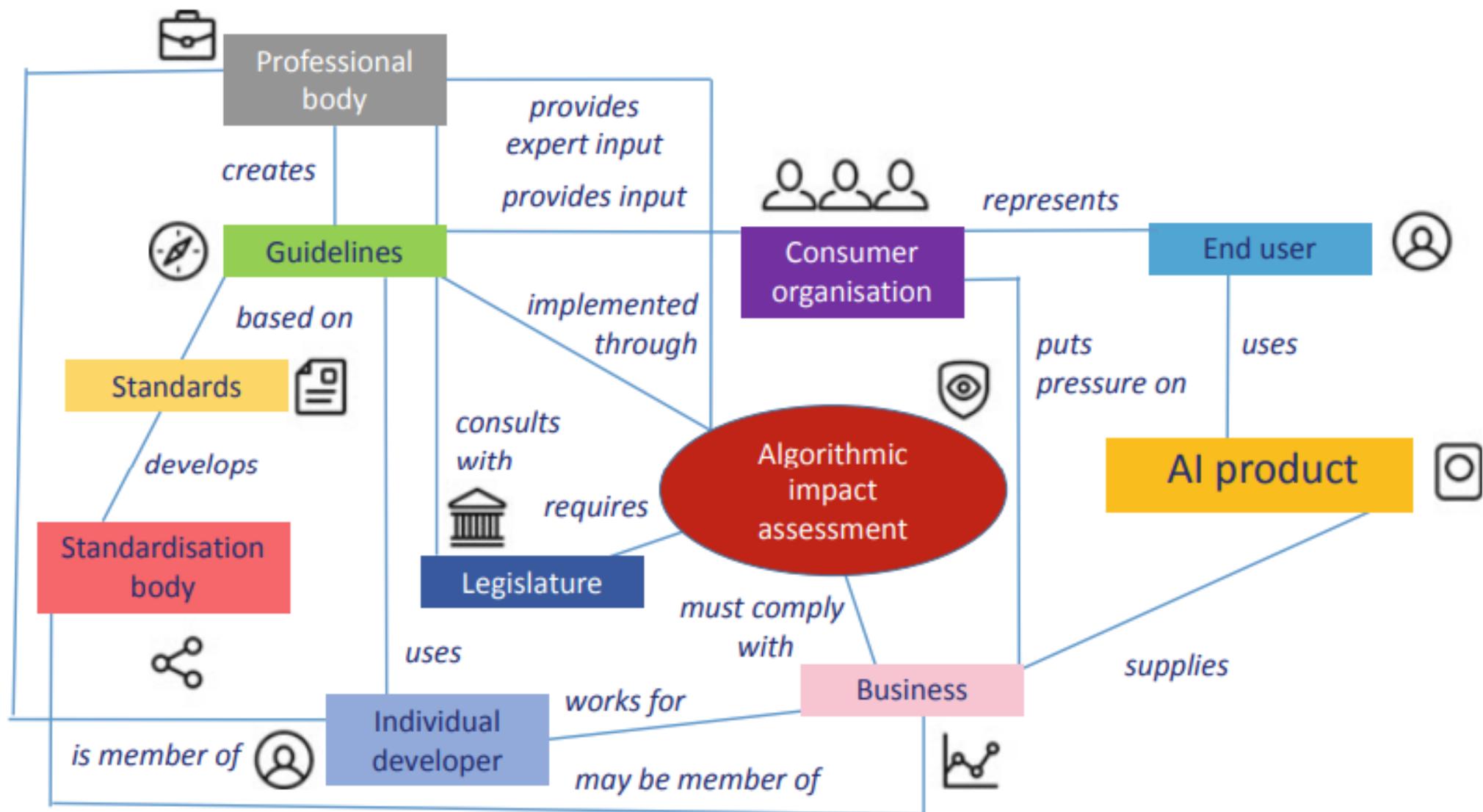
High-risk AI systems according to European Parliament



