Artificial Intelligence

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Applications of AI Methods for Driving Innovation in Modern Astronomy

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MACE telescope operated by BARC at Hanle in Leh

ABSTRACT

Astronomy is the oldest branch of science which evolved through the observations and data logging of the key studies of the solar system. As telescopes grew more powerful, the study expanded to the entire Universe thereby generating "astronomical" volumes of data. Artificial Intelligence is a new branch of science that astronomers are using as a powerful discovery tool to study rich but complex data and sift through data in search of signals. A whole new world of unexplored objects is being experimented with, thus generating a new world order-the "AI-powered Astronomy". In this article, we discuss general and mega-science applications of AI-based study of astronomy.

KEYWORDS: *Artificial intelligence, Machine learning, Astronomy*

Introduction

Artificial Intelligence (AI) name was proposed by J. McCarthy in 1956. AI can be considered as science that enables machines to take decisions as opposed to natural intelligence, similar to what humans would do. The AI methodology involves learning from the human intelligence and then developing computer algorithms for its execution. Based on the problem at hand, a flexible but efficient approach is used for problem-solving. The human intelligence is a manifestation of the biological brain which consists of a massively parallel set of neurons that can succeed at cognitive and control tasks. The advantage of the brain is its effective use of massive parallelism, a highly parallel computing structure with imprecise information processing capability. The human brain is a collection of ~11 billion interconnected neurons, where each neuron receives, processes and transmits information. The neurons use chemical reactions to process information. This collective model and processing is referred to as the biological neural system. AI are computational models which have been developed as generalizations of the mathematical models of the biological nervous system[1]. AI models e.g like the Artificial Neural Networks (ANN) have been developed as generalizations of mathematical models of biological system.

Need for Artificial Intelligence in Astronomy

Astronomy is one of the oldest branches of science which humans studied while AI is one of the newest branches of science. Study of astronomy is an observational science which developed due to mankind's quest for observing the night sky, which was not only fascinating, but also helped in day today tasks like creating calendars and navigation. An important development was the use of mathematical and geometrical models to study motion of the planetary objects. Early astronomers maintained a detailed record of the position of the celestial bodies. It is since then that data analysis has played a pivotal role in astronomy. Astronomers required the formulation of theories and mathematical equations in order to explain the universe. As the interest in astronomy grew, especially in last 100 years or so, it lead to generation of voluminous data which started becoming extremely cumbersome to analyze. Fortunately, due to the incredible progress in computational field due to availability of highly efficient processors, coupled with theoretical understanding of techniques such as Machine Learning (ML) have allowed AI to advance at a frantic rate. The exponentially increasing astronomical data raises the requirement for an efficient paradigm. Data analysis must become more automated and efficient, particularly through AI. In our efforts to understand the Universe, mankind is developing satellites and telescopes which will yield hundreds of tera-bytes of data/year. It will become impossible for scientists to sift through the data to generate meaningful science. This is where AI has proved to be God-sent, with its capability to automate almost anything. It is thus certainly an understatement that artificial intelligence (AI) has taken the astronomy by storm, with breakthroughs appearing on a daily basis.

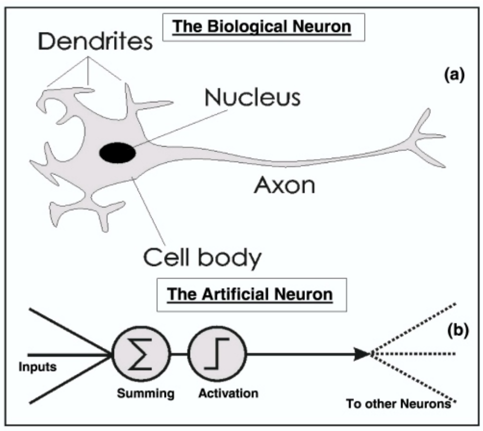

Fig.1: Schematic diagram of a typical neuron or a nerve cell in a biological neuron and the artificial (computer) model of a biological neuron.

