Interpreting Transformer-Based CME Forecasting and the Role of Flare Associations

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7th April 2025

Introduction

Coronal Mass Ejections (CMEs)

- CMEs are one of the main drivers of space weather.
- Forecasting which active regions in the Sun produce them and when can help:
  - Better prepare our infrastructure for potential impacts.
  - Potentially better understand the physical mechanisms behind these eruptions.

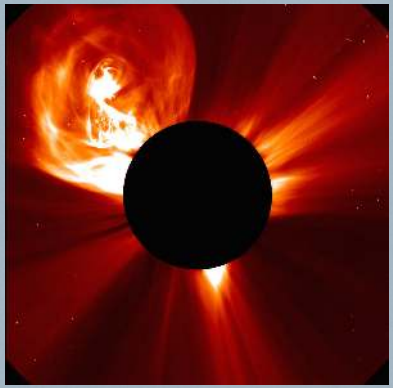

Image credit: ESA/NASA SOHO/LASCO

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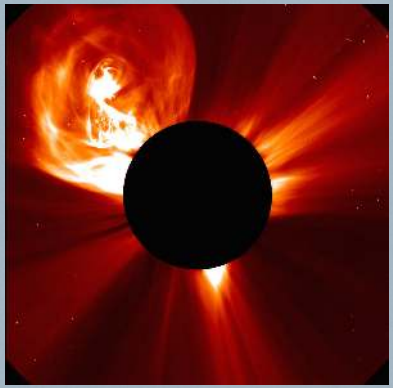

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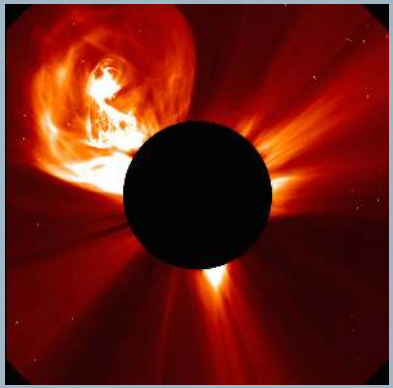

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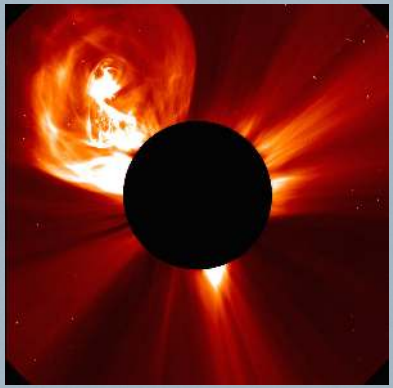

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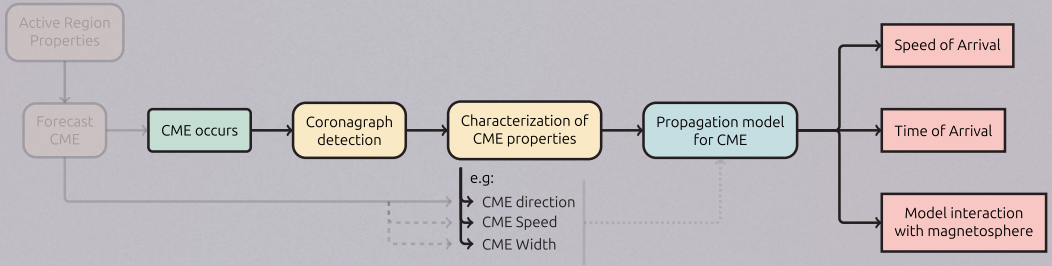
Simple CME impact pipeline



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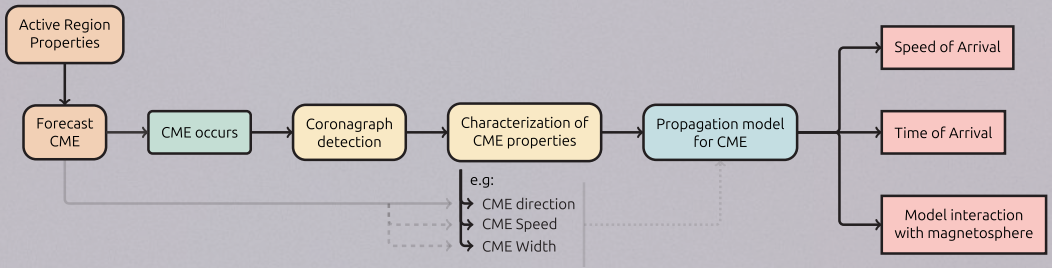

