HOW DOES ARTIFICIAL INTELLIGENCE HELP ASTRONOMY? A REVIEW

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ABSTRACT

Artificial intelligence (AI) is a discipline of computing that focuses mostly on transferring human intelligence and mental processes into machines that can assist humans in many ways. Machine learning (ML) is the approach of choice in AI for creating useful software for computer vision, speech recognition, natural language processing, robot control, and other applications. Some of the most common analyses of large, complicated and multidimensional data sets in astronomy can be performed by using ML methods. It can be used for automating observatory scheduling to increase the effective utilization and scientific return from telescopes. It is also used for image recognition, classification of galaxies and planet recognition. This paper offers an in-depth review of the evolution of artificial intelligence and the use of AI and ML in the field of astronomy, especially for data analysis, image recognition, astronomical scheduling, classification of galaxies and planet recognition. It adds to the existing literature on use of artificial intelligence for astronomical applications and is a useful resource for students and researchers.

Keywords: *artificial intelligence, machine learning, applications, astronomy, review*

INTRODUCTION

John McCarthy, one of the founders of artificial intelligence (AI), was the first to define artificial intelligence in 1955. He stated that the objective of AI is to create robots that behave as if they were intelligent (Ertel, 2017). AI is a field of computing that focuses primarily on the transmission of anthropomorphic intelligence and thinking into machines that can assist humans in many ways (Way et al., 2012)

In astrophysics and cosmology, vast, intricate, and multidimensional data sets must be analyzed. Typical tasks include pattern recognition, data description and interpretation, classification, prediction and compression (Hobson et al., 2014) which can be carried out by using AI and ML (MacKay, 2003; Ball & Brunner, 2010). Also employed extensively in detection and identification of celestial bodies, the uses of AI in astronomy are limitless.

Many scholars in the field of astronomy have started to try to use cutting-edge computational intelligence (CI) techniques for astronomical data processing and analysis, as well as conduct interdisciplinary research of CI and astronomy. In today's data-heavy era of astronomy, it is important to focus on automatic, effective, and intelligent techniques and methods which can comprehend particular functions in astronomical research just as astronomers do and autonomously mine huge scale astronomy data for scientific breakthroughs. Some of these are recognising known objects, finding unknown objects, and searching for rare objects and astronomical phenomena which can be accomplished using CI techniques (Wang et al., 2018).

A huge influx of astronomical data will be caused by the improvement of astronomical observational tools (Wang et al., 2018). Sloan Digital Sky Survey (SDSS) with multi-target fibre spectroscopy had 40 TB of data by the start of this century (York et al., 2000). With an observation time of up to 10 years, the Large Synoptic Survey Telescope (LSST) will collect about 30 TB of data every night. Some estimates mention that 100,000 varying objects are likely to be discovered each night (Borne, 2008).

It is evident that AI and ML techniques will be required to analyse this massive amount of data.

To the best of the researchers' knowledge, there is very little collation of research on how artificial intelligence can contribute to advancing the field of astronomy. Therefore, this study aims to review the applications of AI and ML in the field of astronomy.

More specifically, the study addresses the following research questions:

RQ1: What are the areas in which artificial intelligence can contribute to the field of astronomy?

RQ2. What are the specific advantages brought by AI to the field of astronomy?

The paper is organized as follows. The next section deals with an in-depth literature review about AI and its applications in various sciences. Subsequently, the specific applications of AI in the field of astronomy are discussed, followed by some of the challenges that arise in executing these. Finally, the discussion section provides the practical implications of the study, limitations and further scope for research.

MEANING OF AI

The phrase "artificial intelligence" (AI) is both extensively used yet has no clear definition (Lemmer and Kanal, 1986). Experts have failed to reach an agreement about its meaning and its applications (Müller and Bostrom, 2016). The invention of algorithms, the rise in computational processing capacity, and the readiness of enormous data sets which can be used to train AI systems have all contributed to the significant advancements in this field during the past 30 years. The majority of AI systems used today use deep learning or machine learning. Without human assistance, these algorithms can spot patterns in data, and they can also learn new things on their own over time (Zhai, Yan, Zhang & Lu, 2020).

