

AUTOMATED CME SOURCE REGION CATALOGUE FOR ML TRAINING

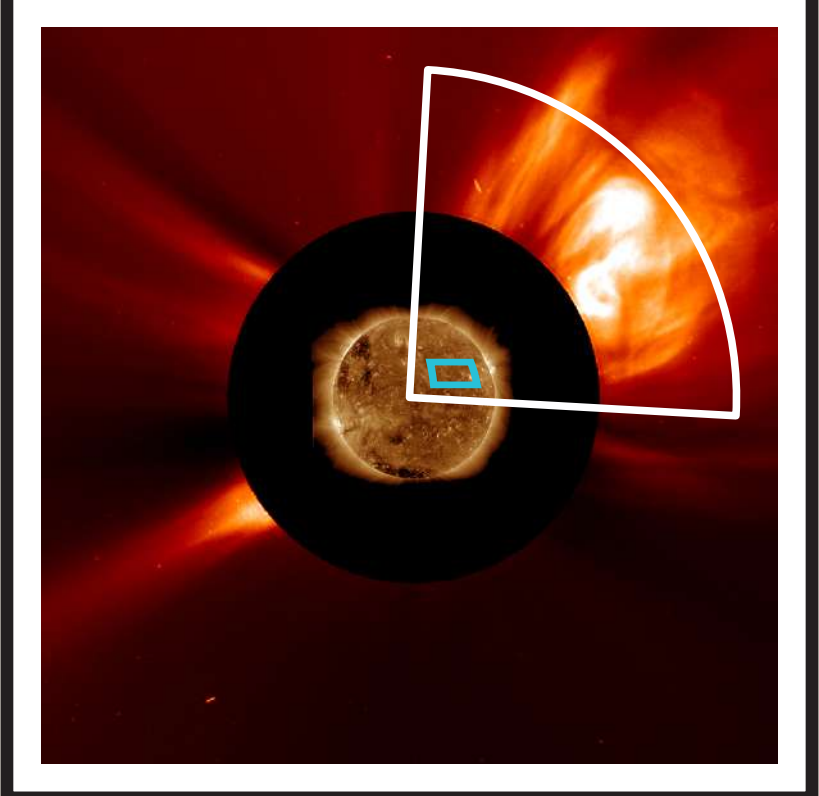
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1 INTRODUCTION

Coronal mass ejections (CMEs) are eruptions that originate in the solar atmosphere which inject plasma, magnetic flux and energy into interplanetary space.

In the event that a CME is directed towards Earth and has the correct magnetic field configuration, it may interact with the magnetosphere, resulting in a geomagnetic storm. These storms can in turn impact satellite operations, communication and location systems and even the electricity grid [1]. It is thus of great importance that we not only understand how these events propagate towards Earth and interact with it but also what the properties of the regions in the Sun that produce them are.



2 WHY?

In recent years, the application of Machine Learning (ML) in heliophysics has become increasingly prevalent. One particular area where ML has been tested is in predicting Coronal Mass Ejections (CMEs) before they leave the Sun. However, the lack of an automated CME source region catalogue makes obtaining training data that distinguishes between active regions that produce a CME and those that do not a difficult task.

Our research focuses on forecasting CME eruptions using images of active regions, in particular the three components of a vector magnetogram and EUV emission structures. To achieve this, we have developed an automated CME source region catalogue based on post-eruptive signatures that can identify the region on the Sun responsible for producing the CME. While we acknowledge the existence of catalogues, such as DONKI, where humans identify the source region, we believe an automated approach offers the benefits of homogeneity, flexibility in selection rules, and no need for human intervention.