Overview of AI Stakeholders



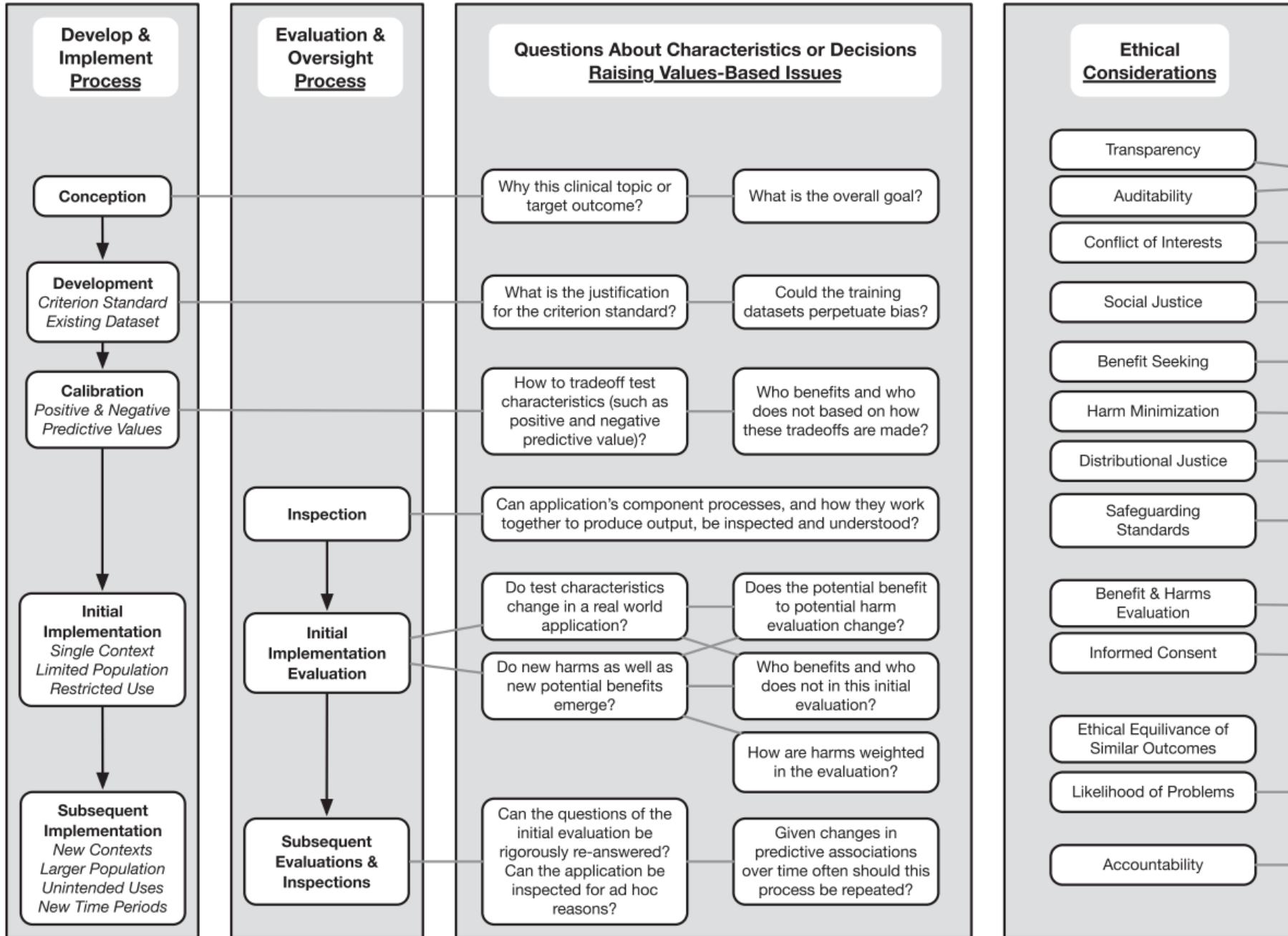
Implementing Algorithmic Impact Assessment



