A Deep Learning Based Approach to Predict the Onset of Magnetic Substorms

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Abstract

In this study, we present the first deep learning based approach to predict the onset of a magnetic substorm, defined as the signature of the auroral electrojects in ground magnetometer measurements. Specifically, we use a time history of solar wind bulk speed (Vx), proton number density (Np), and interplanetary magnetic field (IMF) components (Bx, By, Bz) as inputs to forecast the occurrence probability of an onset over the next one hour. The model has been trained and tested on a dataset derived from the SuperMAG list of magnetic substorm onsets compiled between 1997 and 2017 and achieves ~75 precision and recall rates. The ability of our model to forecast a substorm onset based on solar wind and IMF inputs prior to the actual onset time and the trend observed in IMF Bz prior to onset suggest a majority of the substorms may not be externally triggered by northward turnings of IMF. Furthermore, we find that IMF Bz and solar wind velocity (Vx) have the most significant influence on model performance and thereby provide maximum predictive power. Finally, principal component analysis shows a significant degree of overlap in the solar wind and IMF parameters prior to both substorm and non-substorm intervals. This overlap suggests that solar wind and IMF alone may not be sufficient to forecast all substorms, and perhaps other factors, such as the dynamics of the magnetotail, or stochasticity are also important.

Introduction

- A substorm, often referred to as the magnetospheric substorm or an auroral substorm, is a complex phenomenon involving energy transfer from the magnetotail to the auroral ionosphere (Akasofu, 1964). Figures 1-2 show a substorm observed from Polar UVI satellites and ground magnetometers.
- In this study, we present the first deep learning based approach to predict the onset of a magnetic substorm.

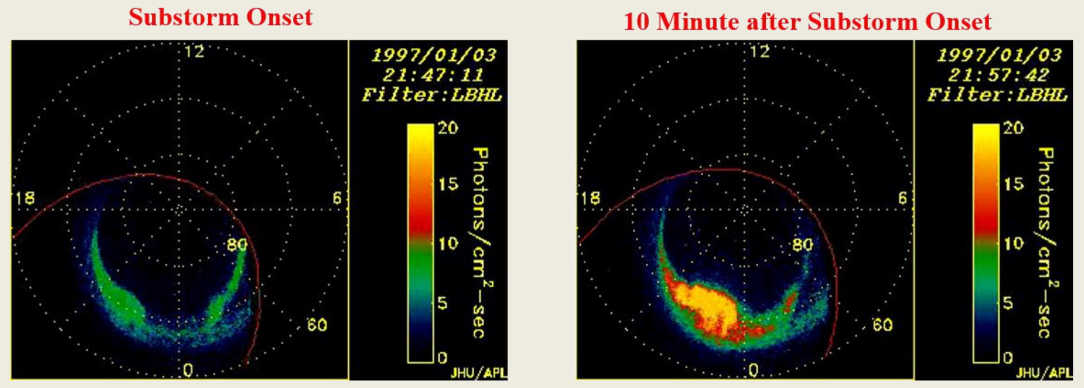

Figure 1: An example of an auroral substorm occurred at 21:47 UT on January 3rd, 1997, captured by cameras onboard of Polar UVI satellites.

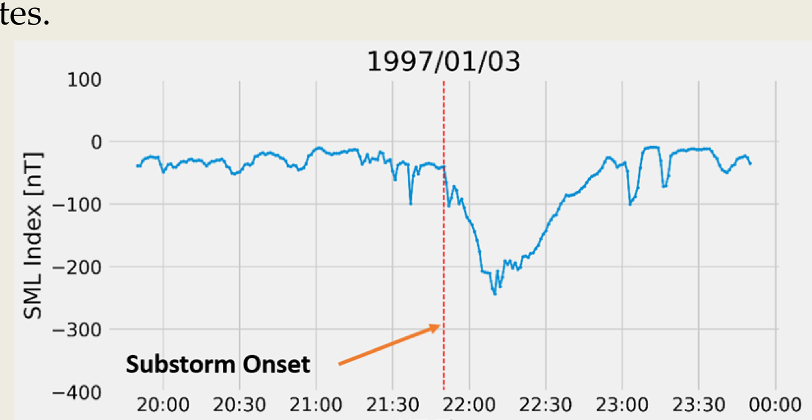

Figure 2: An example of a magnetic substorm occurred at 21:50 UT on January 3rd, 1997, as seen from SML index.