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To quantify the above, as a thumb-rule in astronomy, the information we collect is roughly doubling every year[2]. The Hubble Telescope e.g., operating since 1990 gathers ~20GB of data/ week, the Large Synoptic Survey Telescope (LSST), is expected to gather ~30 TB of data/night. This however is negligible compared to the ambitious Square Kilometer Array (SKA). With its 2000 radio dishes and 2 million low-frequency antennas, it is expected to produce ~1Exabyte/day (~ more data produced in a day in comparison to what internet produces in a year)[3].

General AI applications in Astronomy

Historically, the first astronomical application of AI was the star-galaxy recognition problem and the spectral and morphological classifications of galaxies[4,5]. AI has also been applied to planetary data for prediction of solar activity phenomena[6]. This study enables us to understand the interplanetary magnetic field and stellar astrophysics.

AI application in astronomy can broadly be classified into time series analysis, identification of peculiar objects (QSO's, IR galaxies and Gamma-ray Bursts) and determination of photometric redshifts. Additionally, the new generation mega-science projects like LIGO, James Webb, and SKA have generated interest in AI application to data analysis.

Time series analysis: It concerns finding the variable signal in the time domain of data which was previously thought to be constant. This can be accomplished if and only if the observation and analysis techniques become more sensitive. Typical examples can be found in the study of light curves of variable stars and the study of Active Galactic Nuclei, the extragalactic sources powered by a central black hole[7]. Tools based on the use of Fourier analysis have been employed for such analysis[8,9] but if the astronomy data is unevenly sampled, the above techniques lead to erroneous results. Resampling of the data has been attempted via interpolation but it introduces amplification of the noise and hence Fourier, which is critically dependent on noise, cannot be used. Oppehium & Schafer[10] proposed the use of an algorithm based on a frequency estimator and a Neural Network for finding the Principal Component Analysis (PCA) & auto correlation matrix. After Neural Network training, the signal frequencies estimated are obtained for the weight matrix and eventually fed to the frequency estimator for final analysis.

Object detection using AI

For processing the astronomical data/image, the goal here is to make a catalog of astrometric/geometric morphology and estimate the photometric parameters of the image. However, the problems encountered are related to the low, comparable, or even fainter surface brightness compared to the image threshold. Also, many fainter objects that are present in the image are not detected by the analysis procedure due to extremely faint glow/signal, while others that are not present in the image are spuriously detected (spurious objects). The Neural Network package implemented by the group[11], performs object detection, de-blending and star/galaxy classification through mapping pixel intensities through PCA. Software package 'NExt' is employed to lower the dimensionality of the input pattern and an unsupervised PCA-Neural Network is used to identify significant features.

The photometric redshift of galaxies

The redshift of a galaxy which is recession velocity from the observer is of great importance in astronomy as it provides an estimate of the galaxy distance. Conventionally, redshift is measured spectroscopically, which is time-consuming or via photometry, which is less accurate and has more systematic errors. Baum et.al.,[12,13,14] used the Sloan Digital Sky Survey Early data which has photometric data for ~16 million galaxies and spectroscopic redshift for ~50,000 objects distributed over a large redshift range. They used unsupervised Self-Organizing Maps (SOM) to cluster the data in the training and test set to ensure complete coverage of the input parameter space. A MultiLayer Perceptron (MLP) neural model in the Bayesian framework is then used to estimate the photometric redshifts. A labeled SOM is used to derive the completeness and contamination of the final catalogs. To build the training/test sets, a set of parameters consisting of star magnitudes (namely u, g, r, i&z), flux levels, surface brightness and extinction coefficients,[14] were extracted from the data.

Application in Mega Science Projects

Laser Interferometer Gravitational-Wave Observatory

The Laser Interferometer Gravitational-Wave Observatory (LIGO) is a large-scale physics experiment for the detection of cosmic gravitational waves. LIGO-India is a planned advanced gravitational-wave observatory to be located in India as part of the worldwide network. The LIGO project operates three gravitational-wave (GW) detectors [15]. Two of these are situated in Hanford, Washington, and one is in Livingston, USA. The LIGO-India project is an international collaboration between the LIGO Laboratory and DAE institutes IPR-Gandhinagar, IUCAA- Pune and RRCAT- Indore.

