COIT20277 Introduction to Artificial Intelligence

Week 4 - Lecture

- Reinforcement Learning
- Responsible AI

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Acknowledgement of Country

I respectfully acknowledge the Traditional Custodians of the land on which we live, work and learn. I pay my respects to the First Nations people and their Elders, past, present and future

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Acknowledgment

The contents of this lecture have been adopted from the following references:

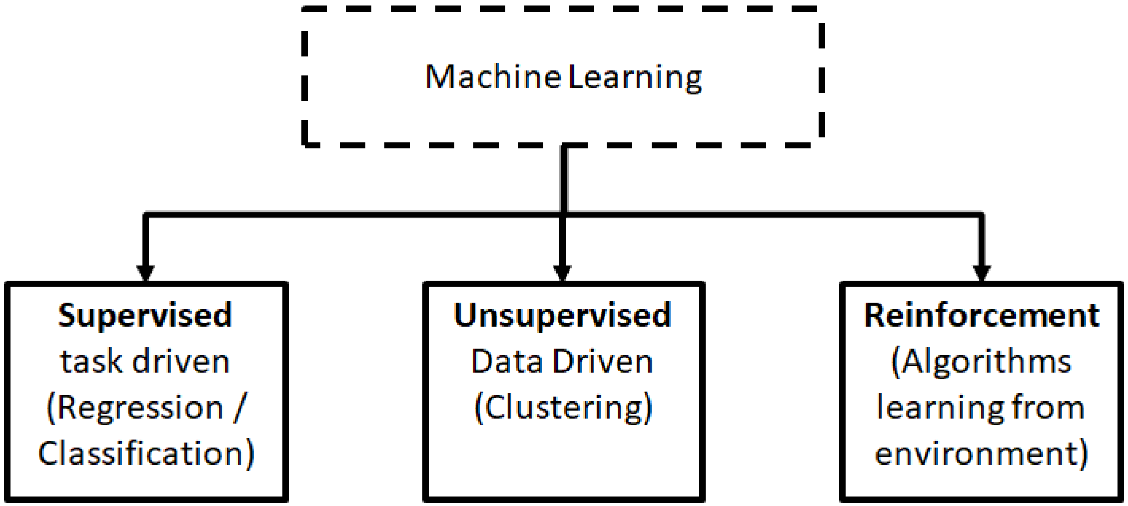
- Artificial Intelligence Programming with Python - From Zero to Hero, 2022, Perry Xiao, ISBN 978-1-119-82086-4:
  - Chapter 3.6
- Introduction to Responsible AI: Implement Ethical AI Using Python, Manure *et al.*, 2023, ISBN 978-1-4842-9981-4:
  - Chapter 1 and 2

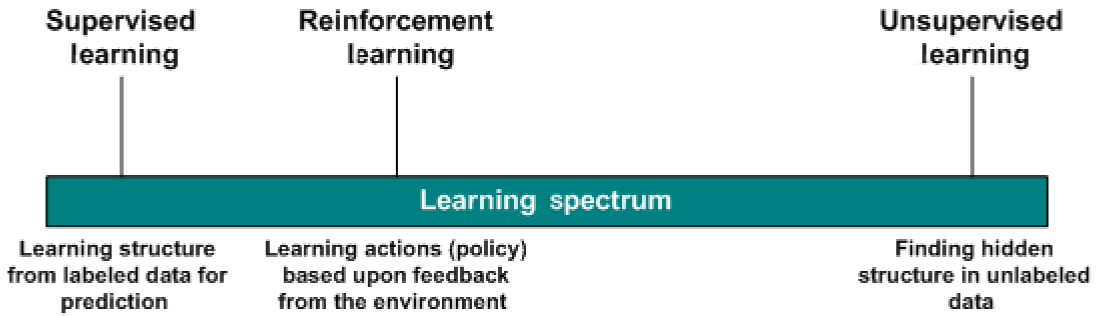
Topics

- **Part I: Reinforcement Learning**
  - What is Reinforcement Learning?
  - Key Terminology
  - Reinforcement Learning Algorithms
  - Applications of Reinforcement Learning
  - Popular Reinforcement Learning Platforms

