

Correctly featurizing time series data that describes the solar magnetic field is critical for predicting solar flares.

Time Series Analysis of Flaring Active Regions

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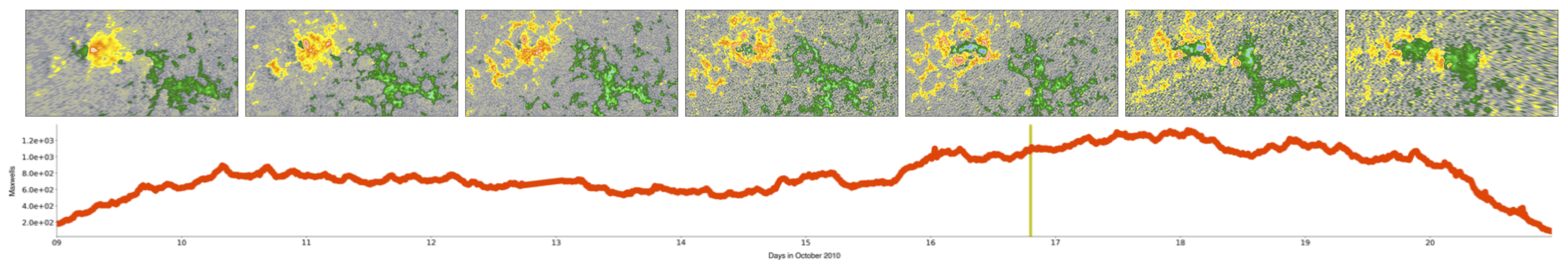


Figure 1: Flux vs. time
Top row: HMI photospheric magnetic field data for NOAA Active Region 11112, which produced an M2.9-class flare on October 16, 2010
Bottom row: time versus current helicity data for the same active region (time aligned with the pictures); the yellow line represents the flare

INTRODUCTION

- Solar flares are sudden releases in energy due to rapidly changing magnetic fields.
- Since flares are the result of a buildup of energy over time, we can analyze time series data to forecast and understand flares.
- We analyzed many variables that characterize solar active regions such as magnetic flux, electric current, and free magnetic energy.

RESULTS

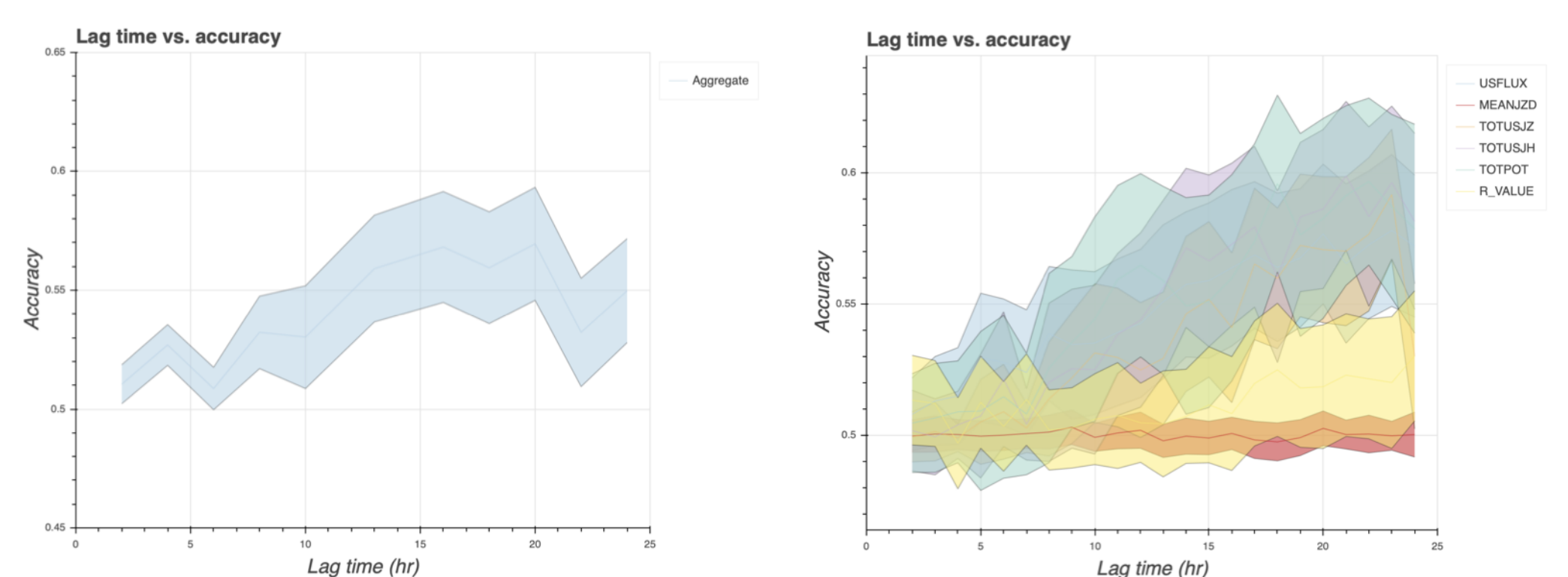


Figure 3: Model accuracies vs. lag time
Left figure: combined feature model accuracies vs. lag time
Right figure: individual feature model accuracies vs. lag time

CONCLUSIONS

- Over time, the testing accuracies for the single-variable models increase over time.
- Training on a model with all the HMI features consistently performs better than any single feature, showing that time series analysis is important for flare prediction models.
- The highest-performing features are total magnetic flux, total electric current, and free energy.
- The lowest-performing features are mean electric current and polarity inversion line flux.

FUTURE WORK

- More robust model: state space modeling to capture variability.
- Change negative case to assert that there are no flares for some time after the data ends.
- Predicting different solar events with time series data.

METHODS

Positive and negative classes for training

- Positive class: 24-hour period before a flare.
- Negative class: 24-hour period without flares in a flaring active region.

Feature extraction

- Polynomial fits have high error on the edges of data due to Rudge's phenomenon.
- Used cubic spline fitting model: fit multiple polynomials to data.

Learning model

- Stochastic gradient descent: fast, easy to interpret.
- AdaBoost: boosting algorithms have high accuracy.



The code to obtain these results and an accompanying research note in RNAAS will be uploaded in the next week.