AI is all about using algorithms to operate in a manner similar to how a human would, but in a much more efficient, reliable, and faster way. It also demonstrates information obtained by running a variety of algorithms with little to no human assistance. People could use situational activities, general reasoning, and make well-informed decisions much more quickly. An expert system is just a machine that has the capacity to think for itself and it seeks to enhance personal capabilities (Vasista, 2022).

Artificial intelligence, a phrase coined by John McCarthy in 1956, is a discipline of computing that focuses mostly on transferring human intelligence and mental processes into machines that can assist humans in many ways. AI is being increasingly used in a variety of fields, including engineering, mathematics, physics, and technology (Müller and Bostrom, 2016). It encompasses features such as machines that can learn, adapt to a given circumstance, correct their own mistakes and think independently without being instructed (Phan, Feld and Linnhoff-Popien, 2020).

Intelligent systems are made up of three main parts: a learning part, a thinking part, and an acting part. The learning part, which is typically done with ML is trained either with the help of generated data, which is learned automatically through trial-and-error methods such as reinforcement learning, or with a substantial amount of information that is already available to assess changes based on supervised or unsupervised learning (Phan, Feld and Linnhoff-Popien, 2020).

The thinking part requires making clear arguments about possible steps to take and their outcomes. In a game, several possible futures may be used to figure out the next move which will give a player the best chance of victory. But in a job related to navigation, such as getting a car to its destination safely without extra costs, accidents, or detours, meticulous routing and online planning are needed. Technically, this kind of artificial thinking is done with meta-heuristic optimization (such as Evolutionary Computation), search or optimization methods like tree search (such as Monte Carlo Tree Search), or routing algorithms (such as Dijkstra).

When there are no models available, ML can bridge the divide between learning and thinking (Phan, Feld and Linnhoff-Popien, 2020).

MACHINE LEARNING

Machine learning is at the intersection of statistics and computer science. It is the basis of AI and data science. ML has made progress in recent years because new learning theories and algorithms have been made, and the amount of online data and low-cost processing keeps growing. According to Jordan and Mitchell (2015), this has increased the use of evidence-based judgement in many fields, such as manufacturing, financial modelling, health care and marketing (Jordan and Mitchell, 2015). The study of ML is crucial for answering fundamental problems in science and engineering as well as for the incredibly useful computer software it has generated and deployed in a variety of applications. Over the past two decades, ML has progressed dramatically, transforming from a laboratory curiosity into a practical technology with extensive commercial applications. It has become the preferred method in AI for developing effective software for speech recognition, computer vision, robot control, natural language processing and other applications (Jordan & Mitchell, 2015)

EVOLUTION OF AI

The history of AI can be traced to 1950 when George Boole defined the formal language for logical interpretation in 1847. In 1936, Alan Turing first put forth the Turing test, which was a benchmark question for determining machine consciousness – whether a machine would be conscious if could imitate human conscious behavior. Turing's question fundamentally affected the philosophy of AI (French, 2000). The very next year, J. Neumann and O. Morgenstern revealed the theory of decisions. Later in 1956, McCarthy, Minsky and others were the first to put forth the concept of AI at what is now called the Dartmouth Symposium. In 1965, Herbert Simon proclaimed that "machines can do practically anything that men can do" (Baber, 1988, p.330). The initial progress in AI including the arrival of the perceptron and the first patent for the industrial robot "Unimate" (Rosenblatt, 1958). PROLOG, a language for developing artificial intelligence systems, was codified by Alain Colmerauer in 1972.

The period between 1970 and 1985 saw the rise of expert systems, which made it possible for AI to move into real-world applications and help solve problems automatically. Throughout this time, expert systems were successfully used in medicine, biology, environment conservation and more areas (Larkin et al., 1980; Turban and Watkins, 1986). As the expert system's range of use grew till mid-1990s, some bugs started to show up and lack of funding led to AI projects halted (Searls, 2007). However, since then, the era of "big data" and the rise of computer algorithms have sped up the growth of AI.

