Snowmass2021 - Letter of Interest

An Intelligent Platform for Theoretical Understandings of Type Ia Supernovae

Thematic Areas: (check all that apply □/■)

■ CompF2: Theoretical Calculations and Simulation
■ CompF3: Machine Learning
■ (CF4) Dark Energy and Cosmic Acceleration: The Modern Universe
■ (CF6) Dark Energy and Cosmic Acceleration: Complementarity of Probes and New Facilities

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Artificial intelligence (AI) is rapidly changing the landscape of many research fields including that of supernova cosmology. One extremely difficult task in theoretical models of complicated systems such as Type Ia supernovae (SNe Ia) is to map from model products backwards to infer the initial theoretical inputs. By carrying out a comprehensive project of calculating a large number of first principle 3-D thermonuclear explosion and radiation transport models of SNe Ia, we hope to develop AI Assisted Inversion (AIAI) of the highly non-linear theoretical models to allow us to retrieve the theoretical input based on model results (spectra). The AI techniques we develop can be generic and define a new frontier of theoretical modeling of similarly complex systems. We aim to form an AI enabled platform that will grow organically with the participation of the entire community of theorists working on Type Ia supernovae. We aim to cross calibrate these models with observations to improve the precision of the physical models up to the level of cosmological applications. Such physical models are valuable in the next generation cosmological experiments using LSST and WFIRST.

Thermonuclear explosions of white dwarfs (WD), SNeIa, are key in cosmology due to their brightness and homogeneity in light curves (LC). However, intrinsic diversity of SNeIa, apparent diversity due to asymmetries, and possible evolution with redshift (z) pose a problem for high precision cosmology. Systematic effects may be due to changes in progenitor population and realized explosion scenarios, which may include WD explosions close to the Chandrasekhar mass M(Ch), namely "classical" and "pulsating" delayed-detonation models(DDT, PDD), the explosion of a sub-M(Ch) WD triggered by a He-layer detonation (HeD), and dynamical mergers of two WDs (Mergers). The structure of the progenitors and resulting explosion properties are governed by nuclear physics. The emerging photon fluxes are Nature's play of atomic physics. As a result, spectral and LC fits to observations may not result in a unique interpretation. Advances in observations pushed models into new physical regimes with even more similarity: For HeD, there was a shift towards higher masses, 0.9 to 1.1 Mo, and a reduction of the surface He-layers by assuming microscopic mixing of C into the He layers. For DDT models, WD masses M(WD) range between 1.28 to 1.37 Mo, progenitors also have surface layers of H/He or He (10^{-4} vs. $0.1 - 5 \times 10^{-3}$ Mo in HeDs), or C/O, and observational evidence emerged for high magnetic fields B which can suppress strong Rayleigh-Taylor (RT) mixing a former weakness, and the transitions between modes of burning. This results in very similar observational relations including dependencies on metallicity Z and main sequence mass M_{MS} but resulting in brightness differing by 10-20%.

Clearly, we need a better understanding of the underlying physics, which requires bringing together experts with diverse expertise from a wide physical background ranging from combustion physics to magneto-radiation hydrodynamics, nuclear and atomic physics to stellar evolution and explosion, along with the observers and data analysts. The new area in large-scale data with robotic surveys such as LSST/WFIRST and new multi-prong approaches requires new mathematical approaches that take advantage of the new analysis techniques presently undergoing rapid development such as Artificial Intelligence.

The power of AI enabled studies of SNeIa was demonstrated in a recent paper (Chen, Hu, & Wang, 2020, ApJS, in press). The application of deep learning techniques allows for a map from the products of radiative transfer models backwards to the initial conditions used in those radiative transfer models. This enables a large array of quantities to be deduced from a spectrum: the layered chemical structure, density profiles, and the kinematic structures. Such AI-enabled inversion gives us a new tool for analyzing observational data. The robustness of the method was tested using observations taken from the Hubble Space Telescope (HST). Future missions such as the LSST and WFIRST may yield similar data in massive quantity. The intelligent platform we aim to construct will be an organic and live platform that draws power from all available theoretical and observational works on SNeIa to move the entire field forward.

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