Module -5

ROBOTICS, ETHICS AND SAFETY IN AI

5.1 ROBOTICS :

Robots in AI refer to physical or virtual agents that utilize artificial intelligence techniques to perceive, reason, act, and interact with their environment autonomously or semi-autonomously. These robots can range from simple autonomous vacuum cleaners to sophisticated humanoid robots capable of performing complex tasks.

6.Autonomy and Navigation: AI enables robots to navigate and operate autonomously in dynamic and unstructured environments. Localization, mapping, path planning, and obstacle avoidance algorithms are used to enable autonomous navigation and exploration.

7.Safety and Reliability: AI techniques are employed to ensure the safety and reliability of robotic systems. Fault detection and diagnosis, error recovery, and fail-safe mechanisms are implemented to mitigate risks and prevent accidents.

8.Domain-specific Applications: Robots in AI are referred in various domains, including manufacturing, logistics, health care, agriculture, transport, entertainment, and space exploration. They perform tasks such as assembly, inspection, delivery, surgery, caregiving, farming, driving, and exploration.

Robots

These are the physical entities designed to execute tasks by interacting with and altering the physical world. They accomplish this through effectors, which are tools or mechanisms to perform various actions. Common effectors include:

1. **Legs**: These provide robots with the ability to walk or run, facilitating movement over diverse and uneven terrains, allowing them to navigate obstacles more effectively than wheels.

2. **Wheels**: These are ideal for smooth and efficient movement on flat surfaces, enabling wheeled robots to travel faster with less energy compared to legged robots.
3. **Joints**: These offer flexibility and mobility to robotic limbs or arms, allowing robots to replicate human-like movements or perform intricate tasks that require precision.
4. **Grippers**: These are used for grabbing, holding, and manipulating objects. They vary from two-fingered claws to sophisticated multi-fingered hands, depending on the complexity of the task.

By integrating these effectors with sensors, control systems robots can carry out a wide range of activities, from simple repetitive tasks in manufacturing to complex operations in hazardous environments.

Effectors assert force on the surroundings. Hence, the state changes (with an autonomous car as an example, spin wheels and make progress on the road . That is the environment state changes from one state to the other. Gripper is used to push mug across the counter by a robotic arm. The state of the people in the surrounding environment changes along with robot. An exoskeleton example can be seen here. It makes a move to make a change in the surrounding environment as the position of a person's leg; or a mobile robot make progress towards the doors of the escalator, and a person notices the change to move out of the way, or push the button for the robot.

Robots can be built using sensors or actuators enabling perceive environment. Present-day robotics employ sensors, example is camera, radars, laser equipment, and microphone for estimation of the state of the environment; gyroscopes, to measure its own state.

The environment is generally monitored by a robot in a continuous state space because a robot has continuous coordinates to position and realize the next move and a continuous action space. The current forwarded by a robot to its motor is measured in continuous units). Autonomous cars need to know the position, orientation, and velocity of themselves in a high dimensional space and the nearby agents. Generally a robot has six or seven joints that can be moved or rotated. Robots that mimic the human body have hundreds of joints and appear as a human.

Hardware

The components of an agent's architecture consist of various components like sensors and actuators, and processors. The success of robots is heavily influenced by how well the sensors and actuators are designed to suit their specific tasks.

Types of robots:

- Consider a robot with a head and two arms. It moves around on its legs or wheels. Anthropomorphic robots are these that are in fiction movies, Terminator and the cartoon Jetson. Real world robots come in many shapes and sizes. Robot arms are called as each Manipulators. They are attached as a joint to a robot or can be mounted or bolt onto a table or a floor, as in industries. Anthropomorphic robots generally have large payload, like in assembling cars. Other are the wheelchair-mountable arms assisting people with motor impairments. These robots carry less and safe in human environments.

Mobile robots use rotors to move in the environment. Quadcopter aerial vehicles (UAV); underwater vehicles. Examples include AUVs that roam the oceans or sea. Many mobile robots stay indoors and move on wheels, like a vacuum cleaner or a towel delivery robot in a hotel. Outdoor robotic counterparts include autonomous cars or rovers that explore new terrain. Outdoor robots explore even on the surface of Mars. Robots with legs move on rough terrain that cannot be accessible with wheels and venicles. Managing the legs of the robot to move about rightly is a challenging task than spinning wheels.

Robots Sense the real world

Sensors usef in robots serve as an `interface between a robot and its environment. Cameras, function as true observers, capturing signals from other sources in the environment. Active sensors, such as sonars, emit light into the environment and detect the reflections of this energy. Active sensors can also provide more info than passive sensors, they require more power and interface with each other when active sensors are used.

Robots Producing motion

Actuator is the mechanism that initiates an effector. Examples include

Emitted transmissions,

Accessing gears,

Wired and wireless cables, and

linkages.

Another type of actuator is electric actuator. Electric actuator uses electricity that spins motor. They are used in robotic armed systems with rotational motion. Example is the joints in a robot arm. A pressurized fluid in the form of oil or water is used in actuators. Compressed air to generate mechanical motion is used in actuators.

Problems that robot solve

Consider agent software that drives the hardware. At first decide the computational framework for this agent. It can be search in environments that are deterministic and non deterministic, fully observable environments, POMDP (Partially Observable Marcov Decision Process) for partial observable environments. In game environments, agent never act in isolation.

With a framework for computation, it is required to list its ingredients:

- Reward based utility functions,
- its state,
- its action,
- and observation space, and others.

Robotic problems and space are

not deterministic,

partially observable environments,

and multiagent robots.

Agents have to be cooperative and competitive using the game of theoretic notions. It is common for collaboration to occur when an agent can go first in a narrow corridor. collaborate because they want to make sure they don't bump into each other. But in some situations they might compete to reach destination quickly. If the robot is polite and always makes room, it gets struck in crowded situations and never reaches goal. Therefore, robots acting in isolation and know their environment can be formulated as an MDP; when they are missing information is a POMDP; and when they act around people it can be formulated as a game.

Robots reward function

Robots act to service a human— Bringing a food to a patient, for instance, is not done for its own sake. The robot must interpret the user's wishes or rely on an engineer to provide a rough idea of what the user wants. The most common form of the robotic action, state, and observation spaces is that the actions are the raw electric currents sent to the motors; the observations are the raw sensor feeds (e.g., images from cameras or laser hits from lidar light detection and ranging); and the state is the information the robot needs to make decisions. It indicates that there is a significant disconnect between the high-level plans the robot must make and perceptions and motor controls.

In order to overcome the differences, roboticists separate and streamline several components of the problem. When solving POMDPs correctly, we understand that perception and action have a mutual influence: perception guides the selection of meaningful activities, while action enhances perception by providing valuable information for future time steps. Robots effectively distinguish between perception and action, by using the outputs of perception and simulating the acquisition of future knowledge. Furthermore, in situations that need hierarchical planning, it is important to take into account the distinction between a high-level objective, such as "reach the cafeteria," and a specific motor order, such as "rotate the main axle." This distinction exists between the lower-level sensory inputs and motor commands, and the higher-level plans that the robot must formulate.

In the field of robotics, a three-level hierarchy is employed.

Task planning level determines a plan or strategy for high-level activities, also known as action primitives or subgoals, such as moving to the door, opening it, going to the elevator, pressing the button, and so on.