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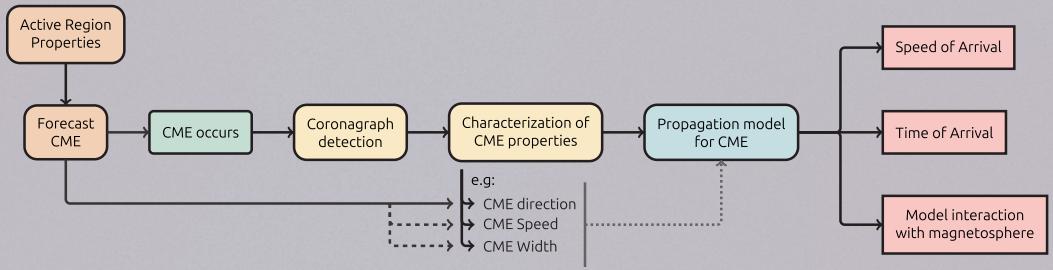

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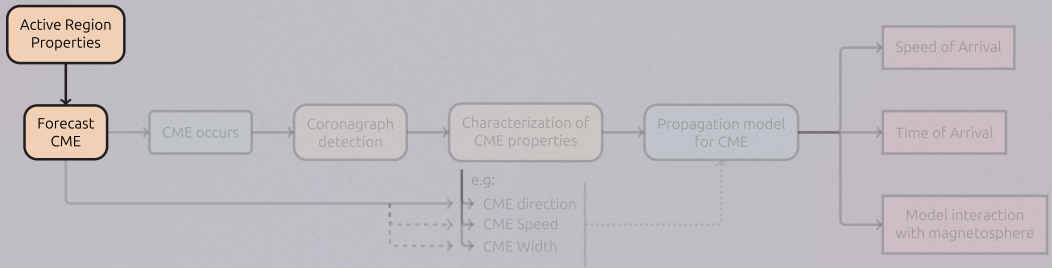
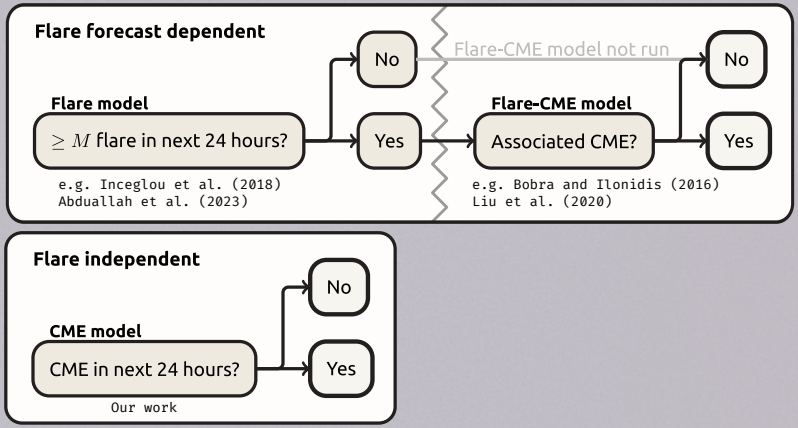


Introduction

Options for forecasting CMEs



Model setup

SHARP keywords (Bobra et al. (2018), Angryk et al. (2020))

- We produce forecasts for Space weather HMI Active Region Patches (SHARPs) between 2010 and 2018.
- Track magnetic field concentrations and *tend* to coincide with NOAA active regions (not always).
- Parameters describing the magnetic field are calculated every 12 minutes. These are our inputs.
- CMEs matched to regions in our previous work (find in **julhcam.com**).

