Using supervised learning to identify flux rope and its and orientation

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Introduction

The identification and reconstruction of monotonic and coherent magnetic configurations observed within Interplanetary Coronal Mass Ejections (ICMEs) is critical for predicting the geomagnetic effect of these structures arriving at Earth. These internal structures of ICMEs are often associated with a spacecraft crossing a large flux rope with a helical magnetic field lines topology, . As inspired by Nieves-Chinchilla et al. (2018, 2019), we use machine learning techniques to interpret the ICME in situ magnetic field observations and understand in depth what in situ magnetic field observations should be expected by spacecraft when it crosses flux ropes with different trajectories (2019).

We examine how effectively a Convolutional Neural Network (CNN) can recognize flux rope signatures from a set of combined hodograms and forecast the flux rope's orientation.

CNN Model Architecture and datasets

Identifying Flux Rope Signatures

- Synthetic magnetic field component hodograms (Figure (b)) data, created using the EC model (Nieves-Chinchilla et al 2018) as input for the CNN (Figure (a)) model.
- Total of 132000 unique events varying all flux rope direction parameters.
- The model was trained for 50 epochs with no-noise data. After, we chose the best performing model for no-noise data and proceeded to train it with data with 5% and 10% noise respectively. We do the stepwise training procedure to evaluate how noise affects the classification's performance and understand how it affects the model learning.

Figure (a) – Example of flux rope observed and fitted by Nieves-Chinchilla et al 2019.

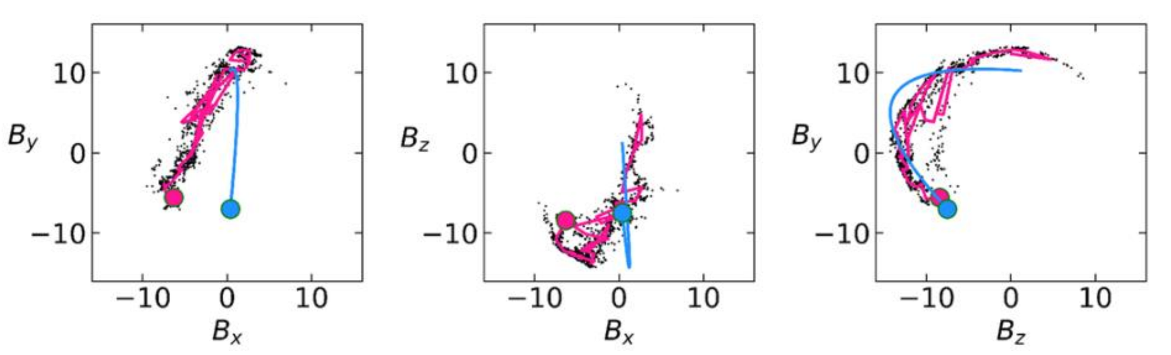
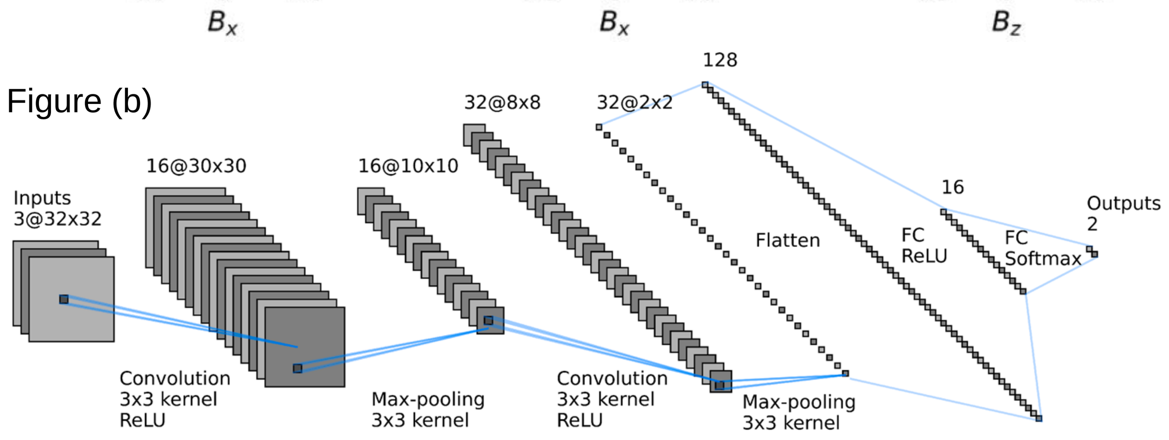


