College of Natural Sciences
& Mathematics
UNIVERSITY OF DENVER

Physics & Astronomy Graduate Student Presentations

Wednesday, October 15, 4:00pm, Olin 105

Emma Lieb

Dynamics and Dust Properties of the Colliding-Wind Dust Producer WR140

Carbon-rich Wolf–Rayet (WR) binaries are a prominent source of carbonaceous dust that contribute to the ISM of galaxies. In the "textbook" episodic dust-producing WR binary, WR140, dust forms in the colliding winds of the two stars and expands outwards, forming the dramatic shell structures we see with JWST. Our observations show that these dusty shells are astrophysical and that their substructure is caused by instabilities in the wind collision region between the stars. The shells also appear to propagate without significant deceleration into the ISM, at a velocity almost 1% the speed of light, suggesting that WR140 and other carbon-rich WR binaries are important contributors of carbonaceous material to the Galactic dust budget. Our current work includes detailed temperature and optical depth maps as well as geometric modelling of the dust.

Elyssa Devisscher

Understanding the Line Shape of Ferromagnetic Resonance Spectrum in a Flip-Chip Measurement

Flip-chip Ferromagnetic resonance spectrum with a coplanar waveguide has been widely used for studying magnetization dynamics of thin films. Typically, the peak position and linewidth are extrapolated, while the line shape – specifically how far the spectrum deviates from a perfectly symmetric Lorentzian – is neglected. To quantify this deviation, we define a deviation phase angle (DPA), and we find that the DPA of the ferromagnetic resonance spectrum depends on frequency, impedance mismatch in the transmission line, as well as the material itself.

Lili Houston

Physics-based machine learning decodes the sequence-conformation link in the disordered proteome

Over a third of the human proteome is disordered. Predicting the behavior of these flexible, dynamic proteins is a challenge, especially compared to folded proteins whose structure dictates function. We integrate physics theory, simulation and machine learning to decode the link between disordered protein sequence and function. We model sequence-dependent electrostatics analytically, while nonelectrostatic interaction is extracted from simulations for many sequences and subsequently trained using ML. The resulting Hamiltonian can predict sequence-dependent properties of intrinsically disordered proteins (IDPs). Combining physics and machine learning yields more accurate predictions than physics alone and enables predictions of untrained observables that are not possible solely using machine learning. Predictions made using this fast, high throughput approach can help study phase separation of protein mutations, investigate protein binding, provide insights into evolution, and more.