Information extracted by the transmitted waves will help to address unsolved questions and mysteries of physics and astronomy. Gravitational waves were first detected in 2015 by LIGO, which marked the birth of gravitational wave astronomy. As LIGO continues to upgrade detector sensitivity to gravitational waves, it will be able to probe a larger volume of the universe-making the detection of gravitational wave sources a daily occurrence rather than weekly or monthly, thereby generating huge volume of data. Recently, Argonne National Laboratory (ANL, USA) along with collaborators developed a new AI framework that allows for accelerated and reproducible detection of gravitational waves. This new framework indicates that AI models could not only be very sensitive as traditional template matching algorithms but also orders of magnitude faster. Furthermore, these AI algorithms would only require an inexpensive GPU, to process data faster than in real-time [16]. The AI ensemble used for this study processed e.g., an entire month (August 2017) of advanced LIGO data in less than 7 minutes. In a significant study, the AI ensemble used for this analysis identified all four binary black hole mergers previously identified in that dataset and reported no misclassifications.

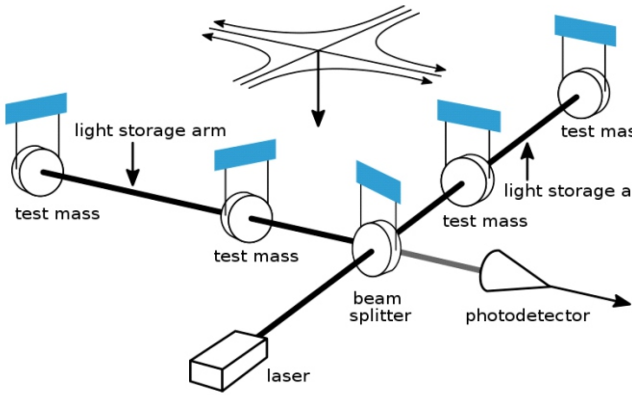

Fig.2: A Schematic of the LIGO Detector (Source: Nuclear Instruments and Methods in Physics Research A517, 1–3, 2004).

James Webb Space Telescope

James Webb Space Telescope (JWST) is the largest and most powerful space-based telescope ever constructed. It is an infrared space observatory with a 25 m^2 aperture (6 m class) telescope that will achieve diffraction-limited angular resolution at a wavelength of 2 μm[17]. The observatory will have four instruments: a near-IR camera, a near-IR multi-object spectrograph, and a tuneable filter imager which will cover the wavelength range $0.6 < \lambda < 5.0$ μm, while the mid-IR instrument will do both imaging and spectroscopy from $5.0 < \lambda < 29$ μm. The key science objective is to determine how galaxies and the dark matter, gas, stars, metals, morphological structures, and active nuclei within them evolved from the epoch of re-ionization to the present day. Keeping the above science goals in view, a rough estimate is that JWST will yield ~60GB of data/day. It will be an extremely cumbersome without any realistic methods for the scientific community to analyse such voluminous data.

To do away with the above difficulty, a machine learning model called Morpheus will be used to detect and classify galaxies in deep space and to map the earliest structures in the universe. Morpheus is a deep-learning-based AI model for image analysis of astronomical sources. It uses powerful AI models for detecting and classification of galaxies. Morpheus was trained on UC Santa Cruz's Lux supercomputer - which has 28 GPU nodes with two Nvidia V100 Tensor Core GPUs each. As data and images are sent from the telescope to Earth, that information will be fed into the AI models. The UC Santa Cruz's Computer Science and Astronomy department has created the deep learning framework that classifies astronomical objects, such as galaxies, based on the raw data streaming out of telescopes on a pixel-by-pixel basis. About half a million galaxies will be surveyed using multiband near-infrared imaging and 32,000 galaxies in mid-infrared imaging, a mammoth task that cannot be accomplished without the application of AI methods.