Figure (b)



Forecasting Flux Rope orientation

- The model was trained for 500 epochs. We use the synthetic time series of magnetic field components ([Bx, By, Bz], Figure (d)) data created using the CC model (Nieves-Chinchilla et al 2016) for training and testing the CNN model (Figure (c)).

Figure (d) – Events of September 18th, 2010. Flux rope observed by Wind spacecraft. The pink line refer to the fitting done by Nieves-Chinchilla et al 2019. From top to bottom we observe the component Bx, By and Bz of the magnetic field.

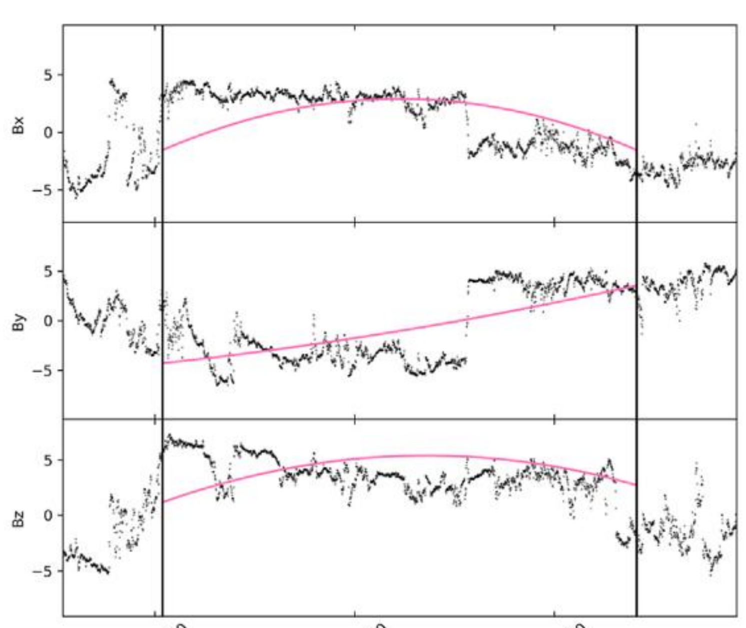


Figure (c)

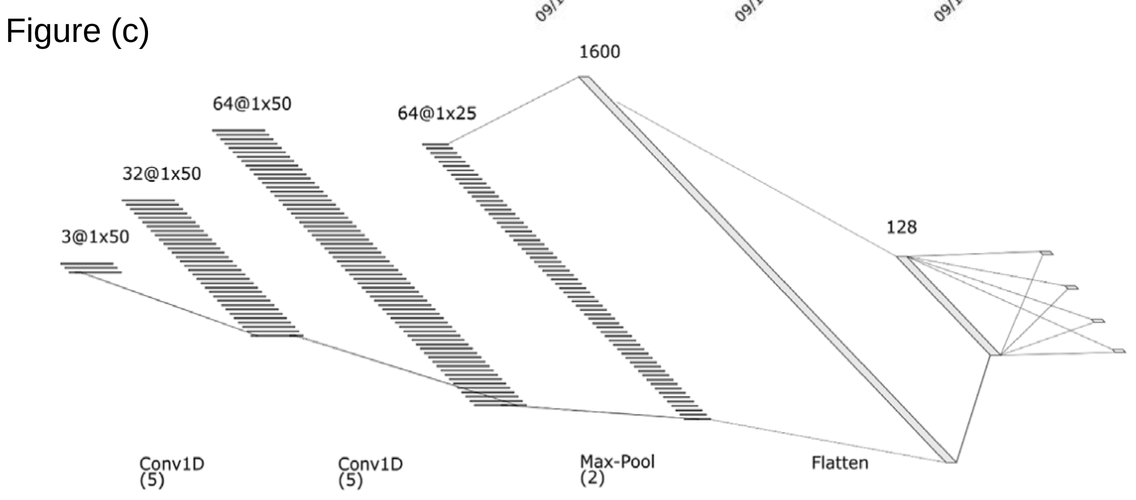


Figure (e) contains 3 confusion matrices with the prediction results when the CNN model is tested on the larger 270 events set. From left to right, we have the results for the model trained with no noise, 5% and 10% respectively