Motion planning involves determining a trajectory that enables the robot to move from one location to another, successfully achieving each intermediate objective.

Ultimately, control is employed to accomplish the intended movement by utilizing the robot's actuators. Task planning is usually characterized using distinct stages and activities.

All of these factors collectively influence the robot's behavior. By dividing a problem into distinct components, we decrease its complexity, but we forfeit the potential for the components to mutually assist one another. Action has the potential to enhance perception and ascertain the type of perception that is beneficial. Similarly, judgments made at the level of individual movements may not be optimal when considering how those movements will be monitored. Likewise, decisions made at the level of specific tasks may make it impossible to carry out the planned movements. Therefore, it is necessary to combine them: to perform the integration of motion planning and control simultaneously, to perform the integration of task and motion planning simultaneously, and to reintegrate perception, prediction, and action in order to close the feedback loop. The field of robotics is currently focused on advancing in every aspect and using these advancements to achieve seamless integration.

Perception

This entails the process of creating a visual representation of the surroundings by collecting and analyzing data for robotic systems. Robotic perception necessitates the integration of supplementary sensors such as lidar and touch sensors. It is difficult because sensors have a high level of noise, and the environment is sometimes only partially viewable and subject to change. Consequently, robots encounter substantial challenges when it comes to determining their current condition.

Robotic representations should include three essential characteristics:

They provide the necessary information for the robot to make efficient and informed judgments.

They should be organized in a manner that allows for efficient updating.

The variables should possess a natural quality, indicating that they represent real-world state variables.

Kalman filters, Hidden Markov Models (HMMs), and dynamic Bayesian networks are capable of representing the transitions that occur within a partially visible environment. Methods encompass both precise and algorithmic approaches for updating the state, namely the posterior probability distribution of the environment's state variables.

In order to tackle these difficulties, the recursive equation (14.5) is altered to employ integration rather than summation.

Localization and mapping

Localization is the process of ascertaining the precise placements of items. For instance, a robot navigating a level, two-dimensional surface. Let's assume that the robot possesses a precise map of the surrounding surroundings. The robot is characterized by its two Cartesian coordinates, \(x \) and \(y \), and its direction, \(\theta \), as shown in Figure 26.5(a). By organizing these three values into a vector, it is possible to express any specific state of the robot. The expression Xp represents a tuple consisting of three elements: xp, yt, and θt, all of which are variables.

The probability distribution is a mathematical representation of the robot's motion model, which describes how the robot's movement influences its position. Once again, our measurements are influenced by noise. Assuming Gaussian noise, the sensor model is determined by the covariance.

The conditional probability of seeing za given xt is represented by P(za |xt) and follows a normal distribution with mean zˆa and covariance matrix Σz. When evaluating a pose \(X_a \), the range along the beam direction from \(X_t \) is denoted as \(\hat{z}_a \). It is important to remember that this measurement is affected by Gaussian noise. Generally, we make the assumption that mistakes in directions are independent and have the same distribution.

Instant localization may not be possible in situations when the robot is confronted with a wall that lacks distinguishing characteristics. Nevertheless, the presence of visible landmarks might expedite the process of determining one's location.

Particle filtering, sometimes referred to as Monte Carlo localization (MCL), is a localization technique that utilizes an implementation approach. The MCL algorithm need suitable motion and sensor models. Figure 26.6 demonstrates the use of the scan sensor model, while the algorithm's functioning is illustrated as the robot calculates its location within a building.

The particles in the first picture are determined by the previous factors, which reflect a general lack of knowledge regarding the position of the robot. Upon the arrival of measurements, particles tend to gather in regions with a strong posterior belief. When there are enough measurements, all particles come together at one specific position.

Robots has the ability to detect and interpret various sensory stimuli such as temperature, smells, sound, and other sensory inputs. Several of these are detected using different forms of dynamic Bayesian networks, which necessitate probability distributions for the development of states over time and sensor models that describe the relationship between measurements and states. Probabilistic approaches provide superior performance in demanding perceptual tasks such as localization and mapping, but less intricate solutions may be adequate in simpler situations.

Supervised and uncontrolled learning in perception

Deep learning plays a crucial role in how robots perceive their surroundings. This generally involves using unsupervised approaches to turn complex sensor data into simpler representations, a process known as low-dimensional embedding. This technique enables robots to learn from data while concurrently discovering representations.

Another use of deep learning is its ability to enable robots to adapt to major changes in sensor readings. Envision the experience of moving from a well-lit space to a poorly illuminated one adorned with neon lights. The alteration not only impacts luminosity but also modifies color interpretation as a result of the diverse light sources. Nevertheless, individuals often acclimate to these alterations without seeing them. Techniques allow robots to make comparable adjustments. For example, in the context of autonomous driving, unmanned ground vehicles have the ability to modify their classifiers to recognize concepts such as "drivable surface" by utilizing sensor data in real-time. By utilizing a laser to assess the local vicinity ahead of the robot, it may ascertain whether the ground is level, so exemplifying the notion of a navigable surface.

Controllers that respond to changes or stimuli

Developing a successful strategy for a robot might be more straightforward than constructing a detailed model of the environment and devising plans based on it. In such instances, rather of employing a logical agent, a reflexive agent is utilized. For example, let's suppose a robot trying to move across an obstacle. We can program this robot to adhere to a specific procedure: raise the leg slightly, go ahead, and if it encounters an impediment, withdraw the leg, move it backward, and then attempt again with a greater elevation. This seems to resemble the modeling world and can alternatively be seen as a variable within the robot's controller, lacking any direct physical relevance.

Example is a hexapod robot specifically engineered for navigating challenging landscapes. Obtaining accurate terrain models for path planning is difficult due to insufficient sensors. This perspective embodies a methodical approach to robotics, in contrast to a responsive vision.

It is possible to define an actuator without a distinct environmental model. When choosing the hexapod, one has the option to pick either a large size or a certain pattern of limb movement. A steady gait is achieved by successively advancing select legs while keeping others stationary, and then alternating. However, when encountering uneven terrain, obstructions may impede the forward motion of a leg. This issue may be resolved by implementing a simple rule: when a leg's forward motion reaches its maximum height, it should be lowered and then attempted again, and vice versa. The controller that is shown in Figure 26.32(b) is a simple finite state machine, which functions as a reflex agent. The current state of the machine is represented by an index.

Subsumption architectures

The subsumption architecture, first proposed by Brooks in 1986, provides a framework for constructing reactive controllers using finite state machines (FSMs). These machines are composed of nodes that can include tests for certain sensor variables, which in turn affects the behavior of the finite state machine based on the results of these tests. Furthermore, the arcs included in these machines may be designated as messages that are produced during traversal and used to control the robot's motors or other finite state machines (FSMs).

These architectural designs possess certain drawbacks. It has difficulties when there is a need for dependable sensor data to make decisions, especially when the data is combined in intricate ways. Subsumption controllers are primarily designed for less complex tasks, such as navigating towards visible light sources. Moreover, the careful consideration in architecture poses difficulties in adjusting the objectives of the robot. Usually, a robot utilizing this structure concentrates on a solitary duty without the requirement to adapt to various purposes.