- **Part II: Responsible AI**
  - Ethics in the Age of AI
  - Mitigating Bias and Discrimination
  - Privacy in the Age of Surveillance
  - Human-Centric Design

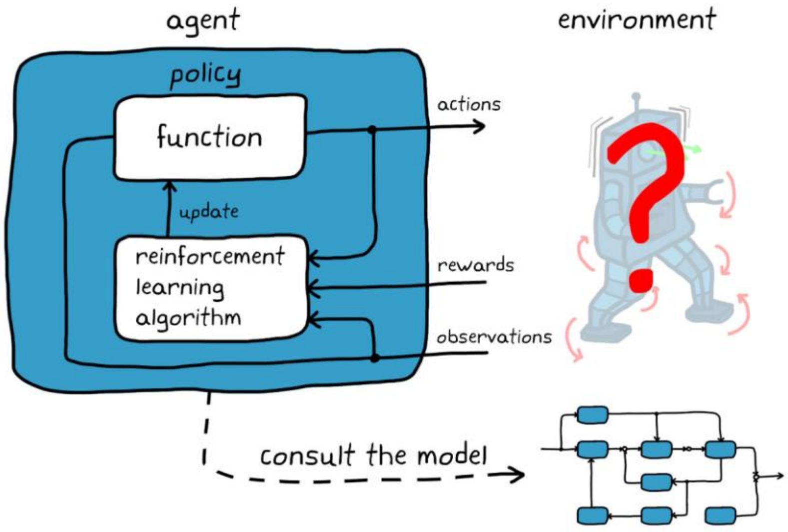
Context of Reinforcement Learning





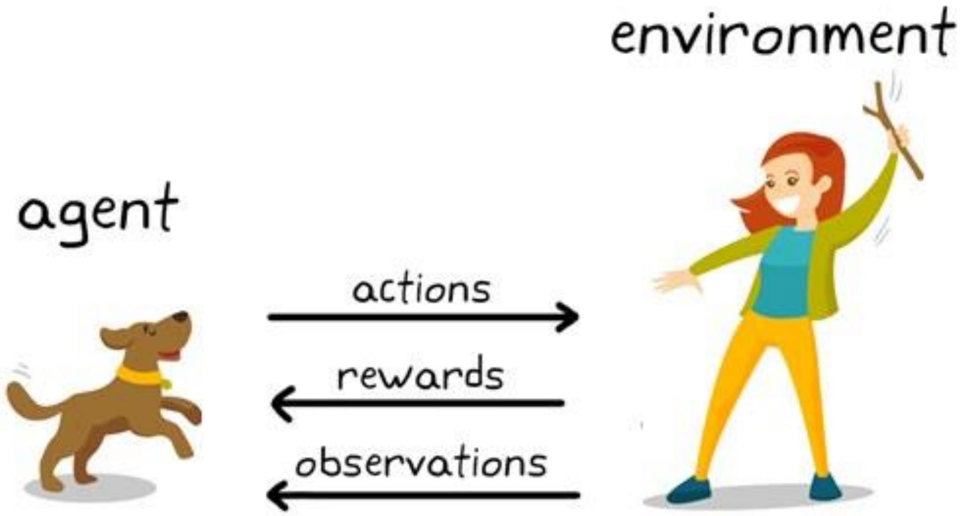
What is Reinforcement Learning?

- Reinforcement learning is a type of machine learning where an agent learns through trial and error in an interactive environment.
- The agent takes actions in the environment and receives rewards or punishments based on those actions.
- The agent's goal is to learn a policy that maps states to actions, so that it can maximize its long-term reward.



