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18. Cosmology Inspired by Technological Innovation

Swapna Sagar Mishra, S. D. Pathak

Department of Physics,
Lovely Professional University,
Phagwara, Punjab, India.

Abstract:

Cosmology studies the composition and evolution of the universe, and the Λ CDM model describes three elements: dark energy, dark matter, and visible matter. Dark energy causes the Earth to accelerate. Dark matter constitutes most of the mass due to the gravitational effect. Visible matter makes the world visible. Although the Λ CDM model is consistent with observational data, important questions remain, including the nature of dark matter, the cause of the acceleration, and the physical background of the initial cosmic structure. Solving these questions is crucial to a deeper understanding of the composition and function of the universe.

Keywords:

Cosmology, ΛCDM standard model, Dark energy, Dark matter, Ordinary visible matter, Accelerated expansion, Universe's mass density, Gravitational interactions, Observational data, Particle nature of dark mat-ter, Origin of accelerated expansion, Formation of the first cosmic structures, Universe's composition, Universe's dynamics, Cosmological research

18.1 Introduction:

Cosmology is the study of the history, evolution, and ultimate fate of the universe and is greatly influenced by technological advances. Historically, advances in technology have continued to improve our understanding of the world. From the invention of the telescope by Galileo, which opened a new field of astronomical observations in the 17th century, to the development of electronic devices and instruments, every technology has provided new tools and ways to explore the deep world.

In modern times, technologies such as powerful cameras with exciting imaging and spectroscopic capabilities, computer simulations, and artificial intelligence have revolutionized cosmology. These innovations are allowing scientists to go deep into space and ahead of time, leading to major discoveries such as detailing cosmic microwave background radiation, detecting gravitational waves, and identifying exoplanets.

In addition, technological advances have led to the construction of large observatories and interferometres such as the Very Large Telescope (VLT) and the Laser Interferometre Gravitational Wave Observatory (LIGO), which have played an important role in expanding our understanding of structure. and the dynamics of the universe. In addition, space missions such as the Hubble Space Telescope, the James Webb Space Telescope, and various Earth rovers have provided us with unprecedented views of distant galaxies and the solar system. As we continue to develop and integrate new technologies, from quantum computing to multimetres to new data science, the field of cosmology is on the verge of profound discovery. These technologies not only improve our observational capabilities, but also help develop theoretical models, bringing us closer to answers to important historical questions such as how many muscles and the fate of the world.

18.2 Cases in Science:

18.2.1 Cosmic Probes:

Cosmology is the study of the content and evolution of the universe. The Λ CDM Standard Model shows three main components: dark energy, which makes up most of the mass of the universe and is cut off by gravitational problems, accelerating the dark matter of the universe; Although observational data support this model, im- portant physiological questions remain unresolved. These include the nature of dark matter, the origin of the expansion of the universe, and the physical background of the first cosmic structure.

Using statistical power from current and future cosmological experiments, many unanswered questions in cos- mology still remain to be resolved or progress toward resolution is being made, and the prospect is exciting. Completing a retrospective survey of the data presented will require a process that can extract as much infor- mation as possible from the survey while controlling for the processes and theoretical models involved in the measurement.

The process of obtaining cosmological limits in various subfields of cosmology; is limited to determining the location, collecting measurements and comparing them with theoretical models for parameter extraction. This section highlights examples where instrument learning has had a major impact on cosmic explorers, as well as further advances in sentiment analysis. The above instructions and functions are representative and not comprehensive.

instrument learning is essential to detect and classify cosmic sources, extract information from images, and demonstrate effective strategies. Important cosmological discoveries include galaxy clusters, supernovae, gravi- tational lensing, and the cosmic microwave background. Combining multiple instruments helps improve cosmo- logical parameters by covering more space models and addressing different astrophysical processes and obser- vations. instrument learning can increase the potential of multisystem cosmology by influencing relationships and integrating knowledge from various fields of science.