Furthermore, in several practical situations, the intended course of action is sometimes too complex to directly program. For example, let's examine the scenario of an autonomous vehicle that needs to perform a lane change while driving alongside human drivers, as shown in Figure 26.28. At first, the automobile may try to gently go towards the desired lane and pause for a reaction from the driver in that lane before continuing or going back. Extensive testing may indicate that the nudge should be applied at different velocities based on parameters such as the velocity of cars in the lane where barriers are present. The conditions necessary for determining the suitable course of action can rapidly escalate, presenting scalability difficulties for subsumption-style architectures. Robotics is a multifaceted problem with various approaches: deliberative, reactive, or a combination of both; grounded in physics, cognitive models, data, or a combination of these. The optimal methodology remains a topic of discussion, scientific investigation, and technical expertise.

Areas of application

The integration of robotic technology is already widespread in our society and holds the capacity to enhance our autonomy, well-being, and efficiency. Illustrative use cases:

HOME CARE:

Robots are now being used in homes to provide assistance to elderly folks and individuals with mobility disabilities, helping them with their everyday routines and allowing them to live more autonomously. These encompass wheelchairs as well as wheelchair-mounted appendages such as the Kinova arm. Initially, these robots are controlled directly by a person, but they are gradually becoming more autonomous. Robots controlled by brain-machine interfaces are being developed to assist individuals with quadriplegia in using a robotic arm to manipulate things and perform tasks such as feeding oneself (Figure 26.33(a)). Additionally, there are prosthetic limbs that possess the ability to intelligently react to our movements, as well as exoskeletons that provide us with extraordinary physical power or allow those who lack control over their lower body muscles to regain the ability to walk.

Personal robots are designed to aid us in performing everyday duties such as cleaning and organizing, so allowing us to have more free time. While manipulation in chaotic, unstructured human situations remains a challenge, progress has been made in the field of navigation. Specifically, several households currently benefit from the use of an automated vacuuming device.

ROBOTIC ASSISTANCE IN HEALTH CARE:

Robots aid and enhance surgeons, allowing for more accurate, less invasive, and safer treatments that result in improved patient outcomes. The surgical robot is being extensively utilized in hospitals around the United States.

Mobile robots provide assistance in business buildings, hotels, and hospitals. Savioke has used robotic systems in hotels to facilitate the delivery of items such as towels or toothpaste directly to guests' rooms. The Helpmate and TUG robots are utilized in hospitals for the transportation of food and medicine (as shown in Figure 26.34(b)). On the other hand, Diligent Robotics' Moxi robot assists nurses by doing logistical tasks behind the scenes. Co-Bot navigates around the corridors of Carnegie Mellon University, prepared to direct you to an individual's office. Telepresence robots like as the Beam can be utilized to remotely participate in meetings and conferences, as well as to monitor the well-being of our grandparents.

AUTONOMOUS VEHICLES:

Many individuals experience intermittent distractions while operating a vehicle, such as receiving phone calls, text messages, or engaging in other activities. Over one million individuals perish in automobile accidents, resulting in loss of life. Additionally, I devote a significant amount of time on driving and would like to reclaim some of that time. As a result, there is currently a significant and continuous endeavor to implement self-driving vehicles.

BOSSs, the winner of the 2007 DARPAA Urbane Challenge. This challenge is a complex road race that takes place on city streets, where robots are required to follow traffic regulations.

ENTERTAINMENT:

Disney has employed robots, known as animatronics, in their parks since 1963. Initially, these robots were limited to pre-planned, one-way, repetitive movement (and communication), but starting from 2009, a variant known as autonomatronics has the ability to produce independent activities. Robots may also be designed as sophisticated playthings for children, such as Anki's Cozmo. Cozmo engages in games with children and may express its dissatisfaction by pounding the table when it loses. Quadrotors such as Skydio's R1, shown in Figure 26.2(b), function as personal photographers and filmmakers. They track our movements when skiing or biking and capture dynamic photos.

Exploration in dangerous and risky environments:

Robots have ventured into locations that are inaccessible to humans. They have played a crucial role in activities like as launching satellites, building the International Space Station, and even surveying the ocean floor to chart submerged vessels. For example, a robot operating in a deserted coal mine and creating a three-dimensional representation by utilizing range sensors. Scientists deployed a quadrupedal robot into an active volcanic crater to gather data for climate studies. Robots have become indispensable instruments for collecting data in regions that are inaccessible or dangerous for people.

In addition, robots are employed in the decontamination of radioactive waste, particularly in Three Mile Island, Chernobyl, and Fukushima. Additionally, they were dispatched following the fall of the World Trade Center, venturing inside structures that were too dangerous for human search and rescue crews. Originally controlled by teleoperation, these robots are gradually gaining autonomy through technology developments, allowing human operators to supervise them without the necessity for specifying each instruction.

Within the industrial domain, the predominant use of robots is observed in factories, where their primary function is to automate jobs that are difficult, hazardous, or repetitive for human workers. This is especially noticeable in vehicle manufacturers. Automation improves the efficiency of creating necessary items, but it also results in the displacement of some human labor. This raises substantial policy and economic concerns, including the need for retraining and education, as well as ensuring an equitable allocation of resources.

The boundaries of artificial intelligence

Philosopher John Searle established a classification in 1980 that differentiates weak AI from strong AI. Weak AI posits that robots are capable of emulating intelligent behavior, but strong AI contends that machines possess the ability to really engage in thinking, rather than only simulating it. Over the years, the meaning of strong AI has expanded to include ideas such as "human-level AI" or "general AI," which refers to computer systems that can do a variety of tasks, including new ones, at a level similar to humans.

The critics of weak AI, who previously disregarded the potential for intelligent behavior in machines, now seem as myopic as Simon Newcomb. In October 1903, Newcomb famously claimed that flight is an insurmountable problem for humans, only to be proven wrong just two months later by the successful flight of the Wright brothers at Kitty Hawk.

In recent years, there has been significant advancement in the field of AI. However, it is important to note that this progress does not imply that there are no limitations to what AI can achieve. Alan Turing, a pioneer in the field of AI, was the first to raise potential objections and anticipate concerns that have been voiced by others since then. One of these objections, known as Turing's "argument from informality of behavior," suggests that the complex behavior of humans cannot be fully captured by any formal set of rules. This viewpoint was supported by a philosopher who critiqued AI in influential works such as "What Computers Can't Do" (1972) and its sequel.

The technology that Dreyfus and other critics disapproved of became known as "Good Old-Fashioned AI" (GOFAI). GOFAI, which relied on logical agent design, faced difficulties in addressing all possible scenarios of appropriate behavior using a set of logical rules, known as the qualification problem. As a substitute, probabilistic reasoning systems and deep learning approaches have emerged as more appropriate for complex and unpredictable environments.

Dreyfus's primary contention supports the use of agents above logical inference engines. He claims that agents, who have real-world experiences like seeing and interacting with dogs, exhibit a more profound comprehension compared to those that rely exclusively on logical words.

Although ongoing research and development have made progress in areas of AI that were once considered impossible, Turing and Gödel's theorems indicate that certain mathematical questions cannot be answered by formal systems. However, the notion that humans have superior mental capabilities based on these limitations is being questioned. It is important to note that these theorems pertain to mathematics and not computers, and assuming human consistency is unwarranted given the presence of human inconsistencies.

In general, Gödel's incompleteness theorem is specifically applicable to formal systems that are highly capable. However, computers, being limited in their capabilities, do not encounter the same limitations as theoretical Turing machines. Additionally, the notion that humans have the ability to alter their opinions while computers do not is also disproven, as computers can adjust their behavior based on new information or learning algorithms.