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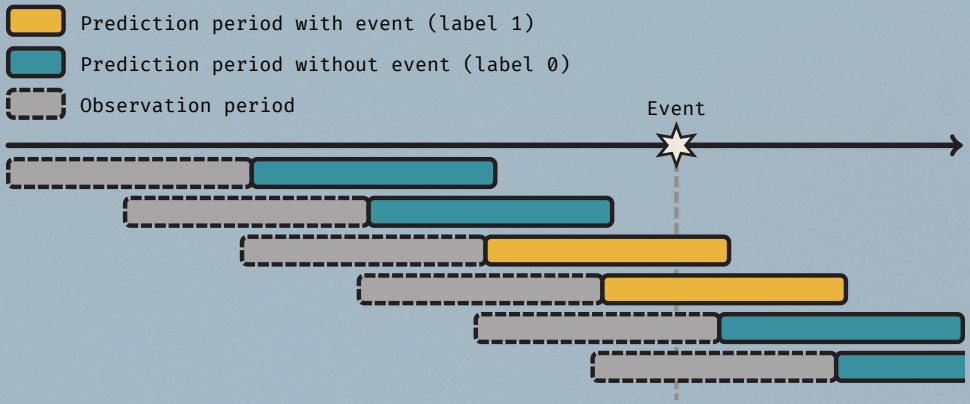

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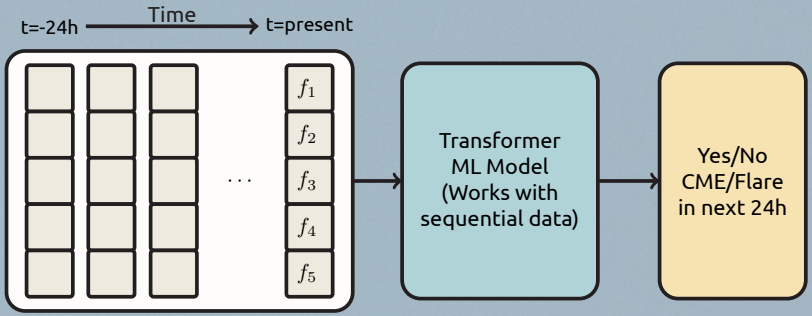
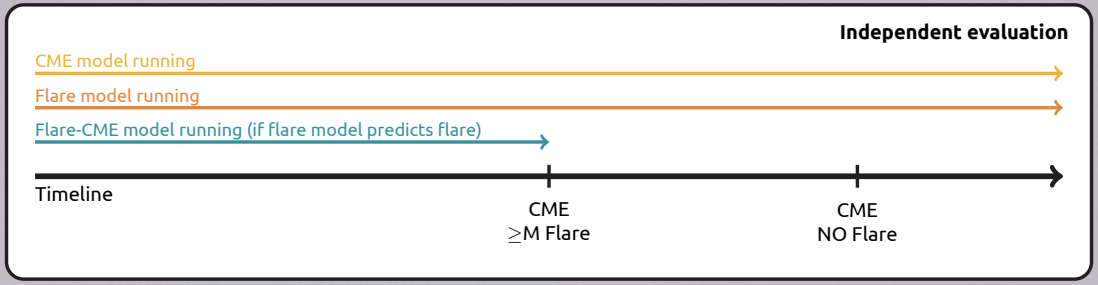