Many cosmological analyzes are based on astronomical catalogs derived from images and often consider the” best” model rather than the distribution of existing objects. This leads to loss of unsaved data and uncertainty in low-level measurements. instrument learning makes it possible to perform the desired action, detect the action, and characterize the object image.A recent demonstration of decoupling in a crowded star field suggests that this approach has the potential to improve the results of cosmological research over the next decade. instrument learning has emerged as a promising method that outperforms statistical methods to detect and strengthen gravitational lenses. Initial successes include community challenges and ongoing applications for Dark Energy Survey (DES) and Dark Energy Spectroscopic Instrument (DESI) data. Recent studies have focused on measurement uncertainty and uncertainty quantification for observed lensed objects and lensed galaxies. In anticipation of the big data future studies like Euclid and LSST will produce, major work is being done to optimize instrument learning for space/lensing characterization, Hubble's continuous thinking, and analyzing dark matter in etail.

Compared to traditional methods, instrument learning has demonstrated the advantages of weak gravitational lensing. It improves cosmological parameter inference using data beyond traditional one- and two-point statis- tics. In addition, instrument learning outperforms traditional estimates on size maps and can improve weak lensing convergence maps by detecting galaxy ellipticities.

instrument learning techniques excel at a variety of cosmic microwave background (CMB) analysis tasks, including CMB lens reconstruction, foreground separation and polarimetric map extraction, even processing scenarios that describe the CMB signal and observations using angular power spectrum estimates. Given the expected complexity of the data, these strategies will improve the results of future studies such as the Simons Observatory, CMB-S4, and experiments such as CMB HD. Additionally, instrument learning was explored to characterize galaxy clusters from CMB lensing features in Sunyaev-Zel-dovich and CMB map analysis.

instrument learning has been proposed as a way to unravel the complexity of the 21 cm middle hydrogen data probing reionization time. Its applications include parameter estimation and signal extraction, providing a good way to improve analysis in this field.

18.2.2 Multi-Massanger in Astrophysics and Domain of Time:

In an era of region-wide research across the electromagnetic and gravitational wave spectrum, instrument learn- ing is particularly time-sensitive. Observers such as the Vera C. Rubin Observatory's Survey of Ancient Space and Time (LSST) will produce approximately 10 million observations of time domain phenomena per night, beyond the capabilities of human observations. In addition to LSST, future facilities such as the Very Large Space Telescope (ngVLA), CMB-S4, and collaborations such as LIGO-VIRGO-Kagra will provide diverse, multi- person precursors to climate change and the world over the next decade.

Field-wide surveys produce periodic alerts of rates exceeding spectral capabilities. Currently, less than 5% of recent events reported to the International Astronomical Union Temporary Name Server (TNS) are spectrally tracked. An order of magnitude increase in the LSST stimulus will strengthen existing resources. From a cosmo- logical perspective, Type Ia supernovae are important for measuring the Hubble constant. instrument learning techniques are required to classify these events to facilitate spectral monitoring or archival analysis. Significant progress has been made in the development of instrument learning

(ML) methods for ad hoc event character- ization and classification based on comprehensive scientific data, driven by alerting agents such as NOIRLab's ANTARES and algorithms such as RAPID, Superv Nnova, and Super RAENN. However, there are still significant issues to be resolved to understand the expected diversity of events observed before LSST occurs.

Additionally, the instrument learning community has developed new technologies such as transformers, implicit stochastic equations, and neural networks that promise to solve problems in the future. Unsupervised studies will play an important role in the next decade, especially in identifying rare cases (negative detection) hidden in alert streams. Although only one kilonova event (GW170817) is found in the gravitational wave and electromagnetic spectrum, LSST should find more kilonovae than the LIGO-Virgo-Kagra detection limit. The technique can also detect missing in-flight events, as seen by the team processing data from Pan-STARRS, Dark Energy Search (DES), and the Zwicky Transient Facility (ZTF). Research across the region promises understanding of groups of objects over time. However, modeling these populations with important physics, such as cosmological parameters for Type Ia supernovae, introduces multilevel modeling challenges.