Quantifying Artificial Intelligence

In his well-known study "Computing Machinery and Intelligence" (1950), Alan Turing suggested that the more appropriate question to ask is whether machines can successfully pass a behavioral test known as the Turing test, rather than whether they are capable of thinking. During the test, a software engages in a five-minute conversation with a human through typed messages. The goal of the interrogator is to determine if they are being deceived by the person or the program at least thirty percent of the time. If the program manages to mislead the interrogator to this extent, it is considered to have passed the test. Turing argued that this approach evaluates intelligence based on actual performance in a comprehensive behavioral test, rather than relying on philosophical speculation. Examples of software that have been developed to participate in the Turing test include ELIZA, NATACHATA (Jonathan et al., 2008), and MGONZ (Humphrys, 2008).

In 2014, a chatbot named Eugene Goostman successfully deceived 33% of the untrained amateur judges in a test. The chatbot pretended to be a boy from Ukraine and intentionally made grammatical errors to justify its limited command of English. This suggests that the Turing test may primarily assess the susceptibility of humans to deception, rather than the capabilities of the chatbot. However, no judge who is well-trained in evaluating chatbots has been deceived thus far.

Turing test contests have led to the development of improved chatbots, although they have not been a primary area of research within the AI community.

AI researchers focus on developing expertise in several domains such as chess, Go, StarCraft II, 8th grade science exams, and object recognition in photos. In numerous instances, AI algorithms have achieved or even exceeded the performance levels of humans in these competitions.

The objective is to enhance fundamental scientific knowledge and technological advancements, as well as to offer practical instruments, rather than deceiving evaluators.

Artificial Intelligence Ethics

Artificial Intelligence (AI) is a potent technology, and therefore, it is our ethical responsibility to utilize it effectively, emphasizing its beneficial elements while minimizing or addressing its potential drawbacks.

There are several beneficial factors to consider. Some examples include:

- Artificial intelligence has the potential to enhance medical diagnostics, leading to the preservation of human lives.
- Recent advancements in the field of medicine,
- enhanced forecasting of severe weather phenomena
- Enhance driving safety through the utilization of driver assistance and autonomous driving technology.

There are several prospects to enhance the quality of life. Some instances include:

- Microsoft's AI for Humanitarian Action program utilizes artificial intelligence to address humanitarian challenges.

- Overcome the effects of natural calamities,

- Meet the requirements of youngsters,

- Ensure the safety and well-being of refugees.

- Advocacy for the protection and advancement of fundamental human rights.

- Google's AI for Social Good program provides assistance for projects related to

- Preservation of rainforests,

- Legal principles and decisions related to human rights.

- Environmental pollution management and surveillance,

- quantification of greenhouse gas emissions from fossil fuels,

- Therapeutic intervention for those experiencing a crisis,

- Verification of news accuracy.

- Prevention of suicide,

- Recycling, among several other activities.

The Center for Data Science and Social Good at the University of Chicago utilizes machine learning ideas to address various challenges.

- Law enforcement and legal system that deals with the punishment and prevention of crime.
- economic growth,
- Education.
- Public health
- Energy and
- The environment.

The utilization of artificial intelligence in crop management and food production plays a crucial role in addressing global food security challenges.

Implementing machine learning in company operations would enhance productivity, leading to economic growth and generating additional job opportunities. Automation has the potential to supplant the jobs that numerous workers encounter, so liberating them to devote more attention to other captivating facets. Individuals with impairments benefit from AI-powered aid in enhancing their visual, auditory, and physical capabilities.

Machine translation facilitates communication between individuals from diverse cultural backgrounds. Software-based AI solutions possess a marginal cost of manufacturing that is effectively $0, hence enabling the potential for widespread access to advanced technologies.

Notwithstanding these favorable characteristics, the unfavorable ones are:

Several emerging technologies have exhibited unforeseen adverse consequences:

The process of nuclear fission and its potential to wreak worldwide devastation; the internal combustion engine, which has resulted in air pollution, global warming, and the transformation of natural landscapes.

Other technologies that have adverse consequences when employed as intended include :

Sarin gas, AR-15 weapons, and telephone solicitation.

Automation generates economic prosperity, yet, given the existing economic circumstances, a significant portion of this prosperity will be concentrated in the hands of the owners of the automated systems, resulting in income disparity that has the potential to disturb the smooth functioning of society.

In developing nations, the conventional route to economic expansion via low-cost manufacturing for international trade may be obstructed, as affluent nations embrace fully automated manufacturing plants within their own borders.

The extent of inequality generated by AI will be determined by our ethical and governance decisions. Ethical considerations are faced by all philosophers when deciding which projects to undertake and how to ensure their safe and beneficial execution. In 2010, the Engineering and Physical Science Research Council in the UK convened a meeting to establish a set of Principles of Robotics. Over the following years, various government agencies, nonprofit organizations, and companies developed similar sets of principles. The underlying idea is that every organization involved in creating AI technology, as well as every individual within the organization, bears the responsibility of ensuring that the technology contributes to the greater good and avoids causing harm.

The principles that are most frequently mentioned are:

As we conduct our operations online, our vulnerability increases.

Cybercrime, which includes activities such as phishing, credit card fraud, botnets, and ransomware,

Cyber terrorism refers to the deliberate use of technology to carry out harmful acts, which may include disrupting the operations of hospitals and power plants or taking control of autonomous vehicles.

Machine learning is a potent and beneficial weapon in the fight against cybersecurity threats.

Attackers employ automation techniques, such as reinforcement learning, to systematically search for vulnerabilities in order to carry out phishing attacks and automated blackmail.

Defenders employ unsupervised learning to identify abnormal inbound communications and utilize several machine learning methods to detect fraudulent activities.

As cyber assaults become more advanced, it is imperative for all engineers to take on the duty of designing safe systems from the very beginning.

As our reliance on computers grows in various aspects of our daily routines, governments and companies are gathering a growing quantity of data on us.

Data collectors are morally and legally obligated to act as responsible custodians of the data they possess.

The Health Insurance Portability and Accountability Act (HIPAA) and the Family Educational Rights and Privacy Act (FERPA) safeguard the privacy of medical and student data in the United States.

The General Data Protection and Regulation (GDPR) of the European Union compels enterprises to design their systems with data protection in mind and get user consent for any data collection or processing.

The individual's right to privacy must be weighed against the benefits of data sharing. This includes preventing terrorism without suppressing peaceful protest and treating illnesses without compromising an individual's right to keep their health history confidential.

The primary method employed is de-identification, which involves the removal of personally identifiable information (such as name and social security number) to enable researchers to utilize the data for the betterment of society. However, a concern arises since the de-identified data that is provided may potentially be re-identified.

For example, if the data removes the name, social security number, and street address, but still includes the date of birth, gender, and zip code, then according to Latanya Sweeney's research in 2000, it is possible to identify 87% of the U.S. population with this information alone. Sweeney demonstrated this by successfully re-identifying the health record of her state's governor when he was hospitalized.

The Netflix Prize competition involved the release of de-identified information containing individual movie ratings. Competitors were tasked with developing an algorithm capable of predicting a person's preferences for certain movies.