Datasets and Model Architecture

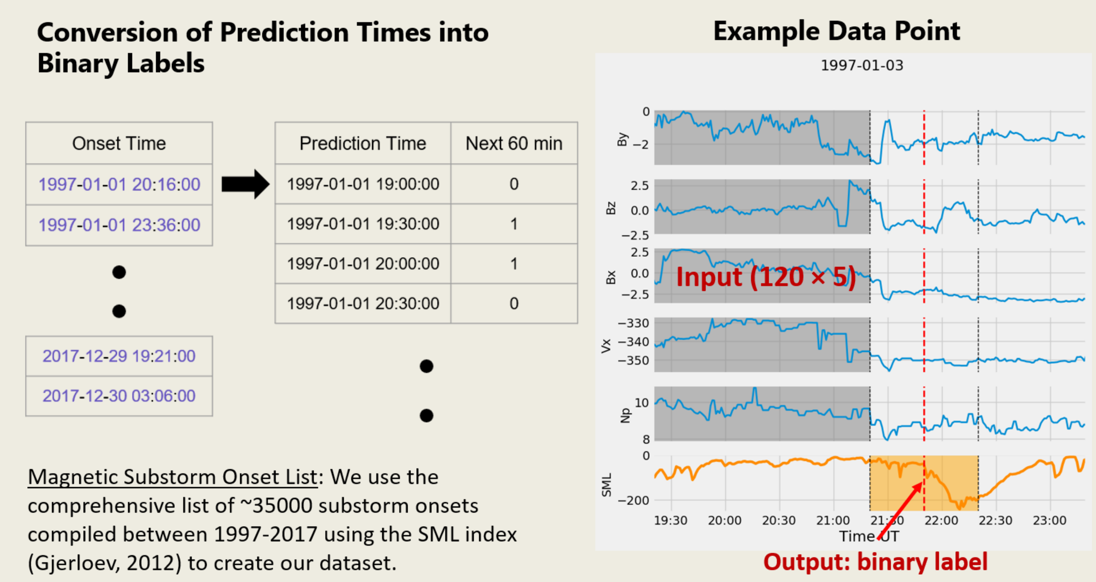

Figure 3: Conversion of prediction times into binary labels based on the presence/absence of a substorm within the next 60 minutes (left). An example of data point classification to a deep learning mode (right).

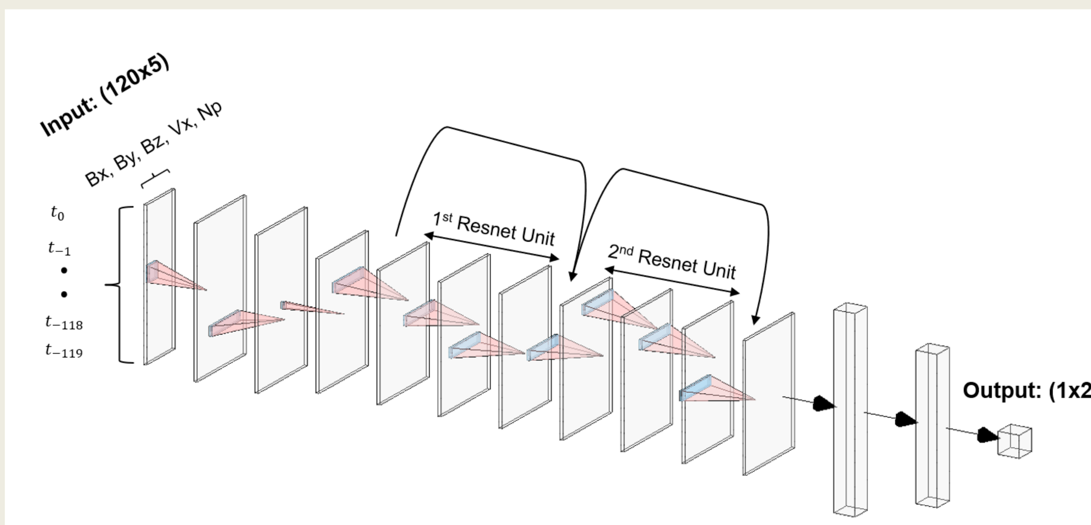

Figure 4: A schematic of ResNet CNN architecture with two ResNet Units for multivariate time series processing of solar wind & IMF data. The input layer takes a 2D input array with 120 × 5 elements and the output layer renders probability estimates for substorm non-substorm classes.