Traditionally, using techniques such as Markov Chain Monte Carlo sampling, simple assumptions are made in the sample to be evaluated, leading to bias. Leveraging instrument learning models such as deep neural networks in schemes such as variational inference can effectively model what is specified in the high domain. The focus group hopes to complement traditional technology with many new methods to improve the perfor- mance of GPUs at high performance. Multi-messenger astrophysics (MMA) brings additional complexity to the above challenges. Events that can produce gravitational waves in warped space-time are rare. In addition, a significant part of these events, such as supernovae approaching collapse, neutron star mergers, and the merger of neutron stars and black holes, evolve rapidly and emit electromagnetic radiation.

For example, a normal MMA event GW170817 will only publish 1-2 detections of the current regulation in stud- ies such as LSST. The identification and characterization of multiple missile astrophysics (MMA) events pose significant challenges due to their rarity and heterogeneous data, many of which are available from different sources. instrument learning (ML) techniques and simulation-based inference techniques, including nonlinear detection techniques and hybrid models such as convolutional recurrent neural networks (CRNN), are impor- tant. These ideas are necessary to make different observations, mark events in an hour and do research work automatically. In addition, in order to understand these mysterious situations, it is necessary to invest in cyber infrastructure in terms of storing, processing and sharing public and private data.

18.3 Relation in Data and Computing:

18.3.1 The Processing of Data:

In today's large-scale research, there are many ways to increase the speed and accuracy of data processing during and after data collection. These improvements can be mentioned in the following nominal steps.New intelligent methods have been found to increase the speed and accuracy of data processing in large-scale cosmological studies. This involves quickly selecting and reviewing important data based on analysis, especially for data changes or time differences that need to be processed in a timely manner. Although different imaging methods have been implemented, such as Antares in LSST, their predictive power is limited in terms of detection accuracy and limits the understanding of selected objects. As seen in particle physics programming, embedding deep learning algorithms into specialized computing units such as TPUs and FPGAs can be solved. This rapid process can process raw data for rapid detection of monitoring sites or long-term operational data, bypassing data changes over time and making rapid changes for updated times. New intelligent methods have been found to increase the speed and accuracy of data processing in large-scale cosmological studies. This involves quickly selecting and reviewing important data based on analysis, especially for data changes or time differences that need to be processed in a timely manner. Although different imaging methods have been implemented, such as Antares in LSST, their predictive power is limited in terms of detection accuracy and limits the understanding of selected objects. As seen in particle physics programming, embedding deep learning algorithms into specialized computing units such as TPUs and FPGAs can be solved. This rapid process can process raw data for rapid detection of monitoring sites or long-term operational data, bypassing data changes over time and making rapid changes for updated times.

18.3.2 High Petrformance Computing:

In the next decade, high-performance computing (HPC) will become essential for the application of instrument learning (ML) in cosmology. Many data from cosmological surveys such as DESI, eROSITA, Euclid, Rome Space Telescope, Vera C. Rubin Observatory, Simons Observatory, and Square Kilometer Array (SKA) will require dedicated data hosting infrastructure. Additionally, the complexity of the models used to explain these studies requires computation and energy storage.