However, researchers were able to identify specific users by comparing the dates of ratings in the Netflix database with the dates of similar rankings in the Internet Movie Database (IMDB), where users occasionally use their real names. To reduce this risk, certain fields can be generalized, such as replacing the precise birth date with just the year of birth or a range like "20-30 years old." However, even with these measures in place, there is no guarantee that records will be completely protected from re-identification.

K-anonymity is a valuable characteristic of a database. It means that every record in the database cannot be distinguished from at least k-1 other records. If the records are more distinct than this, they would need to be made more generalized. Instead of sharing de-identified records, an alternative approach is to keep all records private and only allow aggregate querying.

Currently, several databases are specifically built to provide differential privacy. However, our focus has been on addressing the challenge of sharing de-identified data from a central database.

Federated learning is a strategy that eliminates the need for a central database. Instead, users retain their own local databases to ensure the privacy of their data. However, the parameters of the machine learning model, which is improved using their data, may be shared without compromising the confidentiality of the private data.

5.2 Robot hardware components

Robot hardware in the context of AI encompasses the tangible elements and structures that constitute robotic platforms. These components are combined with artificial intelligence methodologies to empower robots with the ability to perceive, analyze, execute actions, and engage with their surroundings. The following are essential facets of robot hardware in AI:

1. **Sensors**:

Sensors are essential elements of robot hardware that allow robots to detect and understand their surroundings. Different types of sensors are utilized, including:

Vision sensors, including cameras, LiDAR, depth sensors, and RGB-D cameras, are used to perceive visual information. They are utilized for activities such as detecting objects, determining location, creating maps, and navigating.

•**Range Sensors**: Sonar, ultrasonic sensors, and laser rangefinders are used to calculate distances to objects in close proximity, which helps in detecting and avoiding obstacles.

• **Tactile Sensors**: Force-sensitive resistors, pressure sensors, and tactile arrays are utilized to offer tactile feedback for the purpose of grabbing, manipulating, and interacting with items.

2. Actuators:

Actuators are mechanical devices that are responsible for regulating the motion and manipulation of robot hardware. Some commonly used types of actuators include:

Electric motors, including DC motors, stepper motors, and servo motors, are used to power wheels, joints, and manipulators. They enable movement and manipulation.

Hydraulic actuators, such as hydraulic cylinders and pumps, utilize pressured fluid to provide powerful motion for demanding tasks like industrial automation and construction.

Shape Memory Alloys (SMAs) are materials that undergo a change in shape when exposed to temperature variations. They are used to create compact and lightweight mechanisms for small-scale robotics applications.

3. **Embedded Systems**:

Embedded systems provide the computing capacity and supervision required for the real-time functioning of robot hardware. These systems commonly encompass:

Microcontrollers, such as Arduino, Raspberry Pi, and BeagleBone, offer the necessary computing power and input/output capabilities to operate sensors, actuators, and peripherals.

High-performance microprocessors, such as ARM and Intel CPUs, are utilized for intricate calculations, encompassing perception, planning, and decision-making.

• Firmware and Real-Time Operating Systems (RTOS) provide the prompt and predictable execution of control algorithms, sensor data processing, and communication duties.

4. **Power Systems**:

Power systems supply the necessary energy to run the hardware of the robot. These systems encompass:

Power distribution systems are responsible for regulating the flow of electrical power to different parts of the robot, ensuring that it is used efficiently and safely.

Power management systems employ several strategies, including power gating, voltage regulation, and energy harvesting, to optimize energy usage and prolong battery life.

5. Mechanical Structures: Mechanical structures serve as the tangible framework and give support for the physical components of a robot. These structures encompass:

Frames and chassis serve the purpose of providing the essential structural integrity and stiffness to support sensors, actuators, and other components.

•Joints and linkages provide articulation and movement in robot manipulators, legs, and other moveable components.

•End Effectors: End effectors, such as grippers, suction cups, and tool attachments, enable robots to engage with things and carry out tasks.

5.3 Robotic perception:

The following are essential elements and methodologies involved in robotic perception:

1. Sensors: Robots are outfitted with a variety of sensors to gather data about their immediate environment. The sensors can encompass the following:

• Optical sensors used for detecting and interpreting visual information.

Cameras record visual data, enabling robots to recognize objects, forms, colors, and motions in their surroundings.

• Sensors used to measure the distance or range between an object and the sensor itself.

LiDAR and radar sensors utilize distance measurement techniques to enable robots to generate three-dimensional maps, identify barriers, and maneuver through various surroundings.

• **Proximity sensors:**

Ultrasonic sensors, infrared sensors, and capacitive sensors are utilized to identify the existence or closeness of objects, hence assisting in the avoidance of obstacles and navigation.

• **Tactile sensors:**

Pressure sensors, force sensors, and tactile arrays offer information about touch and contact with things, allowing robots to securely hold objects and handle them with accuracy.

•**Additional sensors:**

Gyroscopes, accelerometers, encoders, and GPS sensors offer data on orientation, motion, and position, which assist in navigation and localization.

2. Extraction of Features:

After gathering sensor data, robotic perception systems employ artificial intelligence approaches to extract pertinent characteristics from the unprocessed sensor data. This process entails utilizing preprocessing, filtering, and feature extraction algorithms that are customized to the particular sensor modality and application.

4. Integration of Sensor Data:

Fusion approaches amalgamate data from many sensor modalities, including visual, range, and inertial sensors, to enhance the dependability, resilience, and precision of perception.

5. **Cartography and Position Determination:**

Simultaneous Localization and Mapping (SLAM) techniques integrate mapping and localization in real-time.

6**. Object Recognition and Scene Understanding:**

AI algorithms empower robots to identify things, comprehend their characteristics and qualities, and deduce more advanced knowledge about the environment. This encompasses activities like object identification, semantic segmentation, object tracking, and contextually-aware reasoning.

7**. Mechanisms for directing attention:**

Attention mechanisms emulate human attention by allocating computing resources to pertinent sections of the sensor data or surroundings. These mechanisms empower robots to prioritize significant information, eliminate irrelevant data, and adjust their perception according to job demands and circumstances.

Equity and prejudice

Machine learning is enhancing and substituting human decision-making in some scenarios.

which loan is authorized,

Who is eligible for pretrial release or parole?

However, machine learning models have the potential to sustain and reinforce social prejudice.

Let's examine an algorithm that aims to forecast the likelihood of criminal defendants re-offending, and consequently, whether they should be released prior to trial. It is possible that this system may inadvertently learn and replicate the racial or gender biases exhibited by human judges in the training data. Therefore, designers of machine learning systems bear a moral obligation to ensure that their systems are impartial and just.

However, what precisely constitutes fairness?

There are several criteria, and here are six of the most frequently employed concepts:

Individual equity:

An essential condition that necessitates persons to be treated equitably, irrespective of their social status.

Full group fairness:

An essential condition that mandates the equitable treatment of two classes, as assessed using a certain summary metric.

Equity by lack of knowledge:

Remove the race and gender characteristics from the dataset to prevent the system from making discriminatory judgments based solely on those attributes. However, machine learning models can still infer latent variables like race and gender based on other correlated variables such as zip code and occupation. Despite this, certain countries like Germany opt for this approach in their demographic statistics, regardless of whether or not machine learning models are utilized.

Equitable results:

Demographic parity is achieved when each demographic class has identical outcomes.