Model performance

Two kinds of evaluations



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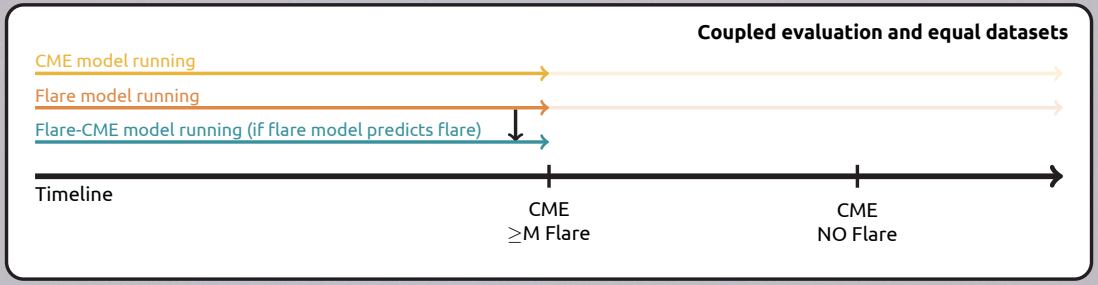
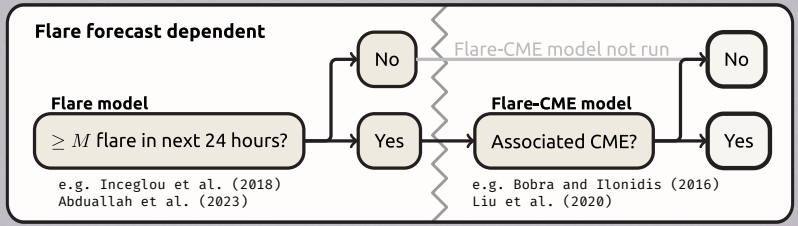


Model performance

Options for forecasting CMEs



Model performance

Overall performances

Table: Individual model performance

Forecast Type	TSS
Flare	0.82
CME	0.52
Flare-CME	0.13

Table: Combined model performance. Evaluated on equal datasets.

Forecast Type	TSS
CME	0.00
Flare + Flare-CME	0.13

Model performance

Some takeaways and hypotheses

- Models that forecast CMEs struggle more: perhaps not as many signatures in photospheric magnetic field?
- TSS inflates the performance of the models without knowledge of event distribution in dataset (look out for submitted paper).
- When evaluated in 24h prior to $\geqslant$M flare, flare-CME model does better than CME.
  - Intuitively makes sense, but both are looking for CMEs
  - Hint that models are looking for different signatures
  - **Next: Can we use explainability methods to see where those two models differ?**

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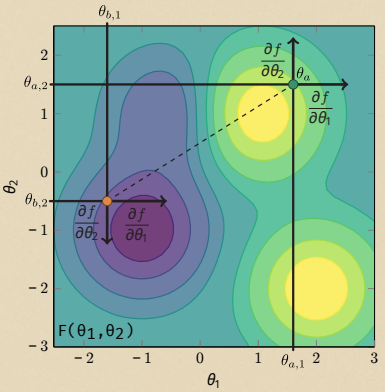
Work in progress: Explainability

Integrated Gradients (IGs) (Sundararajan et al. (2017))

- Attribution method: How much did each of the inputs contribute to the prediction?

$$\mathrm{IG}_i(\theta_{a,i}) = (\theta_{a,i} - \theta_{b,i}) \int_0^1 \frac{\partial F\big(\theta_a + \alpha\,(\theta_b - \theta_a)\big)}{\partial \theta_i}\, d\alpha$$

- Has nice properties like:
  - Completeness
  - Independent of model implementation
  - Sensitivity



Toy model in 2D $F(\theta_1, \theta_2)$

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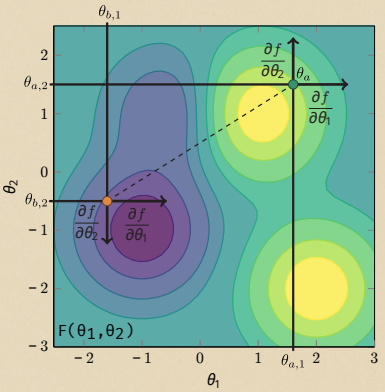

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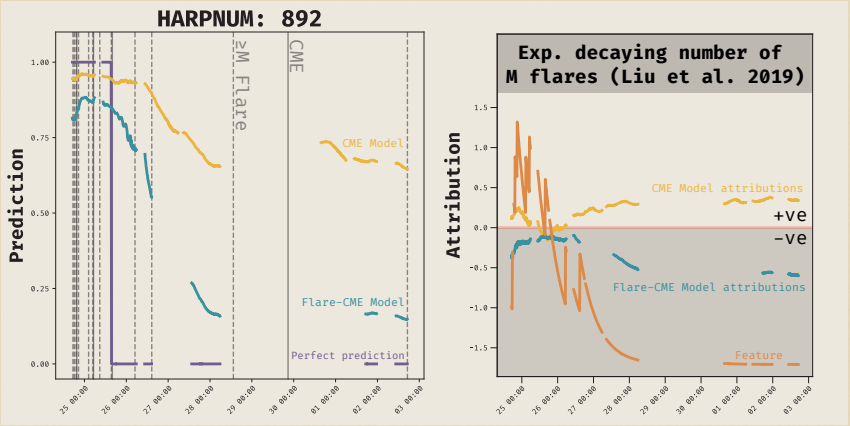
Work in progress: Explainability