Training an ML model to interpret a galaxy survey through comparison to cosmological simulations involves several HPC-intensive tasks:(1)Producing simulations at large HPC facilities, requiring significant GPU or CPU hours.(2)Storing simulation outputs on large, high-throughput file systems, totaling petabytes.(3)Executing analysis (generation of data products) in cluster environments, often using CPUs.(4)Training ML models on these data products, utilizing GPUs or other accelerators. The requirements of these projects should increase in the next decade because future studies will cover a wider area and deeper in the sky, requiring the simulation of larger volumes and better solutions. While instrument learning requires HPC, it also creates opportunities. Traditional simulations can be accelerated or simulated with instrument learning techniques that allow high resolution based on low resolution and replace expensive physics numbers with instrument learning interpolation. This may increase the scalability of simulations but will also create difficulties in storing and managing the resulting data, which is expected to be in the tens to hundreds of petabytes. To improve the use of simulations and analyses, big data should be stored centrally in publicly accessible national or international HPC facilities. Users should be able to access data directly without needing to create a copy elsewhere. Additionally, subsets of the data should be easily downloaded to facilitate searching, requiring only a few megabytes of data items. Because of its extensive storage space and distributed computing resources, cloud computing offers an attractive option for some HPC applications. It provides users with a simple software stack to create a instrument learning-ready environment. However, applications that require efficient communication between multiple operators, such as simulations or some types of instrument learning, will not work well in the cloud. However, HPC opportunities in the cloud are expected to increase over the next decade thanks to instrument learning, and efforts to promote this in research projects will be encouraged and supported. Ensuring reproducible research in an HPC environment requires engaging new users with HPC resources. Reproducibility efforts in astrophysics range from the use of commercial software testing applications to completing studies that make it easier for readers to understand the paper's results. While these operations are typically hosted in the cloud and use little data and CPU time, their transparency and reporting are of significant value to the cosmology instrument learning community. HPC facilities must provide access points to enable these functions, including access to big data and computing resources, primarily GPUs. Increasing demand for astrophysics can spur collaboration between scientists and industry. Techniques used in industry to store certain types of data, such as videos on platforms such as YouTube, can be used to reduce the need for storage in astrophysics. This will allow for a more comprehensive analysis of the data. Over the next decade, it will evolve into a multitasking mission to complement research at the intersection of high-performance computing (HPC), instrument learning (ML), and cosmology. This requires supporting efforts such as hosting large observational databases, running comprehensive cosmological experiments, and training instrument learning models to bridge the two. HPC data centers must ensure that this information is publicly available so that users can perform direct calculations or download subsets of their normal workloads. On the software side, expertise in cloud hosting, packaging, and software environments is critical to the dissemination of researchers' requirements and the performance of HPC hardware.

18.4 How to Simulate?

instrument learning algorithms excel at identifying patterns in high volumes of data, allowing simulations to serve as a laboratory for discovering unknown patterns and understanding processes within the body. For example, instrument learning methods used for fluid dynamics simulations have shown previously unknown relationships between galaxy properties and do not explain the composition of the universe. This shows that instrument learning has the potential to revolutionize many areas of cosmology and galaxy formation that deal with high data.

cosmology, the main problem concerns the distribution of data. Although Gaussian density fields can extract all the information using the power spectrum, non-Gaussian density fields do not have good measurement quality. Research shows that important cosmological information exists at very small scales and cannot be obtained from the energy spectrum alone. Using these scales can improve cosmological constraints but requires non-invasive methods such as numerical simulations. In addition, uncertainty in astrophysical events such as supernovae and active galactic nucleus (AGN) feedback can also affect these scales, creating the need to explain the effects of the baryon in maintaining the conditions by marginalizing them. In the best-case scenario, instrument learning methods can simultaneously work on cosmological and galaxy formation constraints. This will involve using state-of-the-art cosmological fluid dynamics simulations to train neural networks to extract maximum cosmolog- ical and astrophysical information from multi-wavelength observations. This approach represents a theoretical framework for extracting detailed information from cosmological studies. To achieve the goal of extracting com- plete information from cosmological studies, more advanced fluid dynamics simulations as well as instrument learning are required to improve simulation solutions or accelerate simulation processes. Additionally, develop- ing and making publicly available datasets for cosmology missions will facilitate advances in instrument learning techniques necessary for these efforts. Best wishes for extrapolating data from cosmological studies through in- strument learning come with important caveats. First, it is based on the results of numerical simulations, which may not reflect reality, especially when many galactic objects are taken into account. Second, statistical accuracy and error are important to determine confidence in detecting potential effects on role, such as the number of elements using neutrinos. Solving these problems could lead to advances in numerical simulations of fluid dynamics to improve analysis and the development of instrument learning methods to accommodate similar effects due to inaccuracy of numerical and simulation products. As the size and complexity of simulated data and analyzes continues to grow, there is an urgent need to develop a more powerful instrument learning system that can handle multiple readily available datasets. This enables the integration of information from hydrodynamic simulations and astrophysical studies while also learning from their similarities and differences. These differences: It can arise from many sources, including assumptions, numerical properties, computational limitations, or even unknown physical phenomena not involved in the experiment. Additionally, analysis effects, error checking, and data compression may vary additionally. Because of this difference, the model trained in simulation will have a large impact when applied to real data. Field adaptation methods show promise in as- trophysics and cosmology as shown in Refs [92, 93]. This method reveals common features for each data set based on the training model, classifies the data, and allows the model used to be developed simultaneously in many documents. Future progression and implementation of registration changes will be important to create more robust learning systems that are resilient to disparate data, noise, and interference. Additionally, since changes to the record are not based on record information, they can be used for new analyses. This capability is essential for creating electronic systems that are initially studied in simulations but can be operated instantly during cosmological observations.