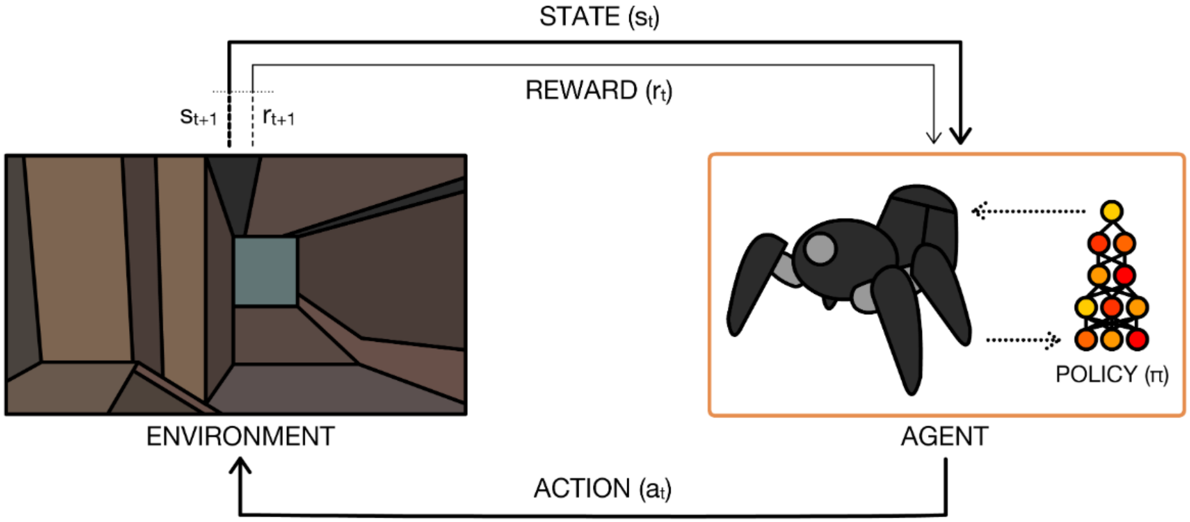
An Example

- Reinforcement learning is similar to how a dog learns tricks. The dog tries different actions, and every time it gets a right action, it gets a reward, or a treat.
- The next time, the dog learns to do the same thing again and gets the treat again. This is how reinforcement learning works.



