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# Predicting Space Weather With Pattern Recognition

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One of the key challenges of space weather forecasting is to predict the severity and time evolution of significant space weather events driven by coronal mass ejections (CME). Sufficiently good predictions of terrestrial space weather effects should be possible provided that a few key ingredients of CMEs can be successfully forecast. Often the most important factor to consider is the evolution of the interplanetary magnetic field in the solar wind during these events. Unfortunately, this is not a trivial task given the resources available. Any sufficiently successful approach will by nature have to be multi-disciplinary: observations of the Sun to capture emerging CMEs, modeling to predict the propagation and large-scale development of CMEs, and plasma parameter predictions to derive a sufficiently long-term prediction (i.e. several hours to a day) for the L1 point. At L1, prediction and data will come together for direct comparison in real-time.

Rudiments of such a prediction exist. But the fusion of the necessarily diverse data sources is not straightforward. We have been investigating a pattern recognition approach to space weather forecasting using self-organizing maps and learning vector quantization, focussing primarily on solar wind patterns at the L1 point. This approach is particularly well-suited to detect and classify representative behavior of the data, which in turn can be used to attempt probabilistic time series predictions without the need of physical models of the system. We see a three-fold potential in this approach: (1) Data processed and analyzed this way can be readily and easily compared to existing studies of the solar wind and related data, allowing a better understanding of the performance of the technique, (2) the combination of diverse and even time shifted data sources (e.g., solar observations combined with in situ observations) is straightforward, and (3) the method can be easily injected into a real-time data analysis pipeline.