18.5 The Operation of Survey and Design of Instrument:

18.5.1 The Operation of Survey:

Cosmological surveys like LSST will recapture images of the sky and revisit the same area up to 1,000 times per decade. Many factors such as scanning speed, exposure depth, filter use can affect search results. The need for a near-current distribution of frequent events, combined with the different objectives of research and survey activities, creates problems in planning surveys. The manual adjustment process is inefficient, especially for short- and long-term conditions such as weather conditions. Coordinating observations from multiple telescopes for spectral monitoring or multiwavelength/messenger measurements often requires months of delay in agreeing to the committee’s time allocation. Measuring the achievement of specific research goals through the discovery of new phenomena is the most challenging task. Current methods, such as those used in Dark Energy Research, involve simulating high-level measurements over many years from a single run. Manual review of these criteria may suggest a new change and retry until the relative value is reached. Adaptive methods such as feature-based planning, designed as a formal optimization problem within the framework of reinforcement learning, have been shown to optimize many competing scientific objectives and outperform conventional telescopes. This process also demonstrates the ability to recover from unexpected events such as device failure. Additionally, unsupervised methods using neural networks show promise in improving research objectives without the need for pre-existing analytical models. These efforts represent a rare example of intelligence-driven resource allocation for reflection algorithms. Investing in automatic programming of glasses will reduce costs and increase efficiency. The time saved is evident in the follow-up of the applicant, review of the home line, and integration of the various site(s). In addition, automatic planning has the ability to optimize scientific results by prioritizing fields and products according to their relevance to research objectives, thereby maximizing data quality for all purposes,

including research. Automatic resource allocation in telescopic observations faces many significant challenges. Tracking algorithms trained on simulations or previous data may be biased when applied to unobserved data, so alternative methods should be explored. In addition, explaining the decisions and policies resulting from planning algorithms and their economic and transportation benefits is important for practical, human centered understanding and security. In order to solve these problems, managing measurement data and problems, realizing measurement results, measuring electricity meter measurements of different sizes and Camera consortia are considered as important steps of this study.

18.5.2 The Design of Instrument and Experiments:

Creating laboratories and equipment to meet research needs is a demanding task. Instrument complexity must also increase as research needs evolve, such as the need for greater analysis and sensitivity. This increase in complexity has a negative impact on the time and cost of future testing. In the design process of laboratories and instruments, people first develop hypotheses, create various research objectives to test these hypotheses, and develop teaching principles from the data set. They then develop tools and custom assessments by de- termining the appropriate type and type of data needed to complete these assessments. Although the process may seem linear, there is usually a brief description of the steps because experiments often involve multiple research objectives and measurements. Each element in the system must be developed independently in essen- tially different software systems, with equipment and communications equipment among them, until a specific model that meets the research needs is created. In the design process of monitoring facilities and equipment, most devices are generally not connected together in a single software base. Input and output communication between experimental devices usually occurs via email, and many simulators run as standalone services that require manual processing. These factors make it difficult to achieve rapid global optimization of measurement and test design. Seamlessly connecting components into an algorithmic framework alleviates bottlenecks and enables rapid co-optimization of experiments and measurements that do not meet scientific objectives. This includes converting process requirements into standard and numerical data. Although the use of this concept is limited, progress has been made in some areas, such as the use of deep learning techniques to improve optical correction and the design of search patterns of optical devices with adaptive algorithms.