IGs in practice



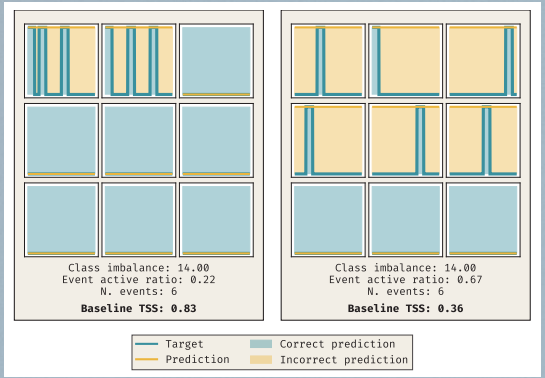
Work in progress: Explainability

Current challenges

- How to choose a meaningful baseline?
- Is a line integral valid from a physical perspective?
- How to test any explanation against what the model really does?

Backup slides

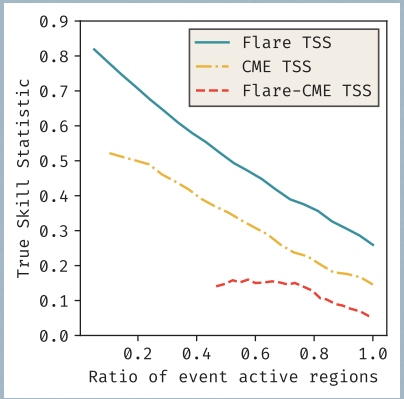
Event active regions



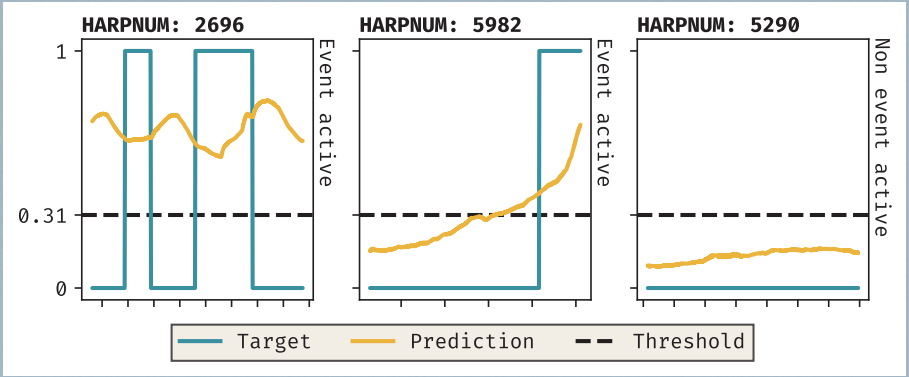
Dataset	Ratio
Flare	0.05
CME	0.10
Flare-CME	0.47

Backup slides

Active regions TSS

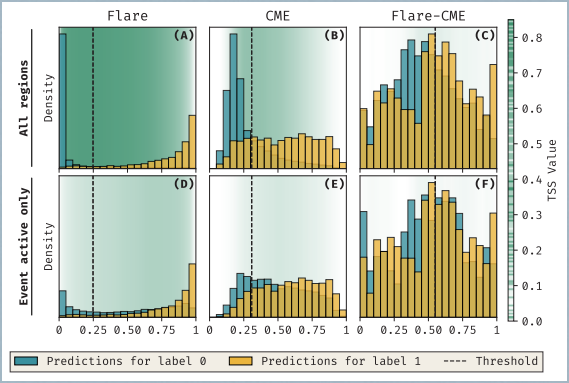


CME predictions examples



Backup slides

Distribution of predictions



Backup slides

Dataset splits