APPLICATIONS OF AI

Technology companies now incorporate AI into a varied array of goods, from self-driving cars and weaponry to TVs, as well as day-to-day activities in the areas of healthcare, news and social media (Zhai, Yan, Zhang & Lu, 2020).

In the last decade, AI systems have proven that they can meet and exceed human performance in image recognition (Linn, 2015), speech transcription (Xiong et al., 2017) and direct translation (Castelvecchi, 2016). They have learned how to identify relevant information in a paragraph to answer a question, recognize human faces even if pictures are blurred and human emotions (Metz, 2016).

Today, algorithms that learn from analyzing email traffic are widely used to power email spam filters. Such algorithms are increasingly sensitive to human personal patterns and actions. Numerous industries and sectors, including the military, industry, banking, and medicine, use sophisticated AII systems (Spiegeleire et. al., 2017).

A variety of intriguing applications, from language translation and image processing to recommender systems and autonomous driving, have been made possible by recent advancements in AI. Machine learning is the foundation of the majority of applications, and it has had significant success thanks to the growing availability of computer resources and data. AI's self-organizing and self-learning capabilities enable generic problem-solving with little effort on requirements (Havlik, 2018). Applied AI can contribute to the fields of research, theory, technology, and application.

AI IN ASTRONOMY

Astronomy is a discipline of science that encompasses the research and examination of all extraterrestrial objects and events. It covers the extremely difficult and complex process of investigating and evaluating astrophysical phenomena and integrates the facets of mathematics, physics, and chemistry to understand the origin, evolution, and functions of the Universe and celestial bodies (Meher and Panda, 2021).

Planetary science, galactic astronomy, extragalactic astronomy, solar astronomy, stellar astronomy and cosmology are some of the many subfields of astronomy. Astronomers can be either theoretical or observational. Theoretical astronomers work to refine existing models and look into their evolution. Conversely, observational astronomers gather information about astronomical objects and locations and conduct in-depth research on stars, planets, galaxies, and other celestial bodies (Meher and Panda, 2021).

Theoretical astronomers use data to create simulation models, and the related observations are used to assess the models or to highlight areas that need to be adjusted. However, the goal of an observational astronomers is to observe, document, and gather information about the subject world. Observational astronomy in the present era has become almost completely virtual (Meher and Panda, 2021).

Virtual world analysis requires a vast amount of data, with increasing complexity that necessitates analysis, visualization, and interpretation in order to extract more knowledge about the universe's creation and evolution. Massive data sets present a number of scientific and technological hurdles for virtual observational astronomy (Long and Souza, 2017; Fluke et al., 2020)

BENEFITS OF ML TO ASTRONOMY

Currently, the size of data sets presents a challenge for virtual astronomy. Machine learning can help with the issue of massive astronomical data analysis. It has the ability to quickly analyze vast amounts of data while also uncovering complicated relationships and extracting knowledge from complex multidimensional data. Most ML techniques are based on artificial neural networks (ANNs) like self-organizing maps (SOMs), multi-layer perceptrons with back propagation (MLP/BP), and deep learning networks including convolutional and recurrent convolutional neural nets.

Because of the unavailability of large template data sets for training the models on, existing research has focused on supervised categorization and/or regression methods applied to a small data set. Longo, Merényi, and Tio (2019) maintain that whenever a new set of data is made public, new ways to use ML techniques are found.

In general, there are two groups of algorithms for machine learning. Supervised machine learning algorithms are used to learn how to map a set of features to a target variable based on examples of inputs and outputs given by a human expert (Norris et al. 2019; Reis et al. 2018). Unsupervised learning algorithms are employed to figure out complex relationships in a dataset without having an expert label the relationships. The second set of algorithms may be more significant for scientific research because they are useful for finding new information in existing datasets and may result in fresh discoveries (Baron, 2019).