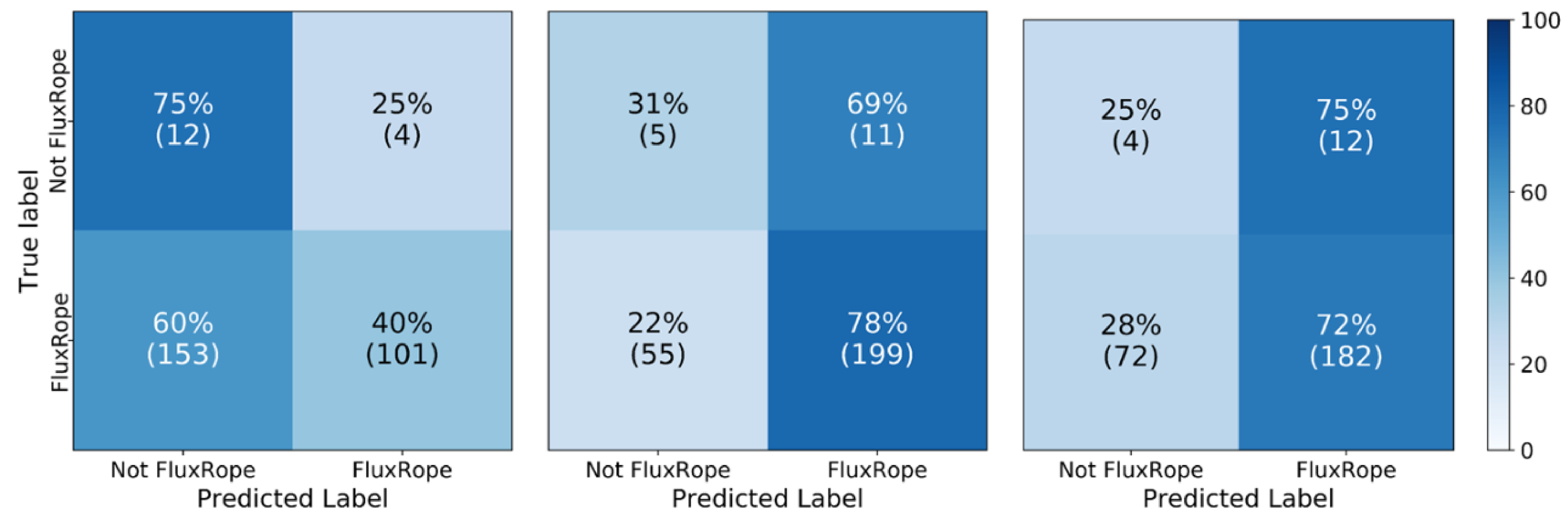


Table 1 contains metrics for the testing CNN model trained in different level of noises when applied to the subset of 32 real events set

Quantities	No Noise	5% Noise	10% Noise
True Positive	16 (89%)	18 (100%)	16 (89%)
False Positive	2 (14%)	5 (36%)	7 (50%)
True Negative	12 (86%)	9 (64%)	7 (50%)
False Negative	2 (11%)	0 (0%)	2 (11%)
Overall Accuracy	88%	84%	72%
Precision	0.89	0.78	0.70
Recall	0.89	1.00	0.89
F1 Score	0.89	0.88	0.78

Table 2 contains metrics for the testing CNN model trained in different level of noises when applied to the lager 270 real events set

	Not including Cx		
	No Noise	5% Noise	10% Noise
Accuracy	42%	76%	69%
Precision	0.96	0.95	0.94
Recall	0.40	0.78	0.72
F1 Score	0.56	0.86	0.81

Identifying Flux Rope Signatures

Training Results

In this part of he project we trained a CNN (Figure (b)) to identifying Flux Rope signatures in ICMEs observed by Wind and reproduce the flux rope identification from Nieves-Chinchilla et. al 2019. For a successful training we did the following:

- Trained the CNN model for 50 epochs, since a strong overfitting was observed after.
- During the training we used a selected 32 well behaved events to validate the model results. The results of training with the 32 selected is available at Table 1.
- In Table 1, we see the machine learning model had good performance across all three levels of noise, with a high F1 Score, Recall, and Precision of 0.89 for the no noise model and 88% accuracy.
- Metrics drop to 0.88 for F1 Score and 0.78 for Precision with 5% noise. In addition, the accuracy decreased a little to 84% with the 5% noise machine learning model.
- With the10% noise results, the Precision of 0.7 and F1 Score of 0.78, demonstrates an even worse performance on classifying NFR cases.

Finally, the model has an accuracy of 72%. The results display a good performance of the model, although no real event were used in the actual training of the machine learning model weights. These numbers represent our model's capability to identify real flux ropes, although being only trained with synthetic data. A more in-depth analysis of the missed events and a one-by-one comparison was done at Dos Santos et al. 2020.

Inference Results

In Table 2 are the results for the remaining 270 events, we didn't included events classified as "Complex (Cx, i.e., having more than one rotation structure inside)". Table 2 contains extracted quantities from the confusion matrices (Figure (e)) from all three machine learning models evaluated and some complementary metrics to understand the classifications. According to the accuracy in Table 2, the 5% noise synthetic data results indicate the machine learning model can predict 76% of Non-flux ropes correctly and has a precision of 0.95, resulting in a high Recall and F1 Score. This results indicate the model is very robust and has a lot of potential to be improved.