Sample Predictions

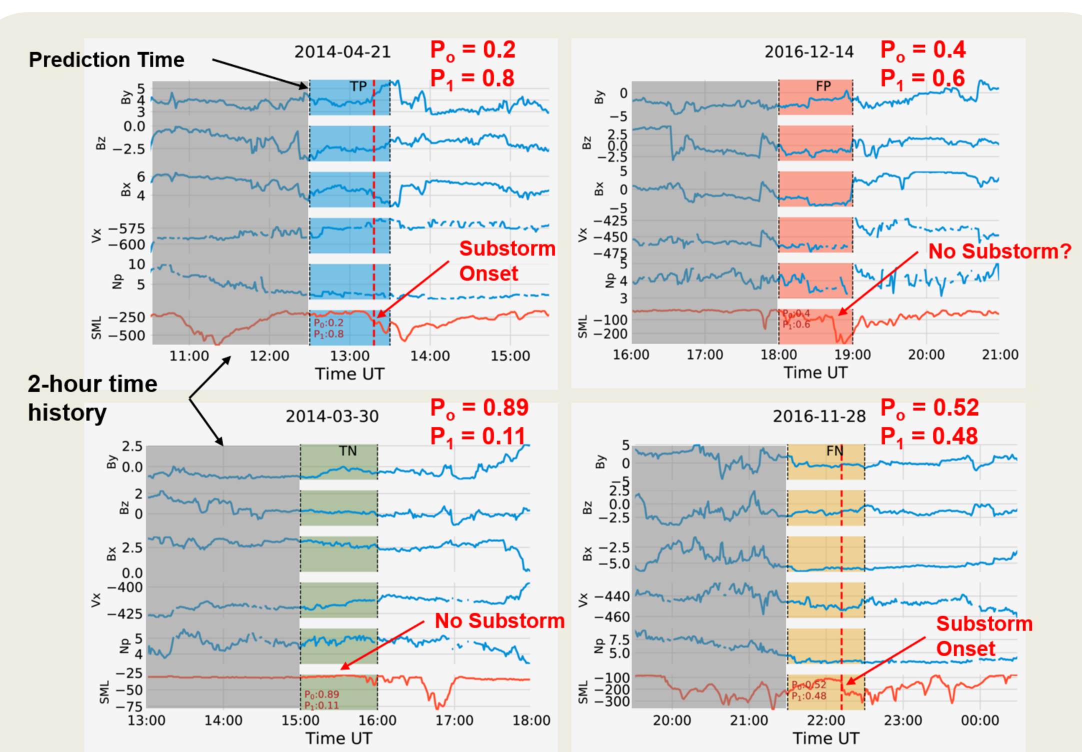

Figure 5: Example model predictions, clockwise from top left are True Positive (TP), False Positive (FP), False Negative(FN) and True Negative(TN) predictions. The dashed black lines and/or the shaded regions mark the prediction interval and the dashed red lines indicate actual onset time provided by SuperMAG. The probabilities associated with each forecast are shown in red text.

Model Performance

Table 1: Model performance for train, validation, and test datasets.

Prediction for Train Data

Class Label	Precision	Recall	F1-Score	Support
0 (non-substorm)	0.77	0.70	0.73	21,236
1 (substorm)	0.72	0.79	0.75	21,236

Prediction for Validation Data

Class Label	Precision	Recall	F1-Score	Support
0 (non-substorm)	0.74	0.80	0.77	4,496
1 (substorm)	0.78	0.73	0.75	4,496

Prediction for Test Data

Class Label	Precision	Recall	F1-Score	Support
0 (non-substorm)	0.74	0.75	0.74	4,607
1 (substorm)	0.75	0.73	0.74	4,607