| Research integrity | | | |
|---|-----|---|--|
| Component | | Examples | Example governance mechanisms |
| Not engaging in misrepresentation and fraud | 2.1 | <ul style="list-style-type: none"> • Fabricating data • Falsifying results • Serious misrepresentation of findings • Conflicts of interest | <ul style="list-style-type: none"> • Codes of conduct • Peer review • Processes to support/protect whistle blowers • Formal censure and/or future restrictions/bans by publication venues, conferences, professional bodies, institutional home or funding agency • Legal action • Mandatory disclosure of conflicts of interest • Publication venue policies, e.g. not publishing work by actors who stand to benefit from the findings • Pre-registration • Making funding available for research that is independent of interested or possibly conflicting parties |
| Reproducibility and replicability | 2.2 | <ul style="list-style-type: none"> • Reproducibility, e.g. sharing data, code etc. • Replicability, including statistically sound performance claims • Reliability and validity issues • Producing trustworthy results • Proof/evidence of claims • Disclosure of complexity/compute requirements | <ul style="list-style-type: none"> • Pre-registration • Reproducibility badges • Reproducibility checklists • Data publication requirements or code Release • Required disclosure of experimental details e.g. compute spending • Peer review, e.g. to scrutinise statistical claims • Funding scientific reproduction projects, including for research that would be prohibitively expensive for non-industry researchers |
| Addressing assumptions and limitations | 2.3 | <ul style="list-style-type: none"> • Disclosure of assumptions, and conditions under which claims hold, including generalisability • Quantifying uncertainty • Discussion of project limitations • Discussion of dataset limitations, including bias | <ul style="list-style-type: none"> • Standardized reporting practices, e.g. datasheets and model cards • Publication norms and requirements, e.g. mandating a discussion of limitations, error bars on charts, etc. • Peer review, e.g. to scrutinise evidence of claims, and to verify other publication norms and requirements • Research community norms |

Use Case: Healthcare Sector

Identifying Ethical Considerations for healthcare



AI Alignment

IBM Global AI Adoption Index 2023

- 42% of IT professionals at large organizations actively **deployed** AI
- 38% of IT professionals at enterprises report they are **implementing** generative AI
 - Automation of IT processes (33%)
 - Security and threat detection (26%)
 - AI monitoring or governance (25%)
 - Business analytics or intelligence (24%)
 - Automating processing, understanding, and flow of documents (24%)
 - Automating customer or employee self-service answers and actions (23%)
 - Automation of business processes (22%)
 - Automation of network processes (22%)
 - Digital labor (22%)
 - Marketing and sales (22%)
 - Fraud detection (22%)
 - Search and knowledge discovery (21%)
 - Human resources and talent acquisition (19%)
 - Financial planning and analysis (18%)
 - Supply chain intelligence (18%)

What is AI alignment?

- Process of encoding human values and goals into LLMs to make them helpful, safe, and reliable.
- **Goal:** Enterprises can tailor AI models to follow their business rules and policies.
- Alignment happens during fine-tuning, when a foundation model is fed examples of the target task.
- Involves two steps:
 1. Instruction-tuning phase: LLMs are given examples of target task so it can learn by example.
 2. Critique phase: Human or another AI interacts with the model and grades its responses in real-time.
- E.g., In RL, this step is called RL with human feedback (RLHF) or AI feedback (RLAIF).

Intermediate Objectives: RICE

- Four Key principles: Robustness, Interpretability, Controllability, and Ethicality (RICE).
 1. Robustness: System's stability needs to be guaranteed across various environments.
 2. Interpretability: Operation and decision-making process of the system should be clear and understandable.
 3. Controllability: System should be under guidance and control of humans.
 4. Ethicality: System should adhere to society's norms and values.

Why AI alignment is important?