Forecast Flux Rope Orientation

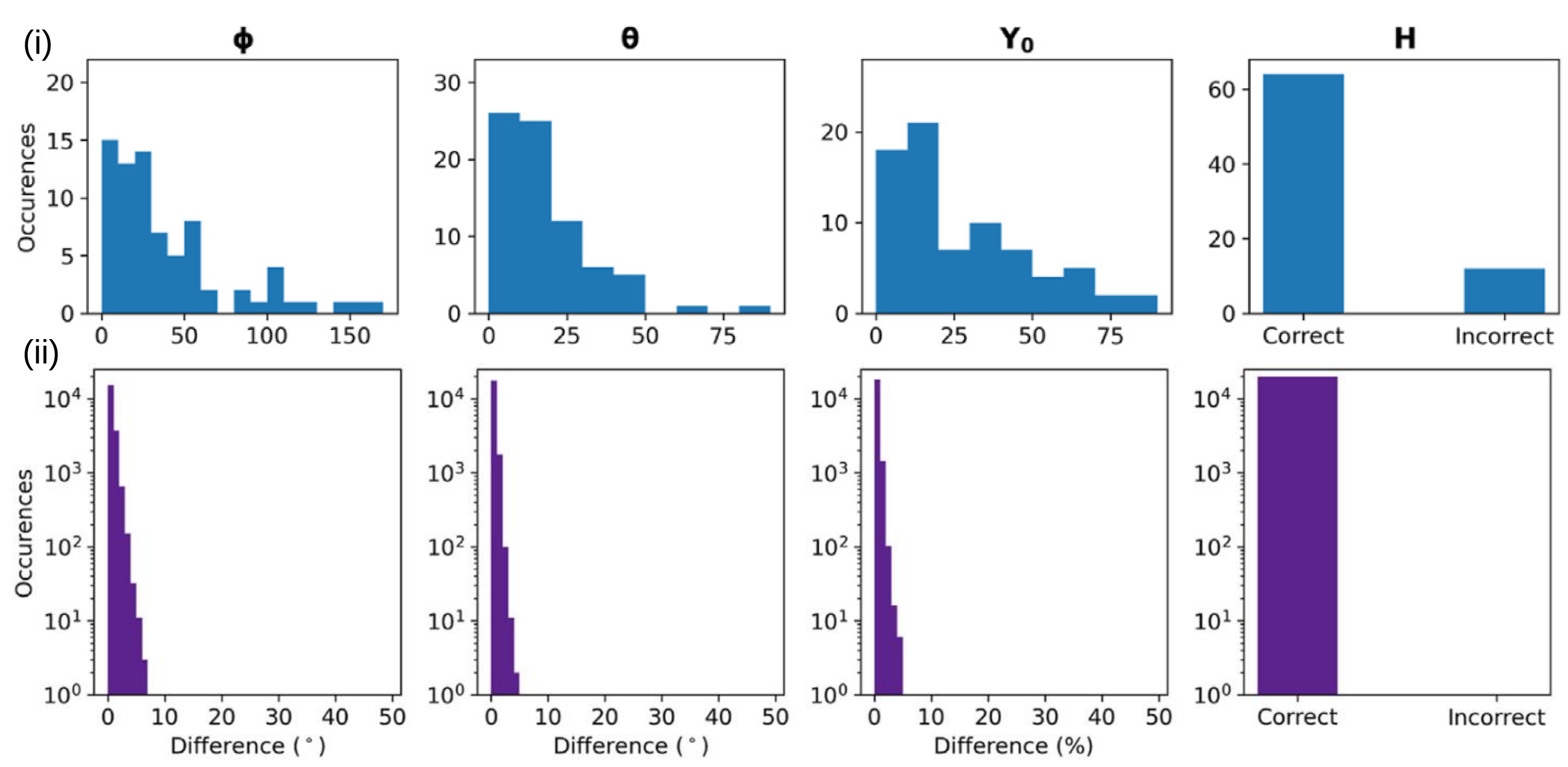
Training Results

In this part of the project, we trained a CNN (Figure (c)) to forecast the flux rope orientation of ICMEs observed by Wind and compare with the orientation found in Nieves-Chinchilla et. al 2018. The flux rope orientation is composed by two angles (phi and theta), impact parameters and helicity. For the model development we did the following:

- We divided the created synthetic data in 60% (58, 800) for training, 20% (19,600) for validation and 20% (19,600) for testing.
- The CNN was trained from 500 epochs.
- Different from the previous project, we only trained on noise-free data for this part.

Looking at these results we can see the model was able to predict all values for the helicity correct. Also, it predicted the angles with 10 degrees less difference from ground truth for both phi and theta angles and 10% less difference for the impact parameter.

Figure (f) contains histograms for the difference of the predicted value and the ground truth. From left to right, there is the difference between ground truth and predicted value for phi, theta and the impact parameter. Lastly it contains a histograms of the correct predictions for the chirality. (i) show the results on testing in real events and (ii) contains the results for testing in synthetic results.



Later we applied the same trained model to 70 events from Nieves-Chinchilla et al. 2019 classified as "Fr". The results show there is a limitation on the model's prediction and all the metrics decrease. Still, there is a clear peak close to zero for the angle's and impact parameter's metrics. In addition, the model could successfully identify the chirality in more than 80% of the cases.

These results shows clear potential on the model to be explored and improved. Many additions can be made on the model like train on data with fluctuations, explore the different architectures, optimize the hyperparameters etc.

Partial Predictions

In addition to the previous work, we decided to extrapolate the model and see if we could predict the flux rope orientation using only partial data, simulating a "nowcasting" of a flux rope orientation during its crossing. Like the previous part we divided the synthetic in situ data in 60% for training, 20% for validation and 20%.

We included data for the same event with 10% to 100% of the event data. Therefore, the dataset is 10 times larger than the previous one. Again, the CNN was trained for 500 epochs. The results for this experiment are in table 3., which in all cases are small. It worth noticing that the peak performance happens with 80-90% percent of the flux rope observed, which goes against our expectations that would be at 100%.

Table 3 - contains the median parameter differences by percentage for all two angles and the impact parameters. From top to bottom it increases the amount of flux rope observed from 10% to 100% in steps of 10%

% Observed	ϕ	θ	Y_0
10	2.10°	1.23°	1.28%
20	1.58°	1.02°	1.08%
30	1.37°	0.90°	0.94%
40	1.23°	0.84°	0.84%
50	1.14°	0.81°	0.79%
60	1.11°	0.80°	0.76%
70	1.04°	0.76°	0.72%
80	1.01°	0.75°	0.71%
90	1.04°	0.76°	0.75%
100	1.10°	0.79°	0.83%