The goal in supervised learning is to figure out a function from a set of training examples that have been labelled. In each example, the values of the "inputs" are known and can be used to guess the values of the "outputs." So, the mapping from inputs to outputs is the function that needs to be guessed. Once the working of this mapping is known, it can be used with datasets where outputs are unknown. Classification and regression are usually the main components of supervised learning (Hobson et al, 2014). The application of artificial neural networks (ANNs), which are partially based on how the brain is built and how it works, is a simple and well-known way to teach machines to learn. They are made up of a group of nodes that are linked together. Each node receives information, processes it, and then sends it to other nodes through weighted connections. In this way, ANNs are a non-linear tool for modelling statistical data that can be used to model complicated connections between a set of inputs and outputs (Hobson et al, 2014). ANN is data-driven and can change on its own. It is different from other parametric models in that it does not need any prior knowledge or assumptions about how the data is structured.

According to Longo, Merényi, and Tio (2019), the transfer of knowledge will be crucial in future applications. When a model is used on a different data set with even a tiny variation in characteristics from the one it was trained on, it usually doesn't work. The data needs to be collected while the algorithms are being trained, because the final data releases cannot be used for future research. Transfer learning, which is not often used in astronomy yet, will make this easier.

The quality of implementation of all supervised learning algorithms is determined by how many features are chosen. This is because most of them are either not meant to deal with large numbers of features as they might become mathematically unstable, or an enormous number of redundant features that makes it harder for the algorithm to tell things apart (Longo, Merényi, & Tio, 2019). In the past, experts' decisions were used to reduce the number of dimensions. However, this method is slowly being replaced by automated methods (Delli Veneri et al., 2019) and comprehensive, but expensive to compute approaches (Polsterer et al., 2013).

In less than a decade, it has become common to use ML techniques to solve problems in astronomy. The main reasons for this rise are the creation of large, detailed data sets through the modern-day multi-epoch, multi-band digital sky surveys and the standardization of different types of data due to the creation of the Virtual Observatory. There are three ways that computer science can be used in astronomy: the evolutionary computation, the fuzzy set, and the artificial neural network (Wang et al., 2018).

ANN is a powerful tool for modelling complicated physical processes because it can come close to any nonlinear function. Since its first use in astronomy was described in 1990, ANN has become the most prevalent form of AI and ML in astronomy (Angel et al., 1990; Ball and Brunner, 2010).

Numerous astronomical tasks such as morphological categorization of galaxies, evaluation of photometric redshifts, classification of stars and galaxies, estimation of stellar atmosphere parameters, and identification of pulsar candidates have successfully used ANN (Wang et al., 2018).

Data analysis

The amount of data and its complexity in astronomy are growing at a rapid pace, creating the era of big data in astronomy. This shift encourages the growth of data-driven science as a valuable complement to the usual model-driven data analysis, in which astronomers create automatic tools for mining datasets and use them to extract new information (Pesenson et al. 2010).

Big data refers to the vast volume of complex data which is difficult to interpret and analyze. This data consists of measurements, observations, numbers, characters, and words and is prepared to be processed by machines/computers. The acquisition, cleaning, curation, integration, storage, processing, indexing, searching, sharing, transfer, mining, analysis, and visualization of astronomical data has many of the same difficulties as any other domain with voluminous data. Traditional tools are incapable of handling such vast amounts of data. Consequently, astronomical research is shifting from a hypothesis-driven to a data-driven methodology (Meher and Panda, 2021).

Data is collected in a variety of spectral bands, including X-rays, ultraviolet, optical, and infrared. Astronomical data is mostly recorded in databases as signals, photos, videos, spectra, time series, and simulations. Additionally, several other types of data are frequently obtained from telescope-based initiatives that are not in sync with the aforementioned formats and present challenges for integration, merging, and analysis. For analysis, the dimensionality problem is brought on by thousands of characteristics. Additionally, understanding data types including semi-structured, unstructured, and mixed is a very challenging task (Meher and Panda, 2021).

The technological advancement of observational instruments has led to enormous collection of cosmological data. This high dimensional and multi-modal data consists of multi-band spectra and pictures, as well as numerous catalogues, time series data, and synthetic data. The Digitized Palomar Observatory Sky Survey had no more than 3 TB of image data at the end of the 20th century (Djorgovski et al., 2002). Sloan Digital Sky Survey with multi-target fibre spectroscopy had 40 TB of data by the start of this century (York et al., 2000). With an observation time of up to 10 years, the soon-to-be-built Large Synoptic Survey Telescope (LSST) will collect about 30 TB of data every night. Each night, it is estimated that 100,000 varying objects will be found. The entire quantity of image data from LSST is expected to be about 70 PB, and the catalogue will be 10–20 PB (Borne, 2008). About tens of petabytes of data are expected to be made by the Euclid space mission. The Square Kilometre Array is bringing astronomical big data to a whole new level. In the first phase which is only 10 percent of its total scale, it will produce raw data at a speed of several Tera bits every second and scientific data amounting to 700 petabytes annually (An, 2019).