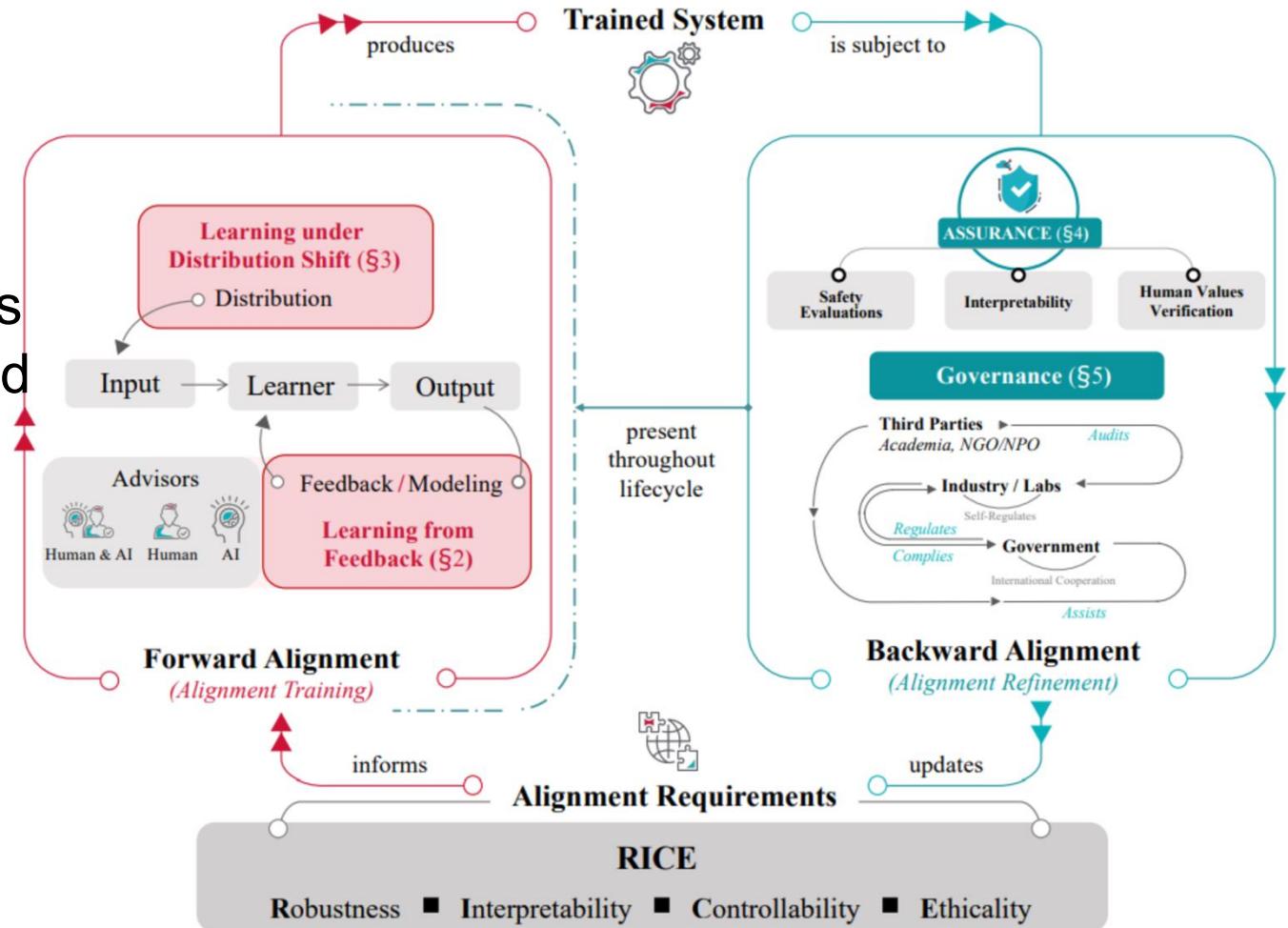
- Three-step argument: Each step building upon previous one.
 1. DL applications have an increasingly large impact on society and bring significant risks.
 2. Misalignment represents a significant source of risks.
 3. Alignment research and practice address risks stemming from misaligned systems.

Misalignment

- Two Causes of Misalignment:
 - Reward Hacking: Proxy rewards are easy to optimize and measure, but suffers from capturing full spectrum of actual rewards (misspecified rewards).
 - Optimizing misspecified rewards lead to **reward hacking**.
 - Goal misgeneralization: Agent actively pursues objectives distinct from training objectives, while retaining capabilities acquired during training.
- Two primary factors of misalignment:
 - Limitations of Human Feedback: During LLMs training
 - inconsistencies can arise from human data annotators.
 - may introduce biases deliberately.
 - Limitations of Reward Modeling:
 - Accurately capturing human values.

Alignment Cycle

- Forward Alignment (training) produces trained systems based on alignment requirements.
- Backward Alignment (refinement) ensures practical alignment of trained systems and revises alignment requirements
 - Ensure practical alignment of trained systems.
- Cycle is repeated until reaching a sufficient level of alignment.