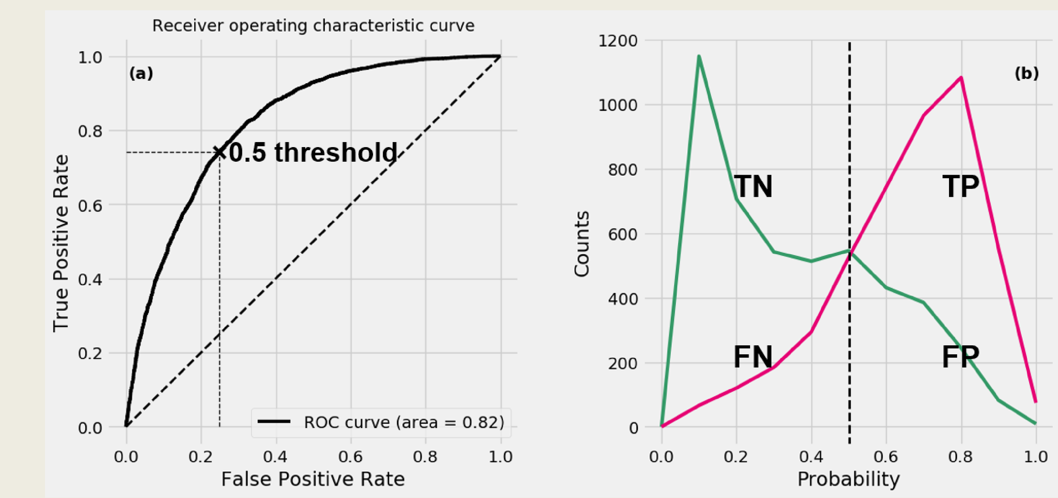

Figure 6: (a) Receiver operating characteristic (ROC) curve for the forecasts. (b) Histograms of predicted probability of substorms forecasted for both onset (maroon) and non-onset (green) classes.

Overlay in the Input Parameters

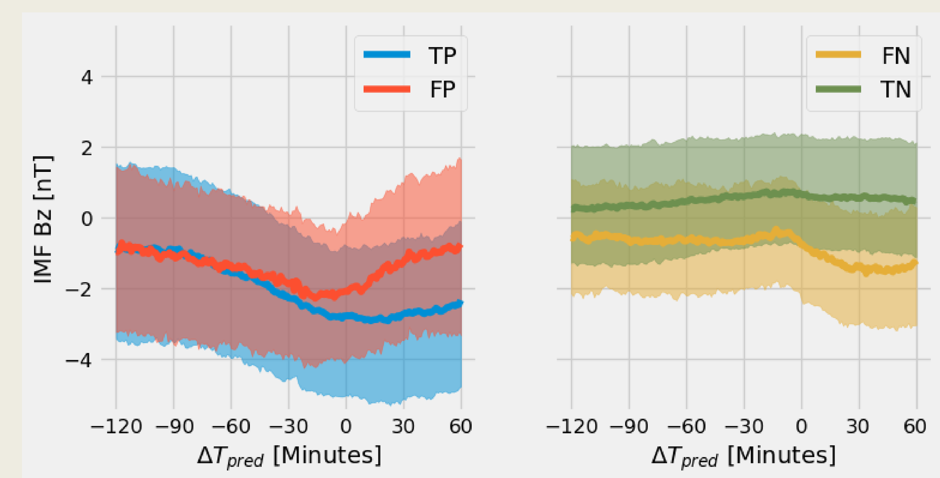

Figure 7: Variability in IMF Bz with respect to prediction time for the four forecast categories.