The capabilities of the present typical centralized data processing system are insufficient (Kremer et al., 2017) to work with this vast amount of data. Additionally, it is very challenging for a single human to find patterns concealed within the data set. Astronomical activities also need a significant amount of computing power which are expensive. Therefore, big data approaches and parallel processing must be used by computer engineers and astronomers. These techniques aid in characterizing patterns and improving the understanding of the universe by culling out potentially valuable information. Utilizing sophisticated machine learning algorithms, data mining tools, and distributed frameworks can speed up astronomical discoveries (Sen et al., 2022).

In addition to automating operations by minimizing human involvement, Sen et al., (2022) maintain that ML algorithms also assist in uncovering hidden patterns in vast astrophysical datasets. ML is crucial for performing improved prediction, visualization, and taking quick decisions. Some of the most common analyses of large, complicated and multidimensional data sets in astronomy are related to data description and interpretation, pattern recognition, prediction, classification, compression and inference which can be performed by using ML methods (MacKay, 2003; Ball & Brunner, 2010; Way et al., 2012).

Several researchers such as Tagliaferri et al. (2003) and Way et al. (2012) have used feed-forward ANNs to solve various astronomy-related ML problems. Standard techniques, like backpropagation, have been hard to use in training networks with many nodes and/or many hidden layers (also called "large" and "deep"), which are often needed to model the complicated mappings between many inputs and outputs in contemporary astronomical applications.

SkyNet, which was made by Hobson et al. in 2014, is a fast and reliable neural network training algorithm that can train large and deep feed-forward networks. One important new use of regression-supervised learning in astrophysics and cosmology is to speed up Bayesian analysis (estimating parameters and selectinng models) of large data sets in the perspective of complicated models. At every juncture in parameter space, Bayesian methods need to evaluate a "likelihood" function that tells how likely it is that the data will be found for a given set of model parameters. For some problems, it can take up to several seconds to evaluate each function in this way. So, if you can expedite the evaluation of how likely something is to happen, you can get big performance gains. An ANN is perfect for this job.

Image recognition

Modern telescopes have dramatically improved image size and quality as a result of sky surveys, which presents both great problems and opportunity for new discoveries. For instance, the categorization and morphology of the 70 million radio galaxies that the Australian SKA Pathfinder all-sky survey is predicted to locate are crucial to comprehending the creation and evolution of the universe. However, identifying the retrieved sources is even more difficult because it is impossible to recognize such a large number of items by eye inspection (Norris et al., 2011). The development of automatic source detection and classification algorithms is necessary to address these needs (Bonaldi et al., 2020).

Early data processing software packages included source detecting algorithms. Numerous standalone source-finding software programs have been developed to process vast amounts of astronomical data and provide more reliability and accuracy than the previous ones. ML can evaluate data without being given instructions and can thus spot unexpected patterns, such as detecting additional types of galaxies (Tino and Raychaudhury, 2012).

In light of the accumulation of massive archives of astronomical data, such as in the Virtual Observatory, automated analysis of big multivariate datasets is needed. For advancements in this sector, swift automated procedures of parameter extraction, classification, characterization, and visualization of multi-dimensional and multi-type datasets must be tailored to the individual challenges using domain knowledge. Astrophysics must handle systematic and random measurement errors as well as the intrinsic diversity of systems. Many sub-fields rely on visual characterization of features in observable spectra, morphologies, and time-series (Tino and Raychaudhury, 2012).

Artificial neural networks or support vector machines are used to examine galaxy evolution using photometric pictures (Lahav et al., 1995; Banerji et al., 2010). With optical spectra of more than 106 galaxies, independent analysis of components and other data-driven techniques have helped analyze star populations within galaxies (Nolan et al., 2007).

