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Chapter 1: Introduction to Predictive Autonomy

1.1. Overview of Predictive Autonomy

Predictive autonomy enables intelligent systems to reason about future states and jointly optimize current and future behavior. The ability to predict is a natural and fundamental part of autonomous behavior celebrated by philosophers for centuries. In the context of physical machines, present actions have future consequences that determine the success of the mission. Unless these consequences can be reasoned about, an autonomous system cannot be expected to act intelligently.

Predictive autonomy is imparted to a machine through predictive sensors, predictive data processing, and predictive architecture. Predictive sensors feed a machine an environment state that has been transformed forward through time, predictive data processing transforms the state of the environment and itself as measured at an instant in time, and predictive architecture possesses an internal configuration that codes all knowledge necessary for prediction-based autonomy.

1.1.1. Introduction to Predictive Autonomy

The term predictive autonomy refers to the capacity of artificial agents or systems, including both software and physical devices, to make predictions and adjust behavior based on those predictions. When implemented well, such agents can exhibit intelligence, integrating models of the world, inference engines, and learning mechanisms. Exact formal definitions of intelligence remain elusive, presenting an ongoing challenge in disciplines like cognition, philosophy, psychology, and artificial intelligence. Predictive autonomy represents a practical approach to addressing the core components of intelligence — prediction, adaption, and selection among alternatives in the pursuit of goals.

History is witness to the gradual introduction of autonomy first in manufacturing, subsequently in defense, astronomy, developing imagery, surveillance, and reconnaissance in several other domains like healthcare and finance. The interaction of high-capacity sensors with various devices including mobile phones, tablets, laptops, autonomous cars, plants, and others associated with the Internet of Things (IoT) results in a vast exchange of information along with definitions that range from the descriptive to the prescriptive. A special group of algorithms — those concerned with machine learning — provide agents with the ability to refine behavior based on experience.

1.2. Historical Context

Predictive Autonomy emerged when experts observed that predictive abilities were a natural extension of autonomous systems in various applications. The concept extends autonomy in a way that it can anticipate events and takes proactive measures accordingly. Historically, many technologies were developed with autonomy in mind, in other words, these technologies were focused on making autonomous predictions by considering and analysing past events. The more developments were made in the domain of artificial intelligence, robotics and internet of things, the more experts realized that it is possible not only to make predictions on the decision on course of action, but it is also possible to anticipate over all events which can take place in future [1,2,3]. Ericsson defines predictive autonomy as existing at the intersection of predictive artificial intelligence (AI), internet of things (IoT) and autonomy. Predictive autonomy enables the creation and management of systems of systems with a high level of autonomy. Machine sets—complex and intelligent systems embedded in the physical world, including autonomous vehicles, robots, drones, smart navigation for city infrastructure, and power grids—can perform intended tasks with a high degree of automation without intervention from humans or others. The degree of autonomy denotes how well interactions between machines, the environment and humans can be handled in fulfilling those tasks. A machine with a high degree of autonomy can understand a vast complex of parameters influencing both internal and external situations and even predict how those might evolve in the future.

The ability to understand present and future situations, the ability to take the best possible decision on possible actions proactively or past events is predictive at its core. Predictive autonomy looks at advanced sensor fusion, data processing models and machine-learning algorithms able to analyse the internal situations and performance parameters of a machine in the context of the environment. It enables the shift from present situation awareness to the ability to predict future situations, possible events and required actions, based on a continuously changing context. Application of these principles is visible in different use cases requiring different types of machine learning algorithms, such as reinforcement learning, supervised learning and unsupervised learning.

1.2.1. Evolution of Predictive Autonomy Through the Ages

The role of prediction in autonomous systems has been, and continues to be, one of the most studied topics in Artificial Intelligence and Robotics. Until now, predictive autonomy has been limited to specific instances of robotic technologies—such as autonomous vehicles, autonomous guidance of flying and underwater robots, and security systems—and other sectors, including finance and insurance. Yet the ability to anticipate possible future scenarios and react with actions that prevent them from reaching unfeasible or dangerous states lies at the basis of Natural Intelligence and, hence, is essential for achieving Robotic Intelligence.