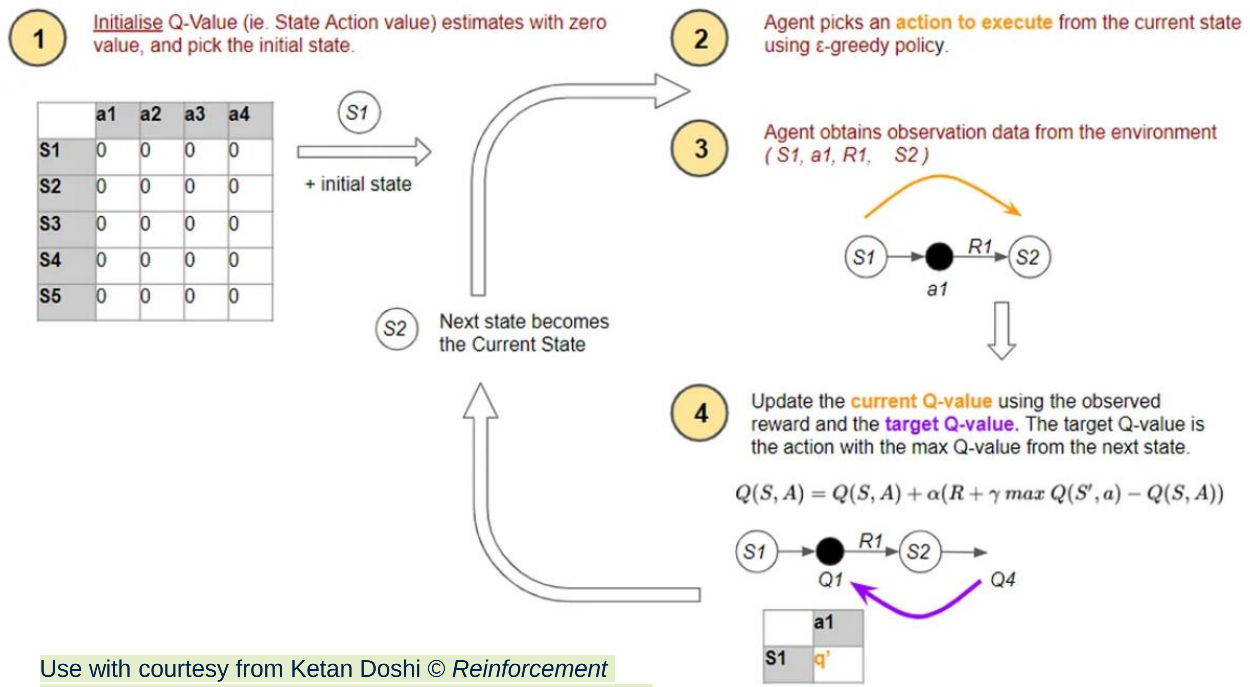
Key Terminology

- ***Environment:*** The physical world in which the agent operates.
- ***State:*** The current situation of the agent.
- ***Reward:*** Positive or negative feedback from the environment.
- ***Policy:*** The rules that change agent's state to actions.
- ***Value:*** Future reward that an agent would receive.



Reinforcement Learning Algorithms

- Q-Learning and SARSA are two commonly used model-free reinforcement learning algorithms.
- Q-learning is a ***model-free*** reinforcement learning algorithm.
- It does not require a complete model of the environment.
- It learns by interacting with the environment and receiving rewards.
- The goal of Q-learning is to learn a Q-value for each state-action pair.



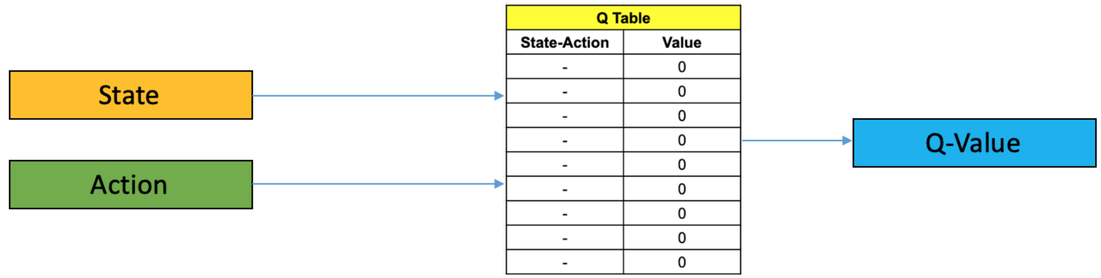
Use with courtesy from Ketan Doshi © *Reinforcement Learning Explained Visually (Part 4): Q Learning, step-by-step* Published in Towards Data Science Nov 28, 2020

Reinforcement Learning Algorithms (cont…)

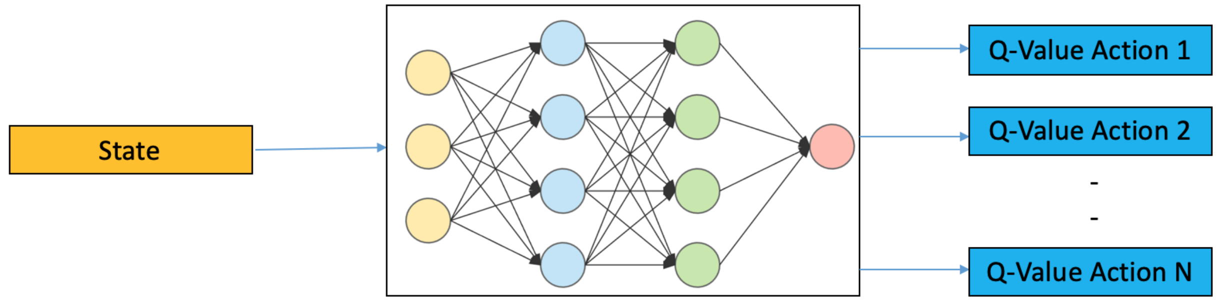
- Like Q-Learning, ***SARSA*** is *model-free and* learns directly from interaction, not a model of the environment.
- SARSA estimates the value of taking different actions in different states.
- It follows an "on-policy" approach, meaning it learns and improves the policy it's currently following.
- At each time step, SARSA selects an action based on its current policy (e.g., epsilon-greedy) and observes the reward and next state.
- SARSA updates its value estimates using the observed reward and the next state-action pair.
- It updates its policy based on the updated value estimates.
- SARSA is particularly suitable for online learning and environments where the policy needs to be continuously adjusted based on new experiences.