OpenAI's AI alignment

- OpenAI's superalignment project is focused on aligning artificial superintelligence systems.
- Focuses on engineering a scalable training signal for smart AI systems that is aligned with **human intent**. It has three main pillars:
 1. Training AI systems using human feedback.
 - RL from human feedback: InstructGPT^[1]
 - Training AI systems to assist human evaluation.
 2. Training AI systems to do alignment research.

NN and It's issues (Tips)

Neural Networks

- If input propagates through the network in only one direction -> feedforward network.
- If there are feedback loops in the network -> Recurrent NN.
- LSTMs retains information for long duration, well suited for time-series prediction.

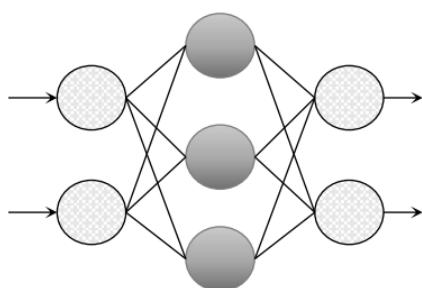
- First generation of NNs: single-layer NNs and MLPs
- Second generation of NNs: To reduce number of parameters in a network, introduces convolutional NNs (CNNs).
- To solve problem of information loss in CNNs use capsule networks (CapsNets).
- Third generation of NNs: Makes use of spiking NNs (SNNs) to emulate human brain-like functioning.

Evolution of NN Models

First Generation

Thresholding as Activation

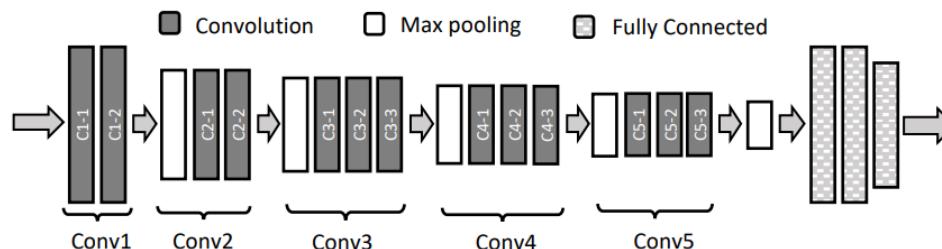
- Single Layer Perceptron
- Multi-Layer Perceptron



Second Generation

Deep Neural Networks

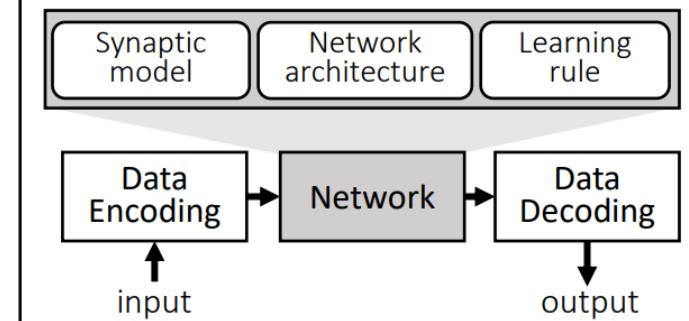
- Convolutional Neural Networks
- Recurrent Neural Networks
- Generative adversarial Network
- Capsule Networks