Fig 1 . 1 : Predictive Autonomy and Robotic Intelligence Diagram

Today, the increasing availability of sensors, the rapid growth in the use of data, advances in onboard data processing, and the maturation of new generations of AI architectures make the implementation of Predictive Autonomy a reality. Supervised, unsupervised, and reinforcement learning constitute the core of the Machine Learning family of algorithms capable of endowing autonomous systems with predictive abilities applicable across a wide range of tasks. This development allows for the evolution of prediction from a supporting role to a pivotal part of Autonomous Systems. An appropriate description of models, algorithms, and applications in the field of Predictive Autonomy during the last decades provides a clear picture of its current state and future trends.

1.3. Key Concepts in Predictive Autonomy

Predictive autonomy stems from the integration of complex sensors, unattended data processing, and advanced machine-learning (ML) algorithms. The core idea is enabling a system to autonomously enact programs ahead of actual events. Like most ML, predictive autonomy is approached through supervised, unsupervised, and reinforcement algorithms, the last including Markov Decision Process (MDP) and partially observable MDP (POMDP).

In the robotics domain, predictive autonomy is closely related to predictive intelligence, a sub-domain of artificial intelligence (AI) focused on prediction and reasoning, as well as to predictive analytics that autonomously forecast future events. Similarly, in the field of autonomous cars, predictive autonomy considers not only the car itself but also the context and condition around it, enabling autonomous vehicles to plan ahead.

1.3.1. Fundamental Principles of Predictive Autonomy

Predictive autonomy applies ideas from predictive processing within the cognition sciences to robotics and control. In the field of predictive processing, the brain is conceived as a control system that actively controls the environment rather than the body. Unpredicted events—termed surprisal and quantifiable as the negative log probability of an event—are inherently threatening both to the system and its homeostasis. Ideally,organisms seek to minimise the long-term average surprisal of their sensorimotor trajectories, an idea know as free-energy minimisation. It is generally impossible to calculate surprisal directly, but the free energy principle states that surprisal can be minimised indirectly through minimising a free energy bound on surprisal. Predictive autonomy extends these models from cognition to encompass adaptive behaviour and control.'

Robots and autonomous control systems such as self-driving vehicles aim to be increasingly autonomous, responsive and intelligent by predicting future states and responses [4,5,6]. By integrating artificial intelligence (AI) with robotics, learning algorithms enable robots and controllers to learn behaviors based on experience without being closely programmed, which both speeds up design and engineering and also enables more complex behaviors. Reinforcement learning trains robots to understand the results of their own actions via trial-and-error, supervised learning methods learn behavior mapping from recorded training data (a demonstration), and unsupervised learning methods learn to discover latent structure in data. Sensory systems collect data about the state of the system and its environment and a processing stage extracts significant features from that data. These features form the input to an AI architecture that generates behavioral responses that are converted into actuator commands.

1.4. Technological Foundations

The technological foundations of predictive autonomy include sensors, data processing, and AI architectures. Sensors are devices that detect and respond to input from the physical environment, such as light, heat, motion, moisture, pressure, or any one of a great number of other environmental phenomena. Predictive autonomy depends on the object‟s ability to respond dynamically to events and environmental cues as they arise. For example, an object might be communicating data about itself and its environment, thus helping to generate the models that inform its decisions (e.g., results of sensor processing or status reports). The development of the Internet of Things (IoT) will further accelerate the rate of change in this area of society.