Square Kilometer Array

The Square Kilometer Array (SKA) project is an international effort to build the world's largest radio telescope, with over a square kilometer of collecting area. The SKA scale is a huge leap forward in engineering, research & development towards building and delivering a unique instrument.

In the first phase there will be about 200 dishes in South Africa and over 130,000 low frequency antennas in Western Australia, to monitor the Universe in unprecedented details, since no similar studies have ever been conducted with such a large array of detectors.

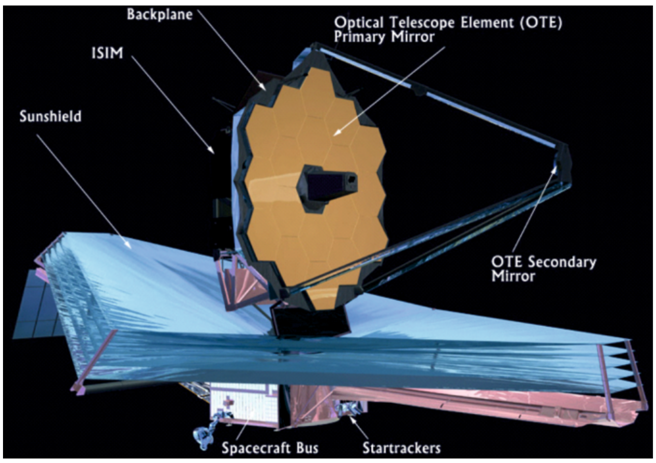

Fig.3: Various components of JWST (courtesy: https://astrobites.org) . AI based analysis is an important part of JWST data analysis.

The unprecedented sensitivity of the SKA receivers will allow insights into the formation and evolution of the first stars and galaxies just after the Big Bang, the nature of gravity and possibly even life beyond Earth. In addition, there could be several serendipitous discoveries to be expected owing to the sheer magnitude of SKA.

The expected volume of data from the SKA has motivated the expanded use of semi-automatic and automatic machine learning algorithms for scientific discovery in astronomy. The robust and systematic use of machine learning, however, faces several specific challenges including a paucity of labeled data for training (although enough data is there, it may still not be sufficient), a clear understanding of the effect of biases introduced due to observational and intrinsic astrophysical selection effects in the training data, and motivating a quantitative statistical representation of outcomes from decisive AI applications [18]. There will be specific challenges in recovering well-calibrated uncertainties from Bayesian neural networks when classifying radio galaxies which are a canonical example of AI application to radio astronomy. Table 1 below gives a summary of a direct comparison of the time taken by experts and by AI methods to analyze the SKA images. It is evident from the figure that AI methodology is the only viable option for analyzing the SKA data.

Fig.4 based on a survey of the arxiv data related to astronomy publications that contain keywords like "machine learning", "deep learning", or "artificial intelligence" in the abstract or title. An exponential increase can be seen in the field since 2010 onwards which is expected to grow at a faster rate once more data becomes available in the next few years within the astronomical community.

*Table 1: Demonstration of the actual time taken by human experts, web analysis and AI methods. (*Radio Galaxy Zoo is an internet crowd sourced citizen science project that seeks to locate supermassive black holes in distant galaxies. It is hosted by the web portal Zooniverse).*

Resource	Time	Remarks
Human Experts	1 source/min	~1,25,000/yr (full time work)
Radio Galaxy Zoo*	3,00,000 sources	12,000 users (5.5 yrs)
AI	100 million sources (15 mins)	AI offers viable solution