Consider the scenario where we need to determine whether to approve loan applications. The objective is to approve applicants who will repay the loan and reject those who will default. Demographic parity states that both males and females should have an equal proportion of approved loans. It is important to note that this criterion focuses on fairness at a group level and does not guarantee fairness at an individual level. Consequently, a highly qualified applicant may be denied while a poorly qualified applicant may be approved, as long as the overall proportions remain equal. Additionally, this approach prioritizes correcting past biases rather than ensuring accurate predictions.

If a man and a woman possess identical qualifications and abilities, with the sole exception that the woman obtains a reduced wage for performing the same work, should she be granted approval due to the recognition that historical prejudices have prevented her from being really equal, or should she be prohibited on the basis that the lower compensation increases the likelihood of her defaulting?

Equal opportunity:

The concept of ensuring equal opportunity for accurate classification of loan repayment ability, regardless of gender, is known as "balance." However, this approach can result in unequal outcomes and fails to consider the influence of bias in the societal processes that generated the training data.

EQUALLY SIGNIFICANT EFFECT:

Individuals with comparable repayment probabilities should possess equivalent anticipated utility, irrespective of their social classification. This concept extends beyond mere equal opportunity by taking into account the advantages of accurate predictions as well as the drawbacks of erroneous predictions.

In a specific context, we can demonstrate how these problems manifest. COMPASS is a commercial system that calculates the likelihood of a person re-offending, known as recidivism scoring. This system assigns a risk score to a defendant in a criminal case, which is then used by a judge to assist in making decisions. These decisions include determining whether it is safe to release the defendant before trial or if they should be kept in jail. Additionally, the system helps determine the length of the sentence if the defendant is convicted and whether parole should be granted. Due to the importance of these decisions, the system has faced intense scrutiny (Dressel and Farid, 2018).

COMPAS is specifically intended to have accurate calibration.

The system should ensure that those who receive the same score are equally likely to re-offend, regardless of their race.

For instance, when the model assigns a risk score of 7 out of 10 to individuals, 60% of white people and 61% of black people are found to re-offend. Therefore, the creators assert that the approach fulfills the intended fairness objective.

Let us analyze how these matters unfold in a specific setting. COMPASS is a commercial system utilized for assessing the likelihood of a defendant reoffending or violating the law. It assigns a risk score to a defendant involved in a criminal case, which is subsequently utilized by a judge to aid in decision-making: Is it secure to release the defendant prior to the trial, or should they be detained in jail? If found guilty, what should be the duration of their sentence?

It is unattainable to have an algorithm that is both well calibrated and equal opportunity. If the base classes differ, any highly calibrated algorithm would inevitably not ensure equal opportunity, and vice versa.

What is the method for evaluating the relative importance of the two criteria?

Equally significant consequences are a potential outcome.

When considering COMPAS, the process involves evaluating the potential harm caused by incorrectly categorizing defendants as high risk and depriving them of their freedom, compared to the societal cost of an extra crime being committed. The goal is to determine the optimal balance between these factors.

The complexity arises from the need to take into account various expenses.

There are distinct expenses incurred by individuals in the criminal justice system. For instance, a defendant who is unjustly detained in jail experiences a detriment, same as the victim of a defendant who is mistakenly freed and commits another offense.

Collective expenses—there is a common concern among individuals that they may be unjustly imprisoned or become victims of crimes, and all taxpayers contribute to the expenses associated with prisons and courts. If we assign significance to these concerns and expenses based on the size of a group, the well-being of the majority may be prioritized over that of a minority.

One issue with the concept of recidivism score, regardless of the model employed, is the lack of unbiased ground truth data. The available data does not provide information on who has really committed a crime; it only indicates who has been officially convicted of a crime.

If there is bias among the arresting officers, judge, or jury, then the data will also be biased. Similarly, if certain locations are subject to increased police patrol, the data will be biased against the people in those locations. It is important to note that only defendants who are released have the potential to recommit, so if the judges responsible for making release decisions are biased, the data may be biased as well.

If one postulates the existence of a concealed, unprejudiced data set underlying the partiality of the given data set, which has been tampered with by a biased agent, there exist methods to retrieve an estimation of the impartial data. Jiang and Nachum (2019) elucidate different scenarios and the associated methodologies.

Another potential risk is the use of machine learning to rationalize bias. In situations where biased individuals consult a machine learning system to make decisions, they may use the system's interpretation to defend their choices and discourage any questioning. However, alternative interpretations of the system could lead to completely different decisions. In certain cases, ensuring fairness may require reevaluating the objective function rather than focusing solely on the data or algorithm.

For instance, while making job recruiting decisions, if the goal is to select people with the most exceptional qualifications, there is a potential to unjustly favor individuals who have had privileged educational opportunities throughout their lives, thereby perpetuating social class divisions.

However, if the goal is to recruit individuals who possess exceptional aptitude for learning while on the job, we increase our likelihood of transcending social class barriers and selecting from a more extensive range of candidates. Numerous companies have implemented initiatives tailored for such applicants and have discovered that, following a year of training, employees hired through this approach perform equally well compared to conventional candidates.

In the United States, only 18% of computer science graduates are women. However, certain institutions, like Harvey Mudd University, have successfully achieved a 50% gender balance by implementing a strategy that emphasizes the encouragement and retention of students who enter the computer science program, particularly those with limited programming background.

One additional complexity involves determining which classes merit safeguarding.

The Fair Housing Act in the United States acknowledges seven distinct protected categories, which include race, color, religion, national origin, gender, handicap, and family status.

Additional municipal, state, and federal regulations acknowledge several categories, such as pregnant, married, and veteran status.

Is it equitable that certain classifications are considered valid for certain laws but not for others?

International human rights legislation, which incorporates a wide range of protected categories, offers a potential foundation for aligning safeguards across different populations.

Even without societal bias, differences in sample size can result in biased outcomes. Typically, data sets have fewer training examples of minority class individuals compared to majority class individuals. Machine learning algorithms achieve higher accuracy with larger training data, which means that individuals from minority classes will have lower accuracy.

As an illustration, Buolamwini and Gebru (2018) conducted a study on a computer vision system designed to identify gender. They discovered that the system achieved almost flawless accuracy in identifying light-skinned men, but had a 33% mistake rate when it came to identifying dark-skinned females.

A constrained model may face difficulties in fitting both the majority and minority class simultaneously. For instance, a linear regression model may prioritize minimizing average error by fitting only the majority class. Similarly, in an SVM model, the support vectors may predominantly correspond to members of the majority class. Bias can also be a factor in the software development process, regardless of whether or not the software incorporates machine learning.

Engineers debugging a system are more inclined to identify and resolve issues that directly pertain to their own circumstances. For instance, it is challenging to recognize that a user interface design is not suitable for individuals with color blindness unless one is colorblind themselves, or to identify flaws in an Urdu language translation without proficiency in Urdu.

What strategies to defend against these biases?

Prioritize understanding the limitations of the data being utilized. It has been proposed that data sets (Gebru et al., 2018; Hind et al., 2018) and models (Mitchell et al., 2019) should be accompanied by annotations, which include declarations regarding their origin, security, compliance, and suitability for use. This is akin to the data sheets that accompany electronic components like resistors, enabling designers to make informed decisions about their usage. In addition to these data sheets, it is crucial to provide comprehensive training to engineers, both during their education and on-the-job, regarding issues of fairness and bias. Having a diverse group of engineers from various backgrounds facilitates the identification of problems in the data or models. A study conducted by the AI Now Institute (West et al., 2019) revealed that only 18% of authors at prominent AI conferences and 20% of AI professors are women.