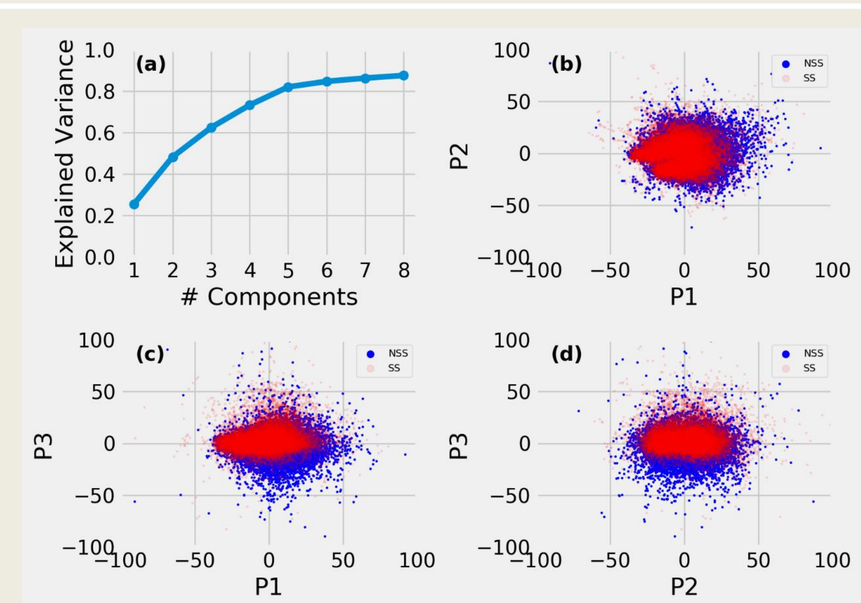

Figure 8: Principal component analysis of the input 2D arrays of substorm and non-substorm events.

Input Parameter Importance

Table 2: Parameter ranking. Precision, recall and F1-score of onsets and non-onsets when different IMF and solar wind parameters are given as inputs to the model.

Full model

Dropping Vx mostly affects the recall.

Dropping Bz affects both the precision and recall.

Bz, Vx, and By are most important features.

	Precision	Recall	F1 − Score
Bx, By, Bz, Vx, Np	0.75	0.73	0.74
Bx, By, Bz, Vx	0.75	0.71	0.73
By, Bz, Vx, Np	0.74	0.73	0.74
Bx, Bz, Vx, Np	0.74	0.73	0.74
Bx, By, Bz, Np	0.73	0.67	0.7
Bx, By, Vx, Np	0.69	0.58	0.63
By, Bz, Vx	0.75	0.7	0.72
Bz, Vx	0.75	0.7	0.72
Bz	0.71	0.68	0.7
Vx	0.69	0.51	0.58
By	0.64	0.49	0.55
Bx	0.65	0.43	0.52
Np	0.58	0.35	0.44

S-M Coupling Function as Input

Table 3: Precision, recall and F1-score of the model when different coupling functions are given as model inputs.

Prediction results from models with different coupling functions as inputs

Prediction results from models with Solar Wind & IMF parameters as inputs

Model Inputs	Precision	Recall	F1-Score
$V_x\ B_T$	0.68	0.52	0.59
$E_{KL} = V_x\ B_T\ Sin^2\ (\frac{\theta_c}{2})$ (Kan & Lee, 1979)	0.74	0.63	0.68
$E_{TL} = N_p^{\frac{1}{2}}\ V_x^2\ B_T\ Sin^6(\frac{\theta_c}{2})$ (Temerin & Li, 2006)	0.75	0.64	0.69
$\frac{d\Phi_{MP}}{dt} = V_x^{\frac{4}{3}}\ B_T^{\frac{2}{3}}\ Sin^{\frac{8}{3}}(\frac{\theta_c}{2})$ (Newell et al., 2007)	0.75	0.67	0.71
B_x, B_y, B_z, V_x, N_p	0.75	0.73	0.74
$B_x, B_y, B_z, V_x, N_p, \frac{d\Phi_{MP}}{dt}$	0.75	0.74	0.74

Summary & Conclusions

- We present the first deep learning based approach to predict the onset of a magnetic substorm. The model can correctly predict substorm onsets ~75% of the time.
- We find that IMF Bz and SW speed Vx have the most significant influence on model performance and provide maximum predictive power.
- External features such as IMF and SW can provide a predictive power of ~75%. Internal features such as the dynamics of the magnetotail may be necessary to further improve the prediction accuracy.

References

- Akasofu, S.-I. (1964). The development of the auroral substorm. Planetary and Space Science,12(4), 273 - 282. doi:https://doi.org/10.1016/0032-0633(64)90151-5

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M. Maimaiti is funded by NSF under Grants AGS-1341918, AGS-1259508 and AGS-1552247. Manuscript is submitted to Space Weather.