Additionally, the in- tegration of observation tools and techniques, especially in areas such as black hole research, is monitored with careful observation. Additionally, many researchers have used instrument learning to design tools or considered instrument learning in their design processes.

SPectr Ooscopy Ken Simulation (SPOKES) is the only successful cosmic experiment to date that completes the structure of the DESpec experimental model, from data collection to weak dark matter analysis. However, SPOKES does not yet include the creation of possible negative hypotheses that could accelerate the desired search, especially in areas where the theory is broad, such as dark matter and dark science.

Continuous improvement in this area can be beneficial in several ways. These include creating twins of successful experiments, exploring the potential of instrument learning to improve design tools, and deriving design theories (which are now the basis of scientific research). In addition, it would be useful to conduct a cost-benefit analysis to evaluate energy consumption and the economic benefits of energy consumption.

18.6 The Architectures of Instrument Learning:

The unique data structure and laws of cosmology highlight the need for adaptive instrument learning. While early methods often used existing techniques in computer science, recent work has focused on developing methods specific to cosmological data. Ongoing and future work aims to meet these specific needs, marking the transition to more specialized systems for cosmological applications. The revolution in deep learning began in 2012 with the breakthrough in neural networks (CNN) such as AlexNet, which had a major impact on cosmology. Cosmological data are often represented as images and derived from CNNs, but the proposed model is used only for processing rectangles. New neural network architectures for cosmological applications have been designed to solve this limitation and extend biases such as translation and rotation to principles as diverse as the heavens. These include convolutional networks, translation- and rotation-invariant normalization flows, and fixed-kernel-based convolution architectures. These developments address specific needs in cosmology and differ from computer vision studies that focus on natural images.

In cosmological studies, analysis of periodic data such as the light curves of type 1a supernovae poses a challenge due to inconsistencies and poor observations. While recurrent neural networks (RNNs), short-term memory networks (LSTMs), and Transformers are successful at classifying tasks, standard neural network architectures often lack flexibility for cosmological applications. It has been shown that inspired physical and non-physical neural networks can reduce the size and information required.

However, existing architectures are not always suitable for cosmological needs and have their own limitations in handling parallel operations and remote learning. Efforts should be made to ensure integration and exchange between communities in order to link the development process in computer science with the needs of cosmology. An important example of this is the widespread use of interpolated physical systems in cosmology applications, thanks to the ease of use of pixelation models such as HEALPix. This situation shows the importance of cooperation and the process of transferring to cosmological rules.

It is important to identify and interpret instrument learning to ensure the reliability of findings. However, the adoption of descriptive intelligence (XAI) in the field of cosmology has been limited, in part due to the lack of a valid method for satisfactory cases. There is an urgent need to develop a system for these guidelines. Recent efforts such as post hoc application of signal regression methods to train neural networks have shown promise in improving model interpretation and discovery in cosmology and are expected to lead to further advances in this field in the future.

18.7 Quantification of Uncertainty and Bias:

Recent work in cosmology has focused on addressing these weaknesses and identifying explanations for the consequences of theoretical models such as deep relativity. These advances are important for the use of this technique in cosmology and the broader community. Key elements of analysis include uncertainty and quantity bias. However, further progress is needed to ensure widespread use of instrument learning in cosmology, high- lighting the importance of continued development in this field.

Parameter inference is a function used in cosmological data analysis to describe physical parameters in pa- rameters represented by observations, such as the Λ CDM parameter. Originally, this task was viewed as a regression problem in supervised learning, where a neural network is trained to minimize the mean square error (MSE) between its output and the mode plan. While this method provides a maximum likelihood estimate (MLE), point estimates such as MLE are of limited scientific value for analysis in comparison of parameters with information, especially in cases where physical degeneracies exist between parameters. Furthermore, comparing and combining results from different experiments leads to undesirable consequences for decisions in cosmology. Uncertainty techniques such as Monte Carlo regression, Bayesian neural networks, and deep clustering have been developed in instrument learning. However, their direct application in cosmology is hampered by the difference in the terms used to describe the uncertainty of the two positions. While instrument learning distinguishes between determinism and uncertainty (data and model uncertainty, respectively), these concepts are not fully consistent with the concepts of statistics and perturbation in physics, causing confusion.

