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Poster
Over the past decade, machine learning has completely transformed space weather forecasting, delivering state-of-the-art predictive models across the Sun–Earth system. Despite this progress, forecasting rare and extreme events remains a major challenge. This limitation stems from the standard training paradigm, in which models minimize a loss function averaged over many samples, inherently biasing performance toward quiet conditions while underrepresenting rare but high-impact events.

We introduce PARIS (Pruning Algorithm via the Representer theorem for Imbalanced Scenarios), a principled framework designed to address data imbalance by directly optimizing the training set. PARIS computes a closed-form deletion residual, which quantifies the exact change in validation loss induced by removing an individual training sample—without requiring retraining.

We demonstrate the effectiveness of PARIS on Dst index forecasting. Results show that the algorithm can reduce the training set size by up to 75% while maintaining or improving overall RMSE. Moreover, PARIS consistently outperforms standard approaches such as re-weighting, synthetic oversampling, and boosting, highlighting its potential as a robust and computationally efficient solution for imbalanced learning in space weather applications.

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