Less than 4% of AI workers are Black, and the rates are similar in industry research labs. To increase diversity, programs should be implemented earlier in the pipeline, such as in college or high school, and there should be greater awareness at the professional level. Joy Buolamwini established the Algorithmic Justice League to bring attention to this problem and create measures for accountability.

Another approach is to mitigate bias in the data by employing techniques such as over-sampling from minority classes. This can help address the issue of imbalanced sample sizes. Notable methods for over-sampling include SMOTE (Synthetic Minority Over-Sampling Technique) proposed by Chawla et al. in 2002, and ADASYN (adaptive synthetic sampling approach for imbalanced learning) introduced by He et al. in 2008. These techniques offer systematic and principled ways to increase the representation of minority classes.

An analysis of the data's origin could be conducted to identify and exclude instances where judges with a history of bias were involved. While some analysts oppose the notion of discarding data, they propose constructing a hierarchical model that incorporates sources of bias, allowing for their modeling and compensation.

Google and NeurIPS have endeavored to increase awareness of this matter by supporting the Inclusive photos Competition. In this competition, participants train a neural network using a dataset of labeled photos gathered from North America and Europe, and subsequently evaluate its performance using images sourced from other regions throughout the globe.

The problem lies in the fact that while it is simple to assign the label "bride" to a lady wearing a typical Western wedding gown based on this dataset, it is more challenging to identify traditional African and Indian wedding attire.

Another suggestion is to develop novel machine learning models and algorithms that exhibit more resilience towards bias.

The ultimate concept involves utilizing a system to generate preliminary suggestions that may possess bias, then subsequently training a second system to rectify and eliminate the biased nature of the first recommendations.

In their 2018 publication, Bellamy et al. unveiled the IBM AI FAIRNESS 360 system, which offers a comprehensive framework including these concepts. It is anticipated that tools of this nature will experience more utilization in the coming years.

How can you ensure the equity of the systems you construct? A collection of optimal methodologies has been developing (although adherence to them is not always consistent):

Ensure that the software engineers engage in discussions with social scientists and domain specialists to comprehend the problems and viewpoints, and prioritize fairness from the beginning.

Establish an atmosphere that promotes the growth of a varied group of software engineers that accurately reflect the composition of society.

Specify the target user groups that your system will accommodate, such as individuals who speak different languages, individuals of various age groups, and those with varying levels of sight and hearing skills. Optimize the system's performance based on an objective function that includes considerations of justice.

Analyze your data to identify any instances of bias and to see if there are any connections between protected attributes and other attributes.

Gain a comprehensive understanding of the process of human data annotation, establish specific objectives to ensure accurate annotation, and check the achievement of these objectives.

Ensure that you not only monitor general metrics for your system, but also measure data specifically for subgroups that may be subject to bias.

Incorporate system testing that accurately represent the user experience of minority groups.

Implement a feedback loop to promptly address any issues related to fairness.

Trust and Transparency or Confidence and openness

Ensuring the accuracy, fairness, safety, and security of an AI system is a challenging task. However, an equally challenging task is to persuade others that these qualities have indeed been achieved. It is crucial for people to have confidence in the systems they rely on. According to a 2017 survey conducted by PwC, 76% of businesses were hesitant to embrace AI due to concerns about its trustworthiness. To establish trust, it is imperative for any engineered systems to undergo a rigorous verification and validation (V&V) process.

Verification refers to the process of confirming that the product meets the specified requirements.

Validation refers to the process of verifying that the specifications effectively fulfill the requirements of the user and other relevant parties.

We have a comprehensive Verification and Validation (V&V) methodology that is applicable to engineering and traditional software development carried out by human programmers. Much of this methodology can also be applied to AI systems. However, machine learning systems require a distinct V&V process that is still being developed. It is crucial to verify the data used by these systems, ensure the accuracy and fairness of the outcomes, even in the presence of uncertainties that prevent exact results, and confirm that adversaries cannot unduly influence the model or extract information through queries. Certification is one way to establish trust. For instance, Underwriters Laboratories (UL), established in 1894 when consumers

were concerned about the risks of electric power, provided UL certification for appliances, which increased consumer trust. UL is now considering expanding its business to include testing and certification for AI products.

Various industries adhere to safety regulations. As one illustration,

ISO 26262 is a globally recognized standard that outlines the guidelines for ensuring the safety of automobiles throughout their development, production, operation, and servicing. In contrast, the AI sector has not yet achieved a similar degree of clarity, but there are ongoing efforts to establish frameworks.

The IEEE P7001 standard establishes guidelines for the ethical design of artificial intelligence and autonomous systems.

There is a current dispute on the type of certification required and the level of involvement by different entities such as the government, professional organizations like IEEE, independent certifiers like UL, or self-regulation by product businesses.

Transparency is another important element of trust. Consumers desire to have a clear understanding of the inner workings of a system and to be certain that the system is not acting against their interests, either via deliberate harm or unintentional actions.

An unintentional software glitch or widespread societal prejudice that is replicated by the system. In certain instances, this transparency is provided directly to the consumer. In other cases, intellectual property concerns prevent certain aspects of the system from being disclosed to consumers, but they are accessible to regulators and certification agencies. When an AI system denies you a loan, you are entitled to an explanation. In Europe, the General Data Protection Regulation (GDPR) ensures this right for you.

Explainable AI (XAI) refers to an artificial intelligence system that possesses the ability to provide explanations for its actions or decisions.

An effective explanation possesses several characteristics: it must be comprehensible and persuasive to the user, it must accurately represent the system's reasoning, it must be comprehensive, and it must be tailored to the individual circumstances or outcomes of different users.

Enabling a decision algorithm to access its own deliberative processes can be easily achieved by recording and storing them as data structures. This has the potential to allow machines to provide more comprehensive explanations for their decisions compared to humans. Additionally, we can implement measures to ensure that the machine's explanations are not deceptive, which is a more challenging task when dealing with humans. However, it is important to note that explanations alone are not enough to establish trust, as they are merely narratives about decisions rather than the decisions themselves.

A system is considered interpretable if we are able to examine the source code of the model and understand its operations. On the other hand, a system is deemed explainable if we can create a narrative about its functioning, even if the system itself is an opaque entity.

In order to elucidate an inscrutable black box, it is necessary to construct, rectify, and evaluate a distinct explication mechanism, ensuring its alignment with the original system. Furthermore, due to the innate human inclination towards narratives, we are readily susceptible to being influenced by a plausible explanation. This phenomenon is evident in contemporary political controversies, where contradictory explanations, each internally coherent, can be observed.

A final issue is that an explanation about one case does not give you a summary over other cases. If the bank explains, “Sorry, you didn’t get the loan because you have a history of previous financial problems,” you don’t know if that explanation is accurate or if the bank is secretly biased against you for some reason. In this case, you require not just an explanation, but also an audit of past decisions, with aggregated statistics across various demographic groups, to see if their approval rates are balanced. Toby Walsh (2015) proposed that “an autonomous system should be designed so that it is unlikely to be mistaken for anything besides an autonomous system, and should identify itself at the start of any interaction.” The legislation passed in California in 2019, known as the "red flag" law, draws inspiration from the UK's 1865 Locomotive Act, which mandated that any motorized vehicle be preceded by a person carrying a red flag to warn of its approach. This Californian law makes it illegal for individuals to employ a bot to engage with another person online in California, with the intention of deceiving them about its artificial nature.