Reinforcement Learning Algorithms (cont…)

- More advanced algorithms such as ***Deep Q-Networks (DQN)*** and ***Deep Deterministic Policy Gradient (DDPG)*** can handle <u>unseen states and high-dimensional action spaces</u>.



Q Learning



Deep Q Learning

Use with courtesy from Ankit Choudhary © *A Hands-On Introduction to Deep Q-Learning using OpenAI Gym in Python*
Published in Analytics Vidhya on 21 August 2023

Q-Learning Example: Routing Problem

- Consider a simple routing problem with seven states (0-6).
- The goal is to find the best route from the start state (0) to the goal state (6).
- We can represent the problem as a graph, where nodes are states and edges are actions.
- Based on Figure 3.19, one can construct a corresponding matrix R, which indicates the reward values from a state to take an action to the next state, as shown in Figure 3.20 (next slide).
- The reward matrix R indicates the rewards for taking an action from one state to another.

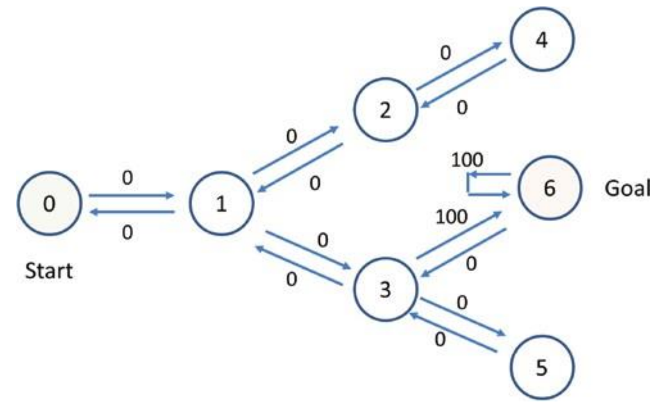


Figure 3.19: A simple routing problem with seven states, with 0 as the start state and 6 as the goal state (Xiao, P., 2022)

Q-Learning Example: Routing Problem (cont…)

- The value 0 means it is possible to go from one state to another state. The value -1 means it is not possible.
- The value 100 indicates reaching the Goal state; there are only two possibilities, from state 3 to state 6, and from state 6 to state 6.
- Based on R, one can also construct a similar matrix Q, and update the values of Q iteratively by using the following formula:

$$Q(s,a) = R(s,a) + \gamma \times max\big(Q(ns,aa)\big)$$

- where

  $Q(s,a)$=Q matrix value at state (s) and action (a).

  $R(s,a)$=R matrix value at state (s) and action (a).

  γ=the learning rate.

  $Q(ns,aa)$=Q matrix value at next state (ns) and all actions (aa).

  Max(.)=is the function to get the maximum values.

Action

$$R = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{array} \begin{array}{c} \begin{array}{ccccccc} 0 & 1 & 2 & 3 & 4 & 5 & 6 \end{array} \\ \left[\begin{array}{ccccccc} -1 & 0 & -1 & -1 & -1 & -1 & -1 \\ 0 & -1 & 0 & 0 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & -1 & -1 & -1 & 0 & 100 \\ -1 & -1 & 0 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & 0 & -1 & -1 & -1 \\ -1 & -1 & -1 & 0 & -1 & -1 & 100 \end{array}\right] \end{array}$$

State

Figure 3.20: The corresponding reward value R matrix of the routing problem (Xiao, P., 2022)