The difference in the perception of uncertainty between instrument learning and physics can be attributed to their focus on different types of uncertainty. In instrument learning, the model usually refers to the learning model itself, while in physics, the model consists of physical processes, including the data generation process. Methods used to account for uncertainty in instrument learning must be adapted to physical applications to adequately account for the uncertainty associated with the data generation process. However, even in simple physical systems, these systems can produce inaccurate or erroneous predictions.

Probabilistic instrument learning, especially within the scope of simulation-based inference (SBI), is promising for scientific applications such as cosmology. This method aims to estimate the full Bayesian posterior, likeli- hood, or probability, even if the probability of the data generation process is not available or cannot be affected. Instead, the structure of the data and parameters can be simulated using a forward model. This method is related to Approximate Bayesian Calculus (ABC), which is widely used in cosmology.

In SBI, domain-specific neural networks or predicted aggregate statistics are used as input to a parametric classifier or density estima- tor to predict the quantity of interest (e.g., after or to be). Cosmology contributes to the development of SBI methods and algorithms.

In instrument learning, training parametric classifiers and density parameters for simulation-based inference (SBI) can be difficult and often requires a series of simulations and calibrations to obtain good results. Recent findings show that widely used SBI algorithms can produce reliable posterior estimates that are unacceptable in cosmological applications. To solve this problem, it is important to perform a diagnostic test to verify that the learning instrument's learning-based predictions are well calibrated and statistically similar. These efforts are necessary for the development of simulation-based theories that lead to scientific discoveries.

18.8 Education and Promotion:

Data-driven evolution in cosmology is accelerating, driven by open-source software and publicly available data, providing revolutionary opportunities to support the scientific community and expand the impact of research. To realize this vision, interdisciplinary training is needed to equip researchers with the skills to navigate dis- parate data and collaborate effectively across fields. In addition, effective promotional programs aimed at the general public are necessary to attract a broad audience and stimulate artistic awareness and interest beyond traditional boundaries.

To keep up with advances in data-driven cosmology, scientists must have a variety of skills, including physics, statistics, and data science. While traditional physics courses provide the foundation, additional resources such as massive open online courses (MOOCs) and academic journals are essential for disseminating knowledge. However, there is a need for physicist-centered knowledge and data based approaches that expand scientific knowledge. The Interdisciplinary AI Center and Open Workshop Series encourage collaboration and knowledge exchange, but efforts to foster discussion and classroom development must continue. Additionally, financial institutions need to prioritize diversity, inclusion and equity initiatives to expand collaboration in this area.

Cosmologists are exploring new ways to leverage advances in technology and online platforms to engage with the public. Electronic devices provide opportunities for interactive simulations and graphs, while participation in online learning communities and instrument learning tools can facilitate access to the dataset. Public compe- titions like PLAsTiCC on platforms like Galaxy Zoo and Kaggle have proven successful in garnering hundreds of entries. However, it is important to recognize that these measures may not be effective in reaching vulnerable populations and may propagate inadequate education. Special training and consultancy is needed to solve this problem.

18.9 Conclusion:

In summary, the intersection of cosmology and instrument learning offers great opportunities for discovery and public engagement. Advances in data-driven cosmology require expertise in the integration of physics, statistics, and data science.

Educational initiatives, including massive open online courses (MOOCs) and intellectual property forums, play an important role in training the next generation of researchers. Additionally, efforts to engage a broader audience through interactive sessions, online communities and public campaigns are ongoing, but these need to be coordinated in an integrated and accessible way. By recognizing these opportunities and solving problems, the cosmological community can support a more efficient and effective economic system.

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