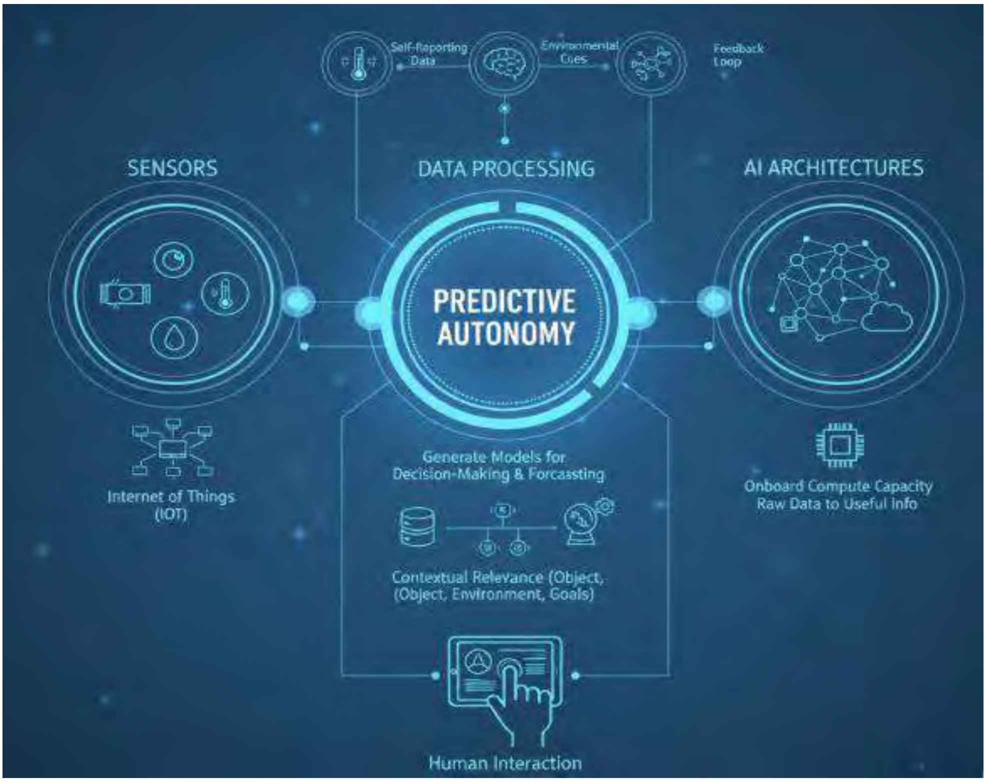

Fig 1 . 2 : Technological Foundations of Predictive Autonomy

Data processing is the act of handling information. An autonomous object uses information to generate models used for decision-making and forecasting. What is relevant and important is a function of multiple factors, including the object‟s characteristics (size, shape, type, function), the environment (circumstances, context, and place), and the system‟s current goals and objectives. Consequently, the information that must be sensed and passed around will differ depending on these variables. Different objects will therefore perform different levels of data handling and will have varying levels of connectivity with one another. An autonomous object should include not only the sensing and communications devices, but also the compute capacity needed to process and transform the raw data into useful information. The system will also require the ability to provide feedback, and it should permit direct human interaction when necessary

1.4.1. Core Technologies Enabling Predictive Autonomy

Predictive autonomy is the capability of a system to make decisions and reach goals based on predictions about its environment. It requires a system to have real-time awareness of the environment as well as deep historical knowledge through a wide array of sources. The system must apply foresight to the interactions within the environment as well as the cause and effect of the decisions made by other actors in the environment. Foresight enables the system to prioritize contingencies in the future that optimally meet its objectives.

In the later sections, the fundamental capabilities required for predictive autonomy include continuous and comprehensive situational awareness (both internal and external), alongside world state models that offer historical, current, and predictive understanding of the environment. Continuous awareness demands a wide array of sensing devices both internal and external, connected to high-throughput, low-latency data transfer systems. World state models require substantial data archives for training models predicting the future in support of association and reasoning capabilities. Machine learning algorithms are the linchpin of predictive autonomy; a wide variety of algorithms can be broadly grouped into three categories: Supervised, unsupervised, and reinforcement.

1.5. Machine Learning Algorithms

The term "predictive autonomy" refers to artificially intelligent systems capable of making decisions independently of human intervention. In contrast to traditional automation—which often operates according to fixed instructions or established rules—

predictive autonomy uses past data to forecast future outcomes. These predictions help the system choose optimal actions in pursuit of predetermined goals.

The core of predictive autonomy comprises three types of predictive machine-learning algorithms: supervised learning, unsupervised learning, and reinforcement learning. Supervised and unsupervised learning analyze historical data to forecast future states. These predictions can, in turn, guide higher-level reinforcement learning agents.

1.5.1. Supervised Learning

Supervised learning refers to machine learning algorithms that employ a training set containing input data that are "labeled" with the correct or expected output. This labeled data set guides the algorithm in producing an accurate output for corresponding inputs in the future. The machine-internal representation or model that serves as the basis for these predictions is typically trained and assessed using sets of labeled input-output examples [2,4,6]. Supervised learning is well-suited for scenarios in which the desired data characteristics and the conditions under which they should emerge are understood and formally quantifiable.

Input Data is "LABELED"
with correct output.
Algortthm leams from
examples to predicrfutre output
outputs. Ideal for
quantintable scenarios.

Discovers hidden
structures/features in
UNABELED data.
No preefined target features.
Used Used orr clustring &
pattern detection.

Learns by evalutieg
CONSEQUENCES of actions.
Optimizes behavior
through rewards & penalitys.
Focuss on goal-driven
trial & error.