The study of images poses another challenge. For instance, personally examining an image, identifying and counting the craters, and then estimating their sizes based on the size of the image were necessary to estimate the number of craters on the moon. This entire procedure can be automated using AI, which will save a lot of time and effort (Silburt et al., 2019). Researchers have attempted to create algorithms in the past to recognize and count the craters, but have had limited success. However, Silburt et al (2019) created an AI algorithm that assisted in identifying and counting the craters for not only regions of the moon but also regions of Mercury. This algorithm was so successful that it could recognize 6000 unidentified craters on the moon (Pruthi, 2019).

Recently, scientists used AI in a study to discover numerous quick radio bursts that had previously gone undiscovered. These are energetic pulses that are thought to have been generated by far-off galaxies. After the data collection was analyzed, AI could find the quick radio bursts in situations where astronomers could not (Pruthi, 2019). Fast radio bursts, according to Tucker (2022), are one of the most newly identified unidentified signals in astronomy and one of the mysteries that may be clarified in the next five to ten years with the use of new technologies.

Kevin Schawinski, an astrophysicist at Oxford University took up a project named, Galaxy Zoo in 2007, in which volunteers were hired to discern between different images online. More than 100,000 individuals were roped in to analyze about 900,000 images of galaxies. Later, an instrument called The Dark Energy Spectroscopic Instrument was created to assess the speed of distant galaxies. AI algorithms have helped make many astronomical tasks faster and more accurate. In 2017, ML was used by a research group from Stanford University to study images of strong gravitational lensing (Lamb, 2022).

In 2018, researchers announced that ML can forecast the stability of planets in binary star system more precisely than astronomers (Byrd, 2022).

Astronomical Scheduling System

Telescope Scheduling: The telescope is the most integral feature of an observatory; hence astronomers would prefer to make the most of it. An astronomical scheduler system runs the observatory and keeps everything in order. Because of the growing complexity of satellite observatories and the high level of automation of telescopes, astronomers need flexible scheduling so they can use these facilities to their fullest potential (Solar et al, 2016).

An astronomical scheduler's main task apart from handling observation requests it to decide the time of execution of each observation, taking into account the limited time and high cost of each observation (Spotts, 2010).

The process of scheduling astronomical observations is a complicated one (Gómez de Castro and Yáez, 2003). Some of the factors that the scheduler has to deal with are technical requirements, weather conditions, whether or not it is possible to point the telescope at the target, dates of scheduled maintenance, available telescope time, the proportion of observational time, and the opportunity cost between parallel observations. Most of these limits can be altered at any time, which makes it even harder to stick to a plan for observations. Finally, since the problem of astronomical observation scheduling has more than one goal, different parts of the observatory can be optimized at the same time (Solar et al, 2016).

The primary objective of automating the process of observatory scheduling is to get more utility out of the telescopes. Even though most sophisticated astronomical observatories are equipped with tools to help with scheduling, a lot of the work still has to be done by hand (Mora and Solar, 2010). That means it is very important to have a fully automated, dynamic scheduler that can respond to any sudden changes in the present. Solar et al. (2016) say that the scheduler should be able to change on the fly as observing conditions change.

ALMA has a systematic procedure for scheduling observations. This approach begins with an early "Call for Proposals" to accept proposals for observation (Nyman et al., 2010). Each proposal undergoes a revision procedure wherein it is scrutinized by a committee based on research impact, telescope time, technical requirements, country, etc., and assigns the approved proposals an observation time. The telescope scheduler selects the time of execution of each observation based on its priority, requirements, and observing conditions.

Solar et al. (2016) used a Mixed Integer Linear Programming (MILP) based algorithm to address a less complicated version of the ALMA scheduling problem. MILP was used as it was rigorous, flexible and had broad modeling potential (Floudas and Lin, 2005). This scheduling algorithm is based on a multi-layer model that works on both short-term and long-term schedules. It also takes into account time discretization, in addition to dynamic and static variables. Scheduling Blocks are set up over the planning time with the help of a MILP-based solver, which is the main job of the scheduling procedure (Solar et al, 2016).