Alternate Robotic Frameworks:

There are several other frameworks for robotics, with 5.4 being one among them.

Besides conventional robotic frameworks, there exist various alternative approaches and frameworks that combine artificial intelligence (AI) techniques with robotics. These alternative frameworks utilize advanced AI algorithms and methodologies to augment the perception, decision-making, learning, and interaction abilities of robots, thereby enabling intelligent behavior and autonomy in robotic systems. Here are a few noteworthy alternative robotic frameworks in AI:

1. Reactive Robotics:

Reactive robotics prioritizes the utilization of behavior-based control architectures, in which robots respond directly to sensory inputs and carry out pre-established behaviors without explicit planning or reasoning. This approach allows for quick and resilient reactions to changing environments and is well-suited for tasks such as avoiding obstacles, navigating, and reacting to manipulation.

2. Hybrid Control Architectures:

Hybrid control architectures integrate reactive control with deliberative planning and reasoning components. This integration allows robots to alternate between reactive behaviors and higher-level planning, depending on the specific task demands and environmental circumstances. Notable examples of such architectures include subsumption architectures and behavior trees.

3. Neuro-Robotics:

Neuro-robotics combines neuroscience and artificial neural networks with robotics to create robot control systems that are inspired by biology. By using neural networks, robots can simulate sensory processing, motor control, and learning mechanisms, allowing them to display adaptive and lifelike behaviors. This approach is especially useful for tasks that require complex sensorimotor abilities and learning from past experiences.

4. Embodied AI refers to artificial intelligence systems that are physically present and capable of interacting with the environment.

Embodied AI is concerned with the creation of robotic systems that are integrated into and engage with real-world surroundings. These embodied agents, such as robots, acquire knowledge through physical interaction and sensorimotor experience, resulting in well-grounded and contextually detailed representations of information. Embodied AI methods frequently involve a combination of sensorimotor learning, reinforcement learning, and developmental learning techniques.

5. The field of cognitive robotics:

Cognitive robotics seeks to equip robots with cognitive abilities, such as perception, memory, reasoning, and learning, which are inspired by human cognition. To achieve this, cognitive architectures and models, such as Soar, ACT-R, and SPA (Semantic Pointer Architecture), are utilized. These models are employed to create robots capable of executing intricate cognitive tasks, comprehending natural language, and engaging with humans in intuitive manners.

6. Evolutionary Robotics:

Evolutionary robotics utilizes evolutionary algorithms, such as genetic algorithms and genetic programming, to autonomously create and enhance robot controllers and physical structures. Robots are viewed as populations of artificial organisms that evolve through fitness-based selection, leading to the development of behaviors and structures. This methodology allows robots to adapt and evolve in various environmental conditions and tasks.

7. Robot Learning from Demonstration (LfD):

Learning from Demonstration (LfD) frameworks empower robots to acquire intricate tasks and behaviors by analyzing demonstrations given by humans or other entities. Approaches like imitation learning, apprenticeship learning, and inverse reinforcement learning are employed to deduce task objectives, action policies, and reward functions from observed demonstrations, thereby facilitating streamlined and intuitive interaction between humans and robots.

8. Distributed Robotics:

Distributed robotics is the study of how to coordinate and control groups of independent robots to achieve common goals. This field utilizes artificial intelligence techniques, such as decentralized decision-making, swarm intelligence, and modeling collective behavior, to enable collaboration, coordination, and self-organization among the robot agents. Some applications of distributed robotics include swarm robotics, multi-robot exploration, and distributed sensing.

5.5 Areas of application or Application Domains:

• Prediction of energy use or production levels in the future.

Artificial intelligence models utilize predictive algorithms to improve energy production and distribution by forecasting energy demand, renewable energy output, and market pricing.

• Energy Optimization:

AI-driven systems oversee energy usage, detect possibilities for energy conservation, and optimize building operations to minimize energy consumption.

7. Agriculture:

• Agricultural technology that focuses on maximizing efficiency and accuracy in farming practices.

Artificial intelligence (AI) technology, like as drones, sensors, and Internet of Things (IoT) devices, are used to observe and assess the condition of crops, improve the efficiency of watering, and reduce the amount of pesticides used in order to promote sustainable agriculture.

• Agricultural surveillance:

Artificial intelligence (AI) utilizes satellite photos and sensor data to evaluate the state of crops, forecast agricultural yields, and identify illnesses or pests.

• Optimization of the supply chain:

Artificial intelligence enhances the efficiency and minimizes waste in logistics, storage, and distribution activities within the agricultural supply chain.

AI Safety

Any technology, including AI and robotics, has the potential to be harmful when misused. However, there is an added layer of concern with AI and robotics because these technologies can operate independently. Numerous science fiction stories have warned about the dangers of robotics or cyborgs turning against humanity. Early examples include Mary Shelley's "Frankenstein, or the Modern Prometheus" (1818) and Karel Čapek's play "R.U.R." (1920), where robots rebel and dominate over humans. In movies like "The Terminator" (1984) and "The Matrix" (1999), we witness robots attempting to annihilate humans, a scenario often referred to as the robopocalypse (Wilson, 2011).

Robots are often depicted as villains because they represent the unknown, much like witches and ghosts in old stories. However, a robot that is intelligent enough to consider exterminating the human race would also be intelligent enough to understand that such an action goes against its intended purpose. Nonetheless, when creating intelligent systems, relying solely on hope is insufficient; instead, we require a design process that guarantees safety. It would be unethical to deploy an AI agent that is not safe. We expect our agents to prevent accidents, withstand attacks from adversaries and malicious misuse, and overall, contribute to benefits rather than causing harm. This is particularly crucial as AI agents are used in applications that involve safety, such as autonomous vehicles, controlling robots in dangerous environments, and making life-or-death medical decisions. Traditional engineering disciplines, such as safety engineering, are essential in this regard.

We have established methods for constructing bridges, airplanes, spacecraft, and power plants that are engineered from the outset to behave safely in the case of component failures. One such technique is failure modes and effects analysis (FMEA), where analysts assess each system component, considering every possible failure scenario and its potential consequences. Drawing on past experiences and physical properties of the components, analysts then devise mitigation strategies. For example, adding additional cross-members to a bridge can ensure its stability even if some bolts fail, or deploying backup servers can ensure service continuity of a primary server failure. The technique of fault tree analysis (FTA) is used to make these determinations: analysts build an AND/OR tree of possible failures and assign probabilities to each root cause, allowing for calculations of overall failure probability. These techniques can and should be applied to all safety-critical engineered systems, including AI system

The objective of software engineering is to create dependable software, however historically the focus has been on accuracy rather than safety.

Correctness refers to the faithful implementation of the software according to the given specification. Safety, on the other hand, goes beyond correctness by ensuring that the specification takes into account all possible failure modes and is designed to handle them gracefully, even in the event of unforeseen failures. For instance, in the case of a self-driving car, it would not be considered safe unless it can handle unusual situations. For example, if the power to the main computer fails, a safe system would have a backup computer with a separate power supply. Similarly, if a tire gets punctured at high speed, a safe system would have been tested for this scenario and would have software in place to correct for the resulting loss of control.

END

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