Fig 1 . 3 : Machine Learning Approaches for Predictive Autonomy

In contrast, unsupervised learning is applied when it is difficult to specify the target features beforehand, for example when its goal is to discover hidden structures or features in unlabeled, unclassified, or otherwise un-annotated data. Reinforcement learning is driven by the repeated evaluation and optimization of the consequences of actions rather than the actions themselves. Predictive autonomy algorithms fall into all three categories: supervised, unsupervised, and reinforcement learning. These core machine learning approaches underpin a wide range of systems designed for preemptive and predictive control of complex technological and organizational processes.

1.5.2. Unsupervised Learning

Unsupervised learning requires no (or barely any) labelled data. It deals with unlabelled data, extracts meaningful features, clusters the data and finally reduces the dimension. This learning mechanism partially resembles how babies discover shapes and objects. Given the input, the algorithm tries to find similarities in it and group the data into clusters. In the output, similar objects are located close together, while different objects are located far apart. It often uses mathematical tricks to reduce the dimension at the same time, instead of having many features it only uses some feature values to distinguish one from the other.

Dimensionality reduction transforms the attributes from a dataset into a lower dimension, which preserves the data characteristics. The most common method is the principal component analysis. This algorithm locates those dimensions which contain the maximum variance and projects the dataset onto those dimensions. For example, if the dataset includes three features: height, weight and age, the principal component analysis algorithm can combine them so that the dataset is described by just two features. Clustering groups data points into clusters based on relationships among the data points. Often, the relationships are measured with distance metrics such as Euclidean distance, Manhattan distance and Cosine similarity.

1.5.3. Reinforcement Learning

Predictive autonomy leverages reinforcement learning to decide appropriate preparedness actions, allowing an autonomous system to take actions beyond mere prediction. While supervised and unsupervised learning can significantly enhance an autonomous system, neither approach supports decision-making or planning. Reinforcement learning enables such higher-level cognition, thus implementing classic autonomy. Supervised and unsupervised learning could help an autonomous vehicle predict future changes on the road, but determining the optimal driving action necessitates reinforcement learning.

Reinforcement learning considers a state $\{S_t\}$ of the system at time t, a set of possible events or actions $\{a_t\}$, information about how the world transitions from one state to another ($\{S_t\}$ to $\{S_{t+1}\}$) when an action a_t is taken, and an associated reward r_t. Its objective is to define an optimal policy π. Although the policy π is described as a probability distribution $\pi(a_t|S_t)$, in many practical applications it takes a deterministic form.

1.6. Applications of Predictive Autonomy

Predictive autonomy is an emerging principle that refers to a system’s ability to choose its actions based on predictions about the future. More precisely, it requires a system to have some measure of free will, along with an internal model of its environment that enables it to generate plausible future scenarios and use them to guide its behaviour [7,8,9]. Predictive autonomy is regarded as a key ingredient for building truly autonomous systems, especially when combined with an explicit framework for reasoning about future consequences—i.e., predictive / foresight artificial intelligence (AI).

A variety of machine learning approaches can provide autonomy with a coherent and detailed model of its environment. Most commonly considered approaches fall into three broad categories: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves training a model on labeled input-output pairs in order to make predictions about new, unseen inputs. Unsupervised learning involves finding structure in unlabeled data; that structure can be extracted from a trained model by asking targeted questions. Reinforcement learning involves training a model to choose actions that maximize long-term reward through repeated interactions with an environment.

1.6.1. Autonomous Vehicles

Autonomous vehicles employ predictive models similar to those used in robotics, facilitating navigation through complex environments. Their controller processes multiple sensors—such as cameras, radar, LiDAR, and sonar—to perceive surroundings, detect privileged vehicles, measure route and speed, and identify passengers. The resulting data inform decisions about movements and actions, with deep learning models predicting future locations and velocities of surrounding dynamic agents. For instance, Tesla has developed a proprietary neural network—the "Tesla Network"—envisioned to manage highly complex autonomous systems.

Integrating controls and sensors, autonomous vehicles are designed to be connected, cooperative, and capable of predictive motion. By continuously updating information about other vehicles and nearby objects, the system processes data with a real-time vehicle-management application and presents it to the user through an interactive interface. These functionalities enable data exchange and aid passenger navigation. Control systems leverage a rich set of technologies from field-proven aerospace components that meet stringent safety requirements.