It is clear that software technology and scheduling methods have advanced to the point where automated scheduling for telescopes is a realistic goal. With the help of AI, software like the HST SPlKE scheduling tools can be devised and adapted to solve a wide range of scheduling problems for telescopes (Johnston, 1988).

The advantages of using these techniques are primarily an accelerated process of software development, a succinct but clear depiction of data scheduling, flexible definition and changes of constraints in scheduling, potent capabilities for search, and a user-friendly graphics-oriented interface (Johnston and Miller, 1989).

Spacecraft Scheduling: The appropriate scheduling of spacecraft is a crucial and demanding topic. The efficient utilization of spacecraft resources is vital, but the relevant scheduling problems are usually difficult to compute and approximate due to the existence of multiple interdependent constraints (Johnston, 1988).

Johnston and Miller (1989) used artificial intelligence algorithms to schedule astronomical observations and other spacecraft activities for the NASA/ESA Hubble Space Telescope. This was a particularly difficult problem due to the sheer size of the an annual observing program, which usually consists of tens of thousands of exposures subject to numerous environmental, operational, and scientific restrictions.

Johnston (1988) established novel strategies for machine reasoning regarding scheduling limitations and goals, particularly in circumstances where uncertainty is a significant scheduling issue and conflict resolution amid conflicting preferences is critical.

Classification

Convolutional neural networks (CNNs) are a key part of recent deep learning-based classification techniques. CNNs are also applied for classification of galaxies based on their shapes. Studies have shown that AI can automatically classify the shapes of galaxies by training a CNN using crowdsourced categorizations of the Galaxy Zoo project (Dieleman et al., 2015). Even though their network was just as accurate as the human volunteers, it also shared all of the human biases.

Sanchez et al. (2018) added towards this by training a CNN on a subset of Galaxy Zoo classifications with lower level of uncertainty. By taking uncertainly classified galaxies out of the training data, DS18 was able to make their AI classifier perform better than the human classifiers. It was also used to train a separate CNN on the Nair and Abraham (2010) database of visual morphologies. Unlike Galaxy Zoo, this database was made by a single expert astronomer who visually categorized about 14,000 galaxies, instead of a large group of amateur volunteers. The CNN trained by DS18 was capable of reproducing Nair and Abraham's (2010) morphological classification with a scatter and offset that was better than other ML techniques (Huertas-Company et al., 2010). After training their CNNs, DS18 applied them to a large database of about 670,000 images of galaxies. This gave astronomers a morphological database with a size that had never been seen before.

Thus, these efforts show how AI may be used to automate the boring and time-consuming task of classification of images of galaxies. This is very helpful because it makes it easy to sort ever-larger sets of galaxies, and also frees up the scientist to do more interesting research (Bekki, Diaz and Stanley, 2019).

In their project "AIverse," Bekki, Diaz, and Stanley (2019) attempted to teach AI to do the same things that scientists can do, and to take those skills to new levels by using them to solve problems that humans could not. Even though earlier studies on the morphological classification of galaxies were pretty accurate, they have a major flaw - the labelling of galactic morphological types (such as Sa and Sb) is only undertaken for galaxies that have already been labelled by humans.

Since there are numerous physical characteristics of galaxies that can tell us about how they formed and changed over time, it is very important for us to figure out what those properties mean (what they "label") in terms of galaxy formation and change. Currently available computer simulations can make many synthetic representations of galaxy properties that can be utilized to train CNNs for a particular task (Bekki, Diaz and Stanley, 2019).

Another way to automatically classify and label galaxies is to look at the spectroscopic or photometric data that the digital sky survey gives (Ball et al., 2004, 2006; Almeida et al., 2010; Banerji et al., 2010; Vasconcellos et al., 2011). This does not require direct analysis of the image. Instead, the automatic classifier may utilize an amalgamation of measurements obtained by the photometric pipeline of the digital sky survey. The digital sky survey pipelines can provide astronomers with information that cannot be revealed from a visual inspection. However, the pipeline can only provide a set of predefined measurements, which do not elaborate upon the shape of the galaxy. Using these measurements alone, it is usually not possible to fully reconstruct the shape of the galaxy.