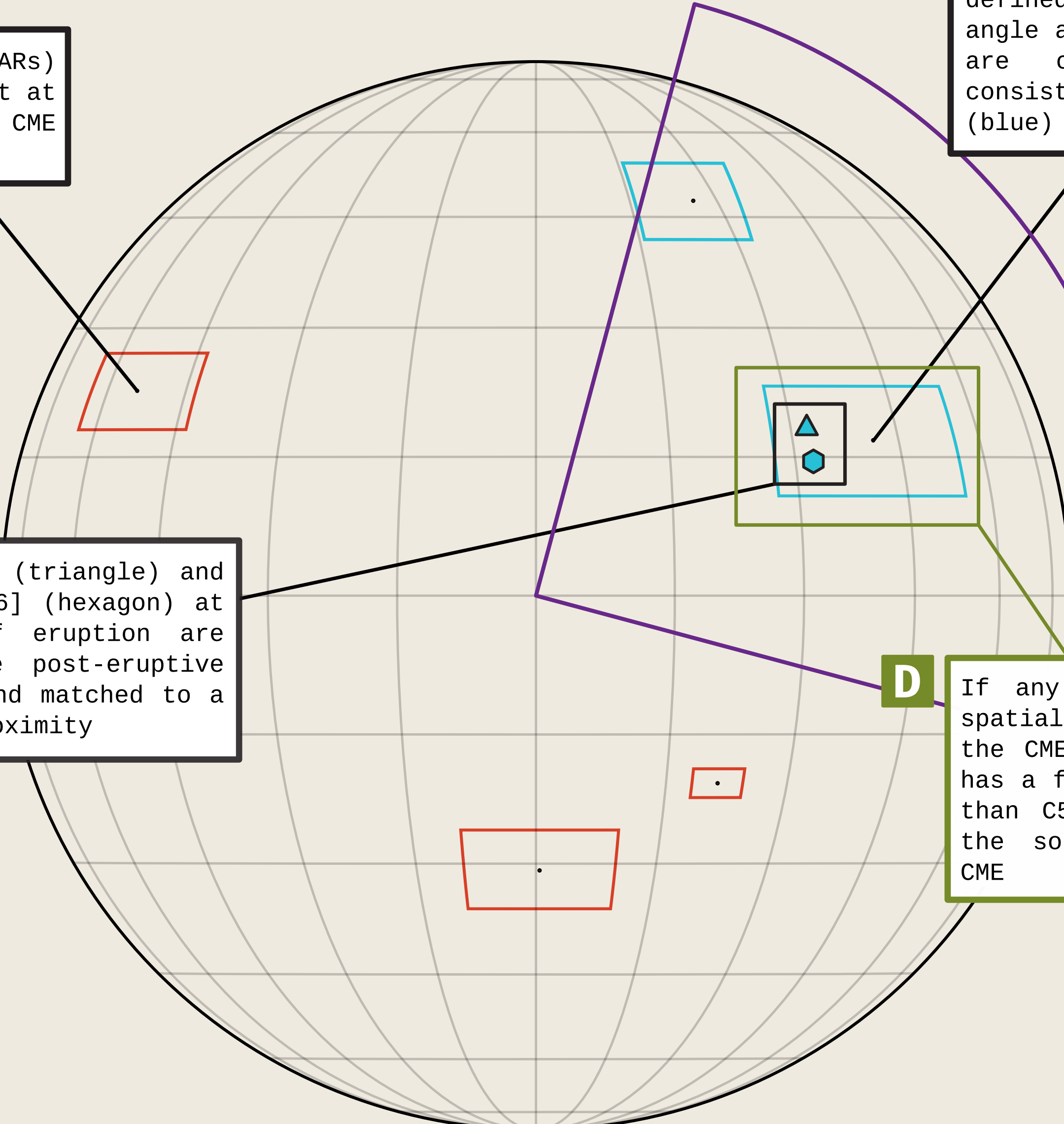
3 HOW?

A Active Regions (ARs) that were present at the time of the CME are identified

B ARs that fall within a wedge defined by the CMEs position angle and width [2] (purple) are considered spatially consistent with the CME (blue)

C Flares [3,4] (triangle) and Dimmings [5,6] (hexagon) at the time of eruption are used as the post-eruptive signatures and matched to a region by proximity

D If any of the regions is spatially consistent with the CME, has a dimming and has a flare of class larger than C5 it is assigned as the source region of the CME



ANIMATED VERSION & POSTER DOWNLOAD

4 RESULTS

Our initial catalogue iteration, following the conditions outlined above, has identified 95 ARs that exhibit spatial consistency with a CME, as well as having a dimming and a flare of class larger than C5.

Although this number of ARs may not be sufficient for machine learning training purposes, it is important to note that we plan on continue building it over time. As such, we will continue to investigate post-eruptive signatures to refine our identification of CME source regions. Specifically, we aim to explore whether certain dimming characteristics alone can signify a CME association, removing the need for a matching flare. Additionally, we will consider data augmentation techniques to increase the variation in a limited dataset.

REFERENCES

- [1] Pulkkinen (2007). Space Weather: Terrestrial Perspective. Living Reviews in Solar Physics, 4.
- [2] Gopalswamy, N., Yashiro, S., Michalek, G. et al. Earth Moon Planet 104, 295-313 (2009).
- [3] Bewsher, Harrison, and Brown (2008). Astronomy & Astrophysics, 478(3):897-906
- [4] Emil Kraaikamp, Cis Verbeeck (2015) J. Space Weather Space Clim. 5 A18
- [5] Yashiro et al. (2005). Journal of Geophysical Research, 110:A12S05
- [6] GOES Soft X-Ray Flare List from Helio V0

5 WHAT NEXT?

Our completed catalogue will serve as the foundation for training a machine learning model for the forecasting of CME eruptions. We will approach the forecasting by combining a Convolutional Neural Network to extract temporal features from solar images and a Recurrent Neural Network to extract temporal features from a sequence of solar images. This combination of features will be used to produce a probabilistic forecast of the likelihood of an AR to erupt in the next X days.

We intend on using pre-trained models and providing them with the X, Y and Z components of the vector magnetic field as measured by the Helioseismic and Magnetic Imager (HMI) onboard the Solar Dynamics Observatory (SDO). However, it is also our intention to eventually combine the HMI data with images from the Atmospheric Imaging Assembly (AIA) to provide the model with magnetogram data as well as images of coronal structures provided by AIA.