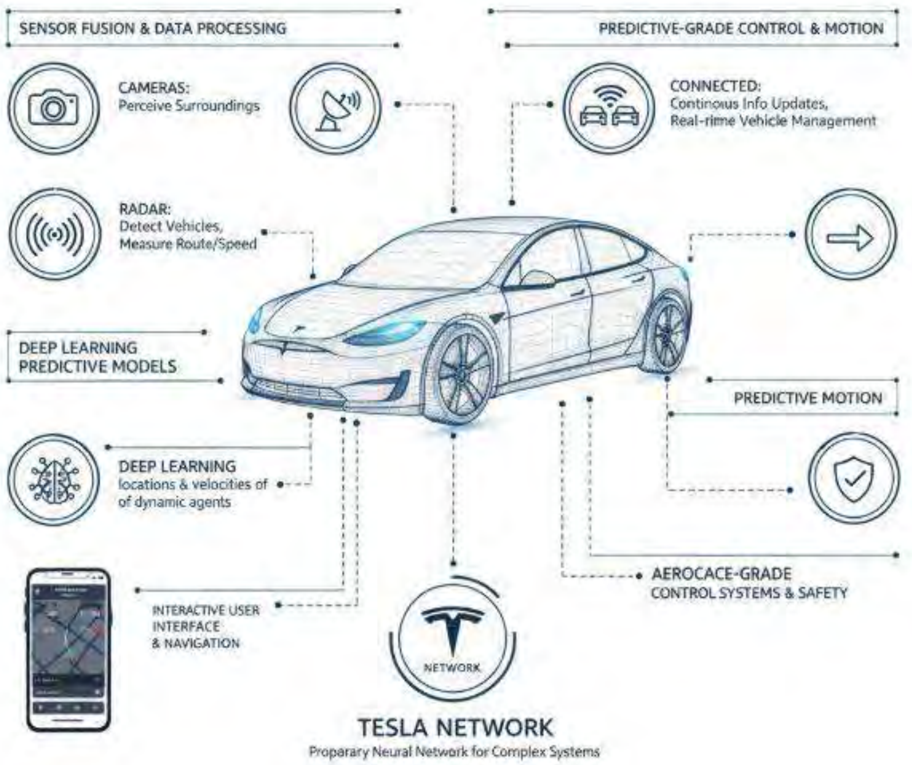

Fig 1 . 4 : Predictive Autonomy in Autonomous Vehicles

1.6.2. Robotics

Predictive autonomy utilizes stored knowledge to anticipate future states of a system, enabling preemptive action. The most advanced forms of predictive autonomy employ historical data and predictive models to take action before issues arise [3,4,10]. Extensive research has developed a range of supervised and unsupervised methods that predict what is likely to occur next in a system. These methods have been successfully applied to autonomous vehicles, robots, stock markets, and healthcare. Their excellent performance across these domains underscores their utility. Looking forward, policy and regulatory trends will continue to support the evolution and adoption of predictive autonomy.

While predictive autonomy has been predominantly explored in self-driving cars, its scope extends beyond this application. Predictions about the future states of the world are equally valuable in other domains, including robotics. Combine a powerful predictive autonomy model with an effective planning algorithm, and the model can influence the system's future state. For example, a humanoid agent might predict a push from an adversary and decide to close its eyes in anticipation of an incoming splatter of paint or gum. Predictive models can essentially allow a system to act before its actions are needed.

1.6.3. Healthcare

Sensors are being connected to patients' bodies and medical instruments to collect real-time data about their health. Artificial intelligence software will continuously analyze these datasets to provide a dynamic preliminary diagnosis. This information will then be transmitted via cloud computing back to the doctor—instantaneously and anywhere in the world. Through machine learning, AI will diagnose diseases during their very early stages of development. Specifically in surgery, predictive autonomy is likely to help the doctor prepare by conducting predictive simulations.

1.6.4. Finance

Credit and Capital Markets Forecasting Predictive autonomy can be a powerful tool to get early warnings about possible future problems in credit and capital markets. Sophisticated algorithms can learn the complicated dynamics of capital and credit markets and produce early forecasts about possible future events. Such early forecasts enable proactive decisions and actions to minimize adverse impacts. For instance, early warnings about a possible credit crunch can spur changes in credit and trade regulations or initiate the development of new financial instruments to stabilize the markets.