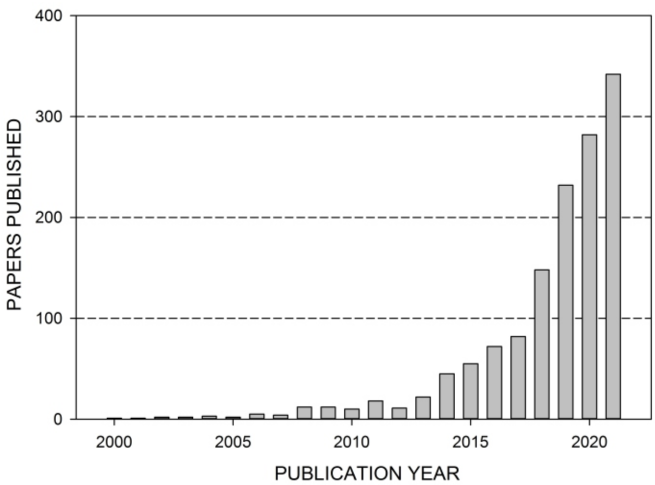

Fig.4: Astronomy research papers with AI title. Figure demonstrates the exponential increase in last decade.

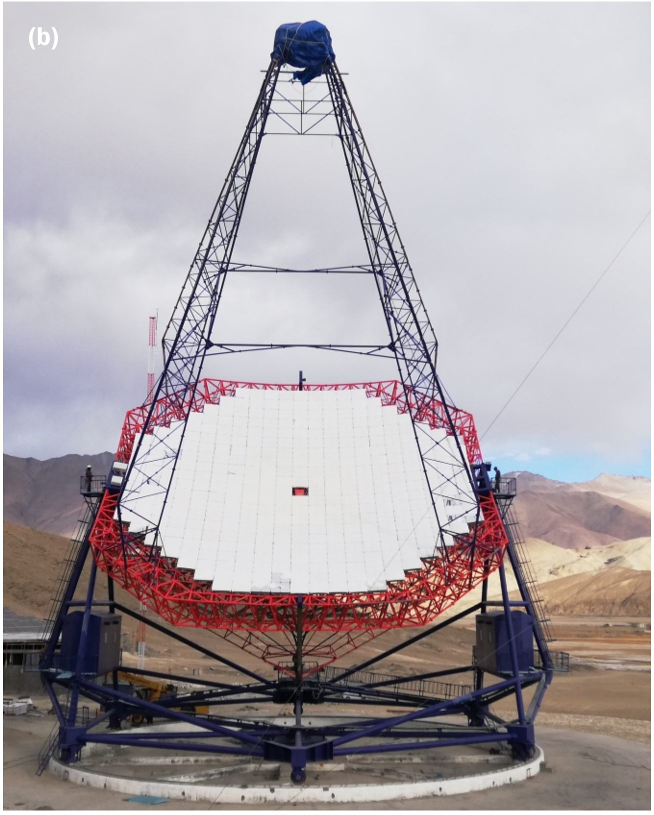

Fig.4: (a) 9.5m^2 TACTIC installed at Mt Abu, Rajasthan (b) 356 m^2 MACE telescope operated by BARC at Hanle in Leh.

Gamma-ray Astronomy applications at BARC

In the last few years, we have explored the application of Artificial Intelligence methods to the ground-based Gamma-ray astronomy activity of the department. While as TACTIC telescope, with a light collector of ~9.5m^2(Fig.5) is operational at Mt Abu, Rajasthan for more than 20 years, it is very recently that a high sensitivity telescope MACE has been commissioned at Hanle, Leh for the study of GeV-TeV γ-ray emission from celestial sources. AI-based methods have been employed for the gamma/hadron segregation and energy estimation of data from the TACTIC telescope. For TACTIC data, we have successfully utilized ANN and Random forest AI methods which have resulted in acceptance of ~ 20% more gamma-ray-like events in comparison to the conventional Dynamic Supercuts Method [19][20]. A novel ANN method was applied for energy estimation of the recorded gamma-ray events obtained with the TACTIC telescope and we have been able to improve energy resolution from ~35% to ~ 25% [21]. For the MACE telescope, we have applied RF & ANN techniques for the estimation of the Gamma-ray signal. For primary energy estimation of the detected events too, we are currently applying the two techniques. In the future also, we have plans to apply more sensitive techniques like deep-learning-based AI techniques for Gamma-hadron segregation for the MACE data.

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