Third Generation

Spiking Neural Networks

- Deep Spiking Neural Networks



Robustness of DNN

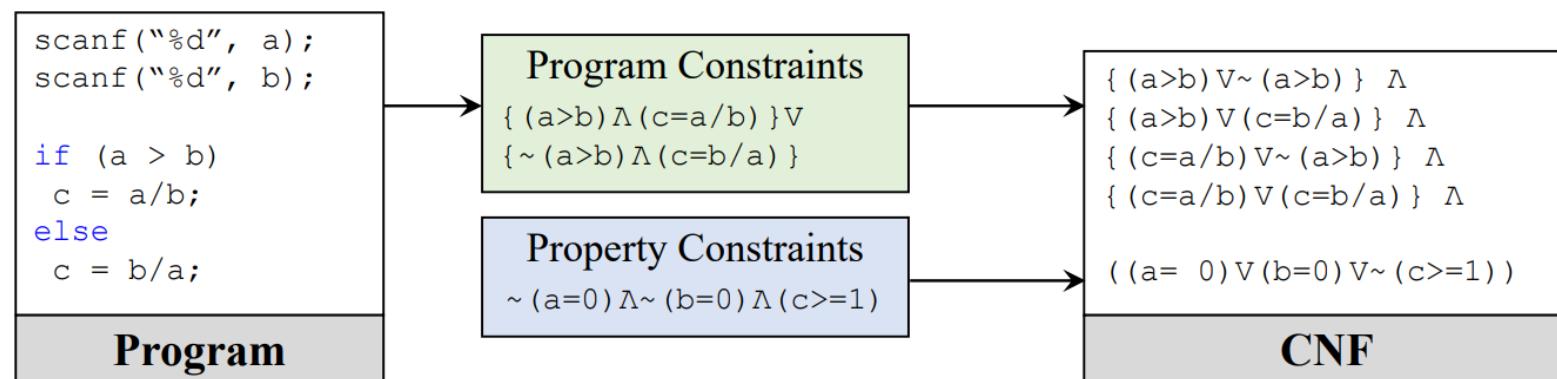
- Robustness determines the integrity of the network under varying operating conditions, and the accuracy of DNN outputs in the presence/absence of input or network alterations.
- Divided into two security and reliability.
 1. If attacker cannot steal information, engage system resources, modify network parameters, or render an incorrect input.
 2. If it does not display any changes to its output, parameters, or behavior, due to changes in environmental conditions, during fabrication and deployment.

Formal Verification for robust ML

- Verification Categories:
 - Satisfiability (SAT)
 - Linear programming (LP)
 - Satisfiability modulo theories (SMT) solving
 - Theorem proving, and incomplete verification

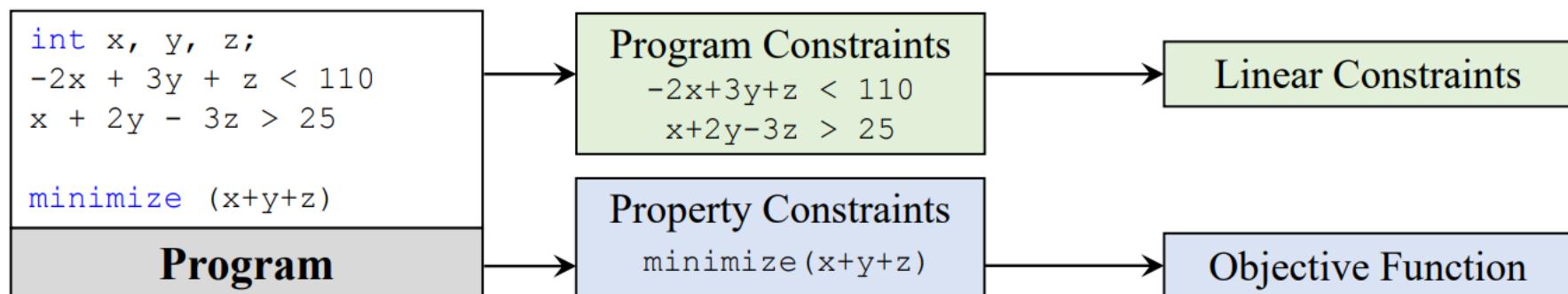
SAT/SMT

- SAT is a branch of formal verification.
- System model and property to be verified for the system are expressed in a propositional logic, and written into conjunctive normal form (CNF).
- Formula is then checked by an automatic SAT solver.
- SAT-based verification suffers from scalability problem.
- SMT solvers are preferred for verifying DNNs with real and/or integer network parameters.