Algorithmic Trading Algorithmic trading is one of the hottest areas in capital markets today. Predictive autonomy technologies are playing an ever-increasing role in such strategies. By analyzing massive volumes of historical and current data concerning company activities and management, these techniques can predict a company’s future performance and stock price movements. They can also learn the dynamics of index futures. Based on these predictions, the algorithms can automate trade executions in different stocks, indexes, and commodities to maximize profits and minimize financial risks. The use of predictive autonomy addresses numerous challenges of algorithmic trading due to its superior ability to use both historical and current data and master the dynamics of stock, index, and commodity movements.

1.7. Future Trends

The integration of artificial intelligence with giant data networks and the Internet of Things has opened avenues for predicting future outcomes and events, enabling systems to take proactive actions. Automobiles and vehicles now use predictive technologies to reversely park in the same spot, alert the driver about hazards, and bring themselves back to the driver's location. Smart home applications aim to predict events—such as someone ringing the doorbell—to trigger predictions involving both home and outside surveillance systems. Modern predictive applications are also supported through progressive policies such as the National AI Strategy of the Republic of Korea and the Artificial Intelligence Framework for the United States [5,11,12].

Alongside developments in pattern recognition and movement prediction, artificial intelligence builds upon supervised, unsupervised, and reinforcement learning techniques to predict future events based on current conditions. Large datasets processed by ML algorithms facilitate accurate future predictions. Current predictive applications allocate appropriate self-driving maneuvers, adjusting the level of autonomy based on the current scenario. Moving from predictive navigation to autonomous autonomy, modern robots and cars can now drive or deliver packages without any human intervention.

1.7.1. Advancements in AI

Predictive autonomy is a next-generation technology, comprising a bundle of capabilities that enable an autonomous system to operate under a wide range of unknown and challenging conditions. The technology enables an autonomous system to predict upcoming obstacles or unknown environments beyond the perception range and take proactive measures to avoid collisions or reduce adverse effects. An autonomous system enhanced with predictive autonomy can interpret data collected from previous missions, predict upcoming changes, and mitigate the impact of those changes on system performance.

Historical advances in autonomous capabilities have been driven by breakthroughs in sensing, data processing, and artificial intelligence (AI). However, even with these powerful technologies, today's commercial autonomous systems in land, air, and maritime domains still require relatively structured and obstacle-free environments. Recent advances in machine learning have enabled a new generation of AI techniques, and their application to autonomous vehicles has led to the development of predictive-autonomy capabilities. Machine-learning algorithms can be categorized based on the presence of an objective function: supervised learning uses a specified objective function, unsupervised learning derives the objective function to identify meaningful features or data clusters, and reinforcement learning is guided by rewards, enabling the prediction of upcoming changes for effective interaction with the environment.

1.7.2. Integration with IoT

Predictive autonomy refers to a system's ability to take autonomous actions based on predictions and forecasts of future conditions. Instead of simply reacting to events, predictive autonomy allows a system to proactively shape events as it forecasts them. For example, rather than waiting for a vehicle to deviate from a lane before activating lane-keeping assist, a vehicle equipped with predictive autonomy would apply the brakes ahead of time to prevent the vehicle from ever deviating from the lane. These systems forecast the state of the world and interact with it in a way to improve those states according to a set of predefined goals. Predictive autonomy anticipates situations and processes powerfully enough to take proactive actions that prevent the loss of human life, destruction of property, or inefficient use of resources.

While autonomy has often been thought of as the opposite of tele-operation, its implementation often requires substantial radio link connectivity to support the machine learning models that enable predictive autonomy. Through the processing of sensor data and machine learning techniques, a system can generate forecasts to perform tasks such as lane-centering. However, these systems often rely on the radio link for data, maps, and remote computing through edge computing capabilities. As the radio link is built out and made available anywhere and anytime through the Internet of Things (IoT), predictive autonomy becomes a practical solution for operating machines without human interaction.

1.7.3. Policy and Regulation

Policy and regulation play an important part in autonomy that helps to ensure that what is being autonomous remains truly autonomous, and does not establish entirely different, unwanted risks. The World Economic Forum highlights the importance of “ensur[ing] clear and consistent policies and regulations that are responsive to market shifts and platform enabled business models.” Automation’s impact on society displays further weaknesses of existing institutions. When adapting to automation, any government must address growing income inequality. Weak policy and regulation could exacerbate this, creating feedback loops of instability—uncertainty and loss of trust in institutions also suppress investment and economic growth.