Topics

- **Importance of Responsible AI**
  - Ethics in the Age of AI
  - Mitigating Bias and Discrimination
  - Privacy in the Age of Surveillance
  - Human-Centric Design

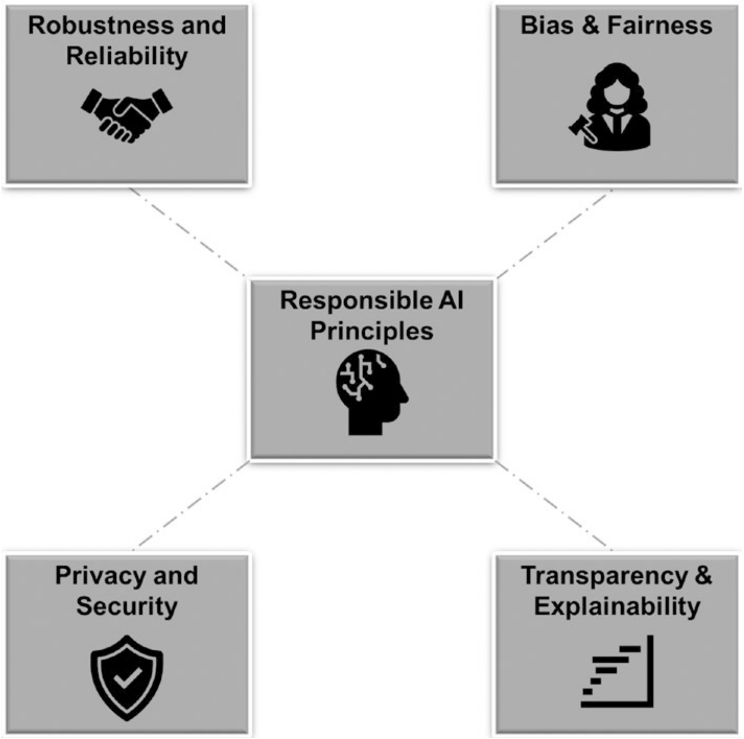


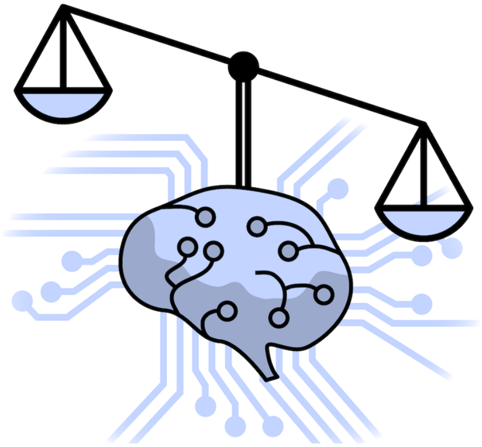
Figure 1-1. Evolution of artificial intelligence (Manure et al., 2023)

Ethics in the Age of AI

- AI has the potential to influence human lives, societies, and economies.
- AI also poses an ethical dilemma: the power to create and wield machines capable of decision making, learning, and autonomy.
- ***Responsible AI*** guides the development, deployment, and governance of AI technologies.
- It aligns technological innovation with societal values.
- It upholds ethical principles, accountability, and transparency throughout the AI lifecycle.
- It safeguards human well being and ensures equitable benefits for all.

Mitigating Bias and Discrimination

- A concern in the AI landscape is the potential for bias and discrimination in algorithms
- AI systems trained on biased data can perpetuate societal prejudices and exacerbate existing inequalities
- ***Responsible AI*** addresses this issue head-on, demanding rigorous data preprocessing, algorithmic transparency, and the pursuit of fairness
- It creates systems that reflect the diverse fabric of human society
- It bridges digital divides, ensuring that AI's impact is not marred by discriminatory practices
- It champions fairness and equity, paving the way for a future where technology is a tool of empowerment, rather than an agent of division.