The method combines the commonly used pre-defined photometric measurements with features derived directly from the images to measure and compare how much information the direct assessment of the images can add to the photometric measurements. Since many modern sky surveys, like the Sloan Digital Sky Survey or the Panoramic Survey Telescope and Rapid Response System, provide both photometry and image data, this method can be used to automatically annotate celestial objects in large astronomical databases (Kuminski and Shamir, 2018).

Carrasco-Davis et al. (2019) suggests a new way to classify variable stars and transients into different groups. They do not use the usual advance processing of temporal series of images to get features, which are frequently light curves that have been additionally simplified into criteria based on the light curves. Rather, they prepare a recurrent convolutional neural network (RCNN) to gather the necessary latent variables from the raw data. They then use the latent variables as inputs to the classification part of the network. This process allows feature extraction in an automatic, data-driven manner without the need to compute different images, make model assumptions, and make corrections at each step. It is also helpful in avoiding errors that could be made by computing light curves. Carrasco-Davis et al. (2019) have explained a way to train the RCNN by simulating artificial image sequences which are based on the instrument and observation features of a particular experiment (in this case, the HiTS survey) which necessitates a great number of labelled samples. The RCNN can use a limited number of the real labelled samples and fine-tune them to match the distribution of real data from the experiment (Longo, Merényi and Tiňo, 2019).

Planet Detection

The ideal planet detection algorithm is quick, noise-resistant, and can abstract systems that are non-linear. An ideal neural network is one that is trained to identify planets using simulated data (Pearson, Palafox and Griffith, 2018). Deep learning with a neural network models how the brain solves issues by linking neural units (Rosenblatt 1958; Newell 1969).

Deep nets have layers of 'neurons' with variable weights to represent input parameter relevance. Pearson, Palafox, and Griffith (2018) developed a neural network that can make judgments based on input characteristics such as a light curve's form and depth, noise, and star-spots.

A deep net has the advantage of being trainable to recognize very subtle features in large data sets. Algorithms optimize the weights to minimize the difference between the deep net output and the expected value from the training data to achieve this learning capability. Deep neural networks are capable of modelling complex nonlinear relationships that are not always analytically derivable. Instead of depending on hand-crafted metrics to discover planets, the network will learn from training data the optimal features required to detect a transit signal.

Manually interpreting potential exoplanet candidates is a time-consuming and difficult task in the age of 'big data,' especially with small transit signals such as received from planets that are the of the size of the Earth. Exoplanet transit shapes vary because of variables such as stellar activity. Consequently, a minimal template is not adequate to grasp the nuances. Pearson, Palafox, and Griffith (2018) trained an artificial neural network in the photometric features of a transiting exoplanet. This was possible because deep machine learning can process millions of light curves in a few seconds.

CONCLUSION

This paper offers an in-depth review of the evolution of artificial intelligence and the use of AI and ML in the field of astronomy, especially data analysis, image recognition, astronomical scheduling, classification of galaxies and planet recognition.

Artificial intelligence is all about using algorithms to operate in a manner similar to how a human would, but in a much more efficient, reliable, and also speedier way. It also demonstrates information obtained by running a variety of algorithms with little to no human assistance.

The use of ML techniques to solve problems in the field of astronomy has become commonplace in less than a decade. Large, extensive data sets produced by contemporary multi-epoch, multi-band digital sky surveys and the standardization of heterogeneous data brought on by the establishment of the Virtual Observatory are the main causes of this increase.

Machine intelligence has the ability to quickly analyze vast amounts of data while also providing the ability to uncover complicated relationships and extract knowledge from complex multidimensional data. Artificial neural networks such as multi-layer perceptrons with back propagation, deep learning networks and self-organizing maps are the most commonly used machine learning techniques in the area of astronomy.

This review adds to the existing literature on use of artificial intelligence for astronomical applications and is a useful resource for students and researchers. Future studies can carry out a comparison of specific algorithms used for each of the applications or can focus on the challenges that are yet to be resolved in the use of AI for astronomy.

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