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A Machine Learning Approach to Surveying Solar Energetic Particle Time Profiles

We have pursued machine learning (ML) techniques to analyze solar energetic particle (SEP) data as supplements to traditional analysis. Machine learning approaches have the potential to execute large surveys of SEP event data much faster than traditional algorithmic approaches and to identify features in large data sets that are unseen by traditional analysis without a priori knowledge of their existence. We apply classifiers to SEP time profiles to distinguish between SEP events with exponential decays (suggesting convective transport and adiabatic deceleration), power law decays (suggesting diffusive propagation), and irregular profile shapes, and we apply regressors to extract time decay constants from exponential or power law decays. These time decay constants can also be used for broad surveys of inferred ionic charge states in SEP events using the technique of Sollitt et al. (2008).

In this presentation, we explain in detail the selection and preparation of ML training data. We extract SEP event data from ACE/SIS and STEREO/LET data, separating time profiles individually by energy and element (e.g. He, CNO, Ne, Mg, Si, and Fe, at energies up to 168 MeV/nuc for Fe). Each individual SEP event can yield 10 or more separate time profiles, depending on selection of energy and element, so over ~1000 time profiles are easily available in ACE and STEREO data going back to at least 2017. Target data, or labels, are generated for each time profile in the ML training data by applying algorithmic fits to identifiable decay phases, classifying decays as exponential, power-law, or irregular.

We have trained ML models with this training data and the target data, and preliminary tests have yielded exponential decay classification with >90% accuracy to date. We have also begun training regression models to extract time decay constants, with >85% accuracy in extracting exponential decay constants. We will outline some of the classifier and regressor configurations used to train the models.

Collaboration(s)

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