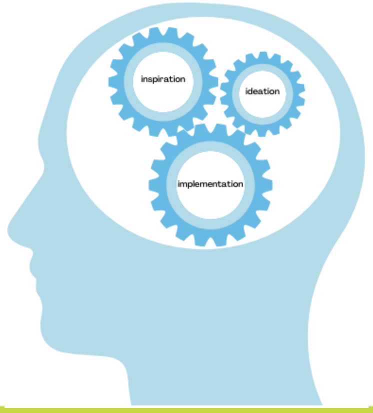


Privacy in the Age of Surveillance

- The era of digital advancement has resulted in an unparalleled rise in data creation, raising worries about individual privacy and the security of data.
- The insatiable appetite of AI for data necessitates a careful equilibrium between creativity and the protection of individual rights in its learning algorithms.
- ***Responsible AI*** highlights the significance of safeguarding data by promoting strong encryption, secure storage, and rigorous access management.
- It cultivates a sense of trust between technology and individuals.
- It empowers individuals to retain agency over their personal information while enabling organizations to harness data insights for positive transformations.
- It fortifies the pillars of privacy, ensuring that technological advancement does not come at the cost of individual autonomy.

Human-Centric Design

- Amidst the AI revolution, the concern that machines will replace human roles resonates strongly.
- ***Responsible AI*** dispels this notion by embracing a human-centric approach to technology.
- It envisions AI as an enabler, amplifying human capabilities, enhancing decision making, and fostering innovative synergies between man and machine.
- The importance of maintaining human oversight in AI systems cannot be overstated.
- It encourages the development of "explainable AI," wherein the decision-making processes of algorithms are comprehensible and traceable.
- It engenders trust and empowers individuals to make informed choices, thereby ensuring that AI operates in harmony with human values and goals.

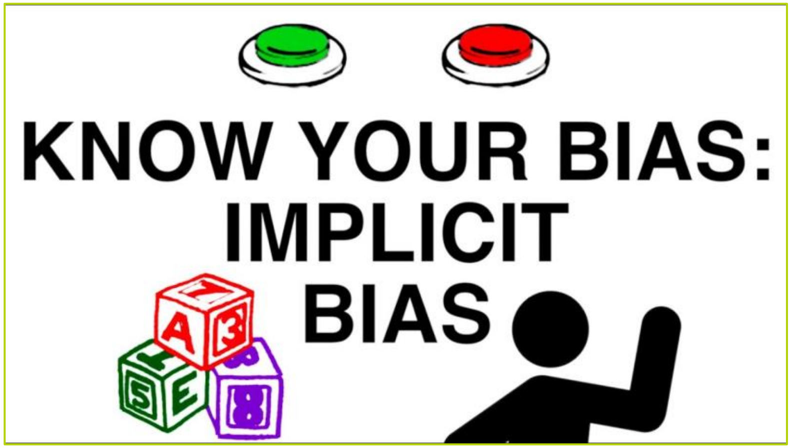


Bias in the AI Landscape

- ***Bias*** is the presence of systematic deviations that lead to inaccuracies or unfairness in decision making.
- Bias can impact various domains, from individual choices to complex models.
- Bias can stem from various sources, such as historical inequalities, flawed data-collection methods, or biased algorithms.
- Bias can distort outcomes and fairness, affecting individuals, groups, and societies.
- Bias can be detected and mitigated by technology, nurturing transparent and responsible AI.

Understanding Bias in Data and Models

- Bias in data and models emerges when data-collection or model-construction processes inadvertently favor certain groups, attributes, or perspectives over others.
- Bias in data and models can manifest in various ways, such as ***sampling bias***, ***measurement bias***, ***label bias***, ***algorithmic bias***, or ***outcome bias***.
- Bias in data and models can affect the performance, reliability, and validity of AI systems.
- Bias in data and models can be identified by analyzing the data distribution, the model assumptions, and the model outcomes.
- It can be addressed by implementing strategies that ensure equitable and unbiased decision making in artificial intelligence systems.