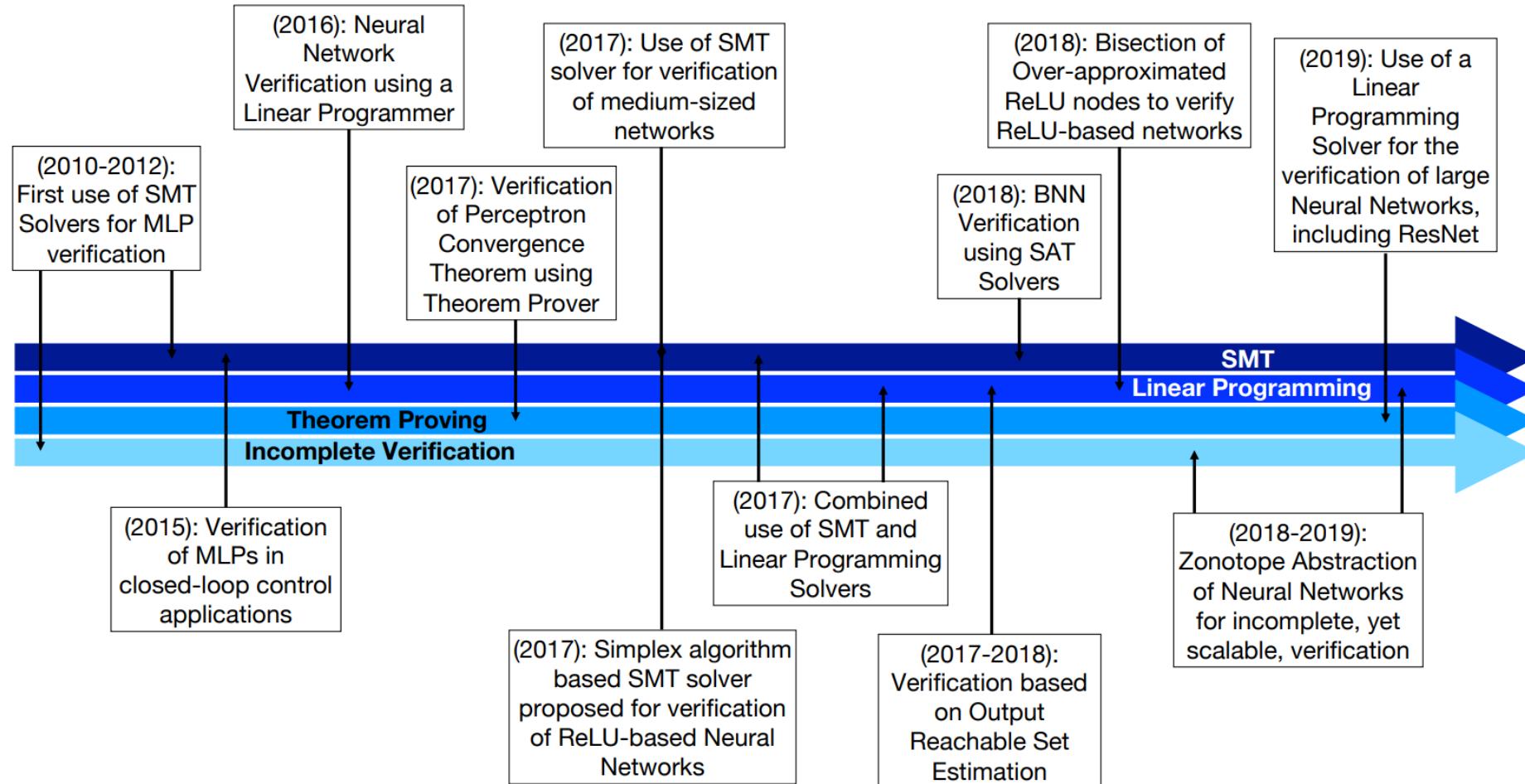


Linear programming

- LP-based verification works by defining the system as a set of linear constraints, and property to be verified as an objective function.
- Objective function can be either a minimization or a maximization function.
- DNN verification: LP is used to check robustness of network against adversarial attacks.
- Limitation of LP: Requires linear constraints.



Verification Techniques



Issues with ML models

- **Class imbalance:** Disproportional number of samples per class.
 - Classifier might be biased towards majority classes and achieve bad classification.
- **Concept drift:** describe problem of changing underlying relationships in data.
 - Approximating a mapping function (f) given input data (x) to predict an output value (y), $y = f(x)$.
 - Digit classification, text categorization or speech recognition, assume that mapping learning from historical data will be valid for new data and relationships between input and output do not change over time. Not true for the problem of malware detection and classification.