Going into the future, there is a significant need to further inform policy and regulation for predictive autonomy. A first-principles evaluation of the roles of the human user and the autonomous asset at different stages of system execution offers multiple new perspectives on the user role for precaution and implementation of the automation voice. Blockchains and other distributed data structures may allow regulators to define the level of predictAndSelect autonomy in the next generation of ML methods. As ML advances towards trading strategies and economic models, these technologies may react well to different autonomy levels from the regulation perspective, as many current operations are likely quicker, more robust, and consistent than humans in similar operations.

1.8. Conclusion

Predictive autonomy enables machines to anticipate, plan, learn, adapt, and acquire knowledge on their own. By combining concepts from planning and predictive analytics, systems with predictive autonomy are capable of choosing sequences of actions to achieve complex tasks and forecasting possible future outcomes. This capacity marks an evolution toward the final frontier of automation, allowing systems to make decisions and take actions based on predictions about the near future.

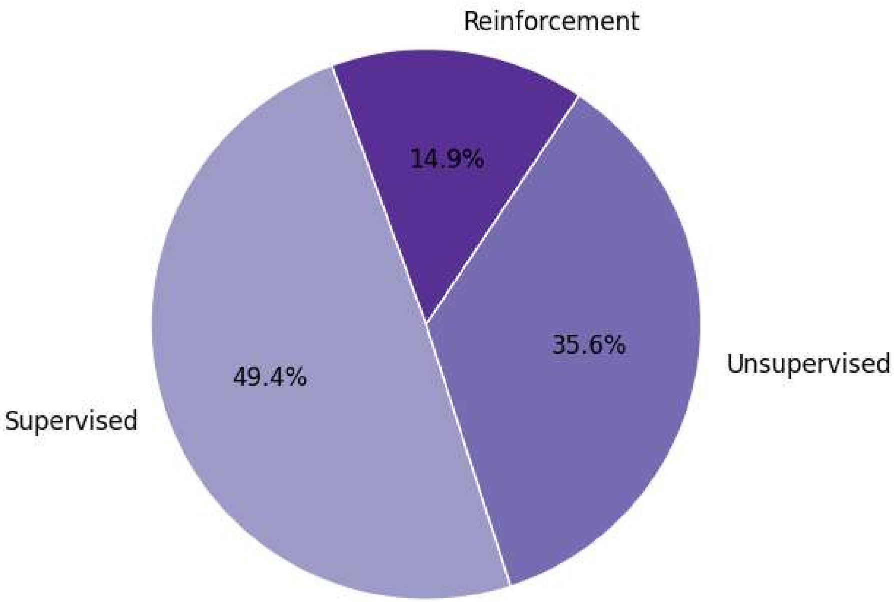

Fig 1 . 5 : Algorithm Distribution

From techniques to the underlying technologies, predictive autonomy has been an active research topic since the 1990s. Interest in the area remains strong today, driven by the advances provided—for instance—by deep learning and the recent proliferation of cheap sensors and processing. As a reflection of this enduring appeal, the user may choose to conclude the presentation of an introductory section to predictive autonomy by examining an overview of the core machine learning algorithms—namely, supervised learning, unsupervised learning, and reinforcement learning—and their applications in domains such as autonomous vehicles, robotics, healthcare, and finance.

1.8.1. Summary and Implications of Predictive Autonomy

Predictive autonomy defines systems capable not only of independent operation and decision-making but also of anticipating their future states and environmental changes. Such systems harness observations, extensive historical data, and mission criteria to forecast future capabilities and conditions, enabling adaptation before adverse outcomes arise. This anticipatory capacity spawns ‘‘predictive’’ autonomy, connecting the present to the future and, in turn, honing decision-making by forecasting consequences.

Predictive autonomy builds upon and broadens existing definitions, origins, concepts, and applications of autonomous systems. Capabilities in autonomous navigation exemplify predictive techniques, ranging from obstacle avoidance to estimated-time-of-arrival calculations and path planning. Remaining uncertainties often guide future-state predictions, which then inform autonomous control strategies. Reinforcement learning techniques, notably Q-learning and deep Q-learning, actively enhance navigation by weighting diverse outcomes, thereby improving future-event or future-state predictions. These techniques rely on forward models of the agent's situation: predicting rewards associated with various navigational choices. Similar predictive autonomy capabilities also benefit other domains, including healthcare, financial investing, robotic manipulation, and cyber-attack simulation and identification.

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