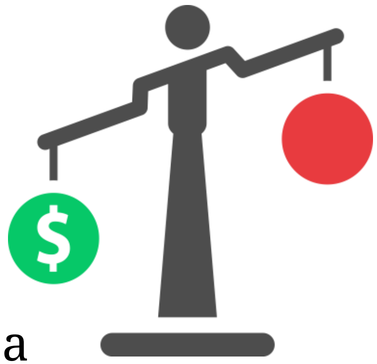
Recognising Bias for Creating Fair and Equitable Systems

- Recognising bias is the first step toward creating fair and equitable systems.
- It involves understanding the context, the stakeholders, and the objectives of the system.
- It requires defining and measuring fairness, which can be challenging and context-dependent.
- It entails evaluating the potential harms and benefits of the system for different groups and individuals.
- It enables the development of explainable AI, wherein the decision-making processes of algorithms are comprehensible and traceable.
- It fosters trust and accountability, ensuring that AI operates in harmony with human values and goals.

Techniques to Detect, Assess, and Mitigate Bias

- Detecting bias involves examining the data and the model for signs of systematic deviations or discrepancies.
- Detecting bias can be done using various methods, such as data visualization, statistical tests, or model evaluation metrics.
- Assessing bias involves quantifying the degree and the impact of bias on the system outcomes and fairness.
- It can be done using various measures, such as disparity, discrimination, or fairness metrics.
- Mitigating bias involves applying interventions to reduce or eliminate bias in the data or the model.
- It can be done using various techniques, such as data preprocessing, algorithm modification, or post-processing correction.

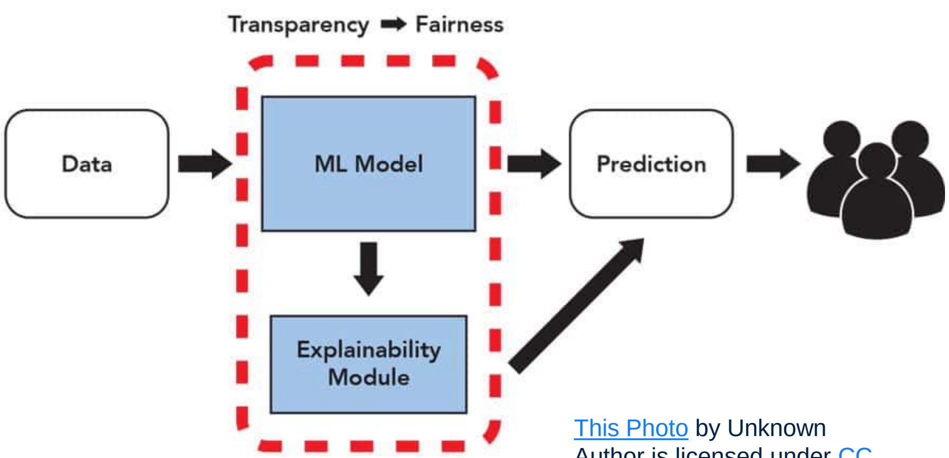
Trade-offs Between Model Complexity and Interpretability



- ***Model complexity*** refers to the number of parameters, features, or interactions that a model uses to learn from data.
- It can affect the accuracy, generalization, and efficiency of a model.
- ***Model interpretability*** refers to the ability to understand how a model makes predictions or decisions.
- It can affect the transparency, explainability, and trustworthiness of a model.
- There is often a ***trade-off*** between model complexity and interpretability, meaning that more complex models tend to be less interpretable, and vice versa.
- The trade-off between model complexity and interpretability can be balanced by using various methods, such as feature selection, regularization, or model-agnostic explanations.

Summary

- Bias and fairness are important concepts in the AI landscape.
- Bias and fairness can impact decision making across various domains, from individual judgments to automated systems.
- Bias and fairness can stem from various sources, such as historical inequalities, flawed data-collection methods, or biased algorithms.
- Bias and fairness can be detected, assessed, and mitigated by technology, nurturing transparent and responsible AI.
- Bias and fairness align with ethics, sculpting AI that champions diversity and societal progress.
- Bias and fairness require a balance between model complexity and interpretability, ensuring that AI systems are accurate, reliable, and understandable.



THANK YOU

TIME FOR DISCUSSION & QUESTIONS