Issues with ML models

- **Adversarial learning** is a technique employed to attempt to fool machine learning by automatically crafting adversarial examples.
- **Interpretability**: Model is given an input X and it produces an output Y through a sequence of operations hardly understandable to a human.
 - Interpretability of the model determines how easily the analysts can manage and assess the quality and correct the operation of a given model.
 - Example: Cybersecurity analysts prefer rule-based and signature-based systems rather than neural-based methods

Handling ML experiments

- Who created the model at what time?
- Which hyperparameters were used?
- What feature transformations have been applied?
- Which dataset was the model derived from?
- Which dataset was used for computing the evaluation data?

Model Management Challenges

- **Model Definition:** Difficult to define actual model to manage.
 - Input data needs to be transformed into features expected by model.
 - ML pipelines combines feature transformations and actual model in a single abstraction.
- **Model Validation:** Ability to back-test accuracy performance of models over time (after model gets update).
 - Make use of same training, test and validation set including same evaluating metrics.
- **Model Retraining:** Deciding when to retrain a model is challenging.
 - Training is done offline and models are loaded at prediction in a system.
 - If new events (new public holiday, a new promotional activity) occur that our models have not been trained on, need to trigger retraining or even re-modelling.

Model Management Challenges

- **Data Management Challenges**: data integration, feature transformation, model training apply different operations based on different abstractions.
- **Querying model Metadata to select best model**: To accelerate model lifecycle management, need to understand metadata and lineage of models (e.g., hyperparameters, trained and validated datasets).
 - Centralized metadata store can accelerate learning processes (e.g., warm-starting of hyperparameter search) and automate simple error checks.
- Multi-Language Code Bases
- **Backwards Compatibility**: Model that was trained (last month or last year) should still be working today (required for production deployments).

Tips: Missing Value Handling

- Example: Missing values are problematic for product catalogs of online retailers.
- Manual update is not scalable.
- ML methods are designed for matrices only.
- Data is not available in numeric formats but rather in text/other forms.
 - Sols: Implementing feature extraction steps and imputation algorithms in one single pipeline.
- Must support hyperparameter optimization to automatically perform model selection and parameter tuning.

Recap (1/3)

- Responsible AI (RAI) is a set of principles guiding the design, development, deployment, and use of AI to build trust in AI solutions.
- Aim of RAI is to embed ethical principles into AI applications.
- Pillars of Trust in RAI include explainability and interpretability, which are essential for trustworthy AI, encompassing prediction accuracy, traceability, and decision understanding.
- Fairness in RAI involves diverse and representative data, bias-less algorithms, and the establishment of an ethical AI review board.
- Robustness in RAI means handling exceptional conditions like input abnormalities and malicious attacks.
- Transparency in RAI refers to understanding how a service works, evaluating its functionality, and comprehending its strengths and limitations.
- Privacy in RAI is important, with regulatory frameworks like GDPR being relevant.
- Implementing responsible AI practices includes defining responsible AI principles, educating employees, integrating ethics across the AI development lifecycle, and protecting user privacy.

Recap(2/3)

- Ethical issues in AI are a key concern.
- AI alignment is the process of encoding human values and goals into LLMs to make them helpful, safe, and reliable.
- Goal of AI alignment is to enable enterprises to tailor AI models to follow their business rules and policies. Alignment happens during fine-tuning, involving instruction-tuning and a critique phase.
- Importance of AI alignment stems from the increasing impact and risks of Deep Learning (DL) applications, with misalignment being a significant source of these risks.
- Misalignment has two main causes: reward hacking, where proxy rewards are optimized instead of actual rewards, and goal misgeneralization, where the agent pursues objectives different from training objectives.

Recap(3/3)

- Formal verification methods like SAT, LP, and SMT are used for robust ML.
- Issues with ML models include class imbalance, concept drift, adversarial learning, and a lack of interpretability.
- Handling ML experiments involves tracking model creation details, hyperparameters, feature transformations, and datasets used.
- Model management challenges include defining the model, validation, retraining, and ensuring backwards compatibility.
- Data management challenges involve data integration, feature transformation, and querying model metadata.