Forecasting solar wind speed by machine learning based on coronal hole characteristics

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This presentation participates in OSPP
Outstanding Student & PhD candidate Presentation contest

Motivation and goal

- Solar wind emitted by coronal holes can damage satellites and causes billions of euros in losses
- Coronal holes can be identified in solar EUV images
- **Goal:** Forecasting of solar wind speed by coronal hole detection in solar images

Data

- Solar wind speed, 1 h averaged (OMNIWeb)
- Solar EUV images, 193 and 211 Å, 1 h cadence, 2010/07 - 2019/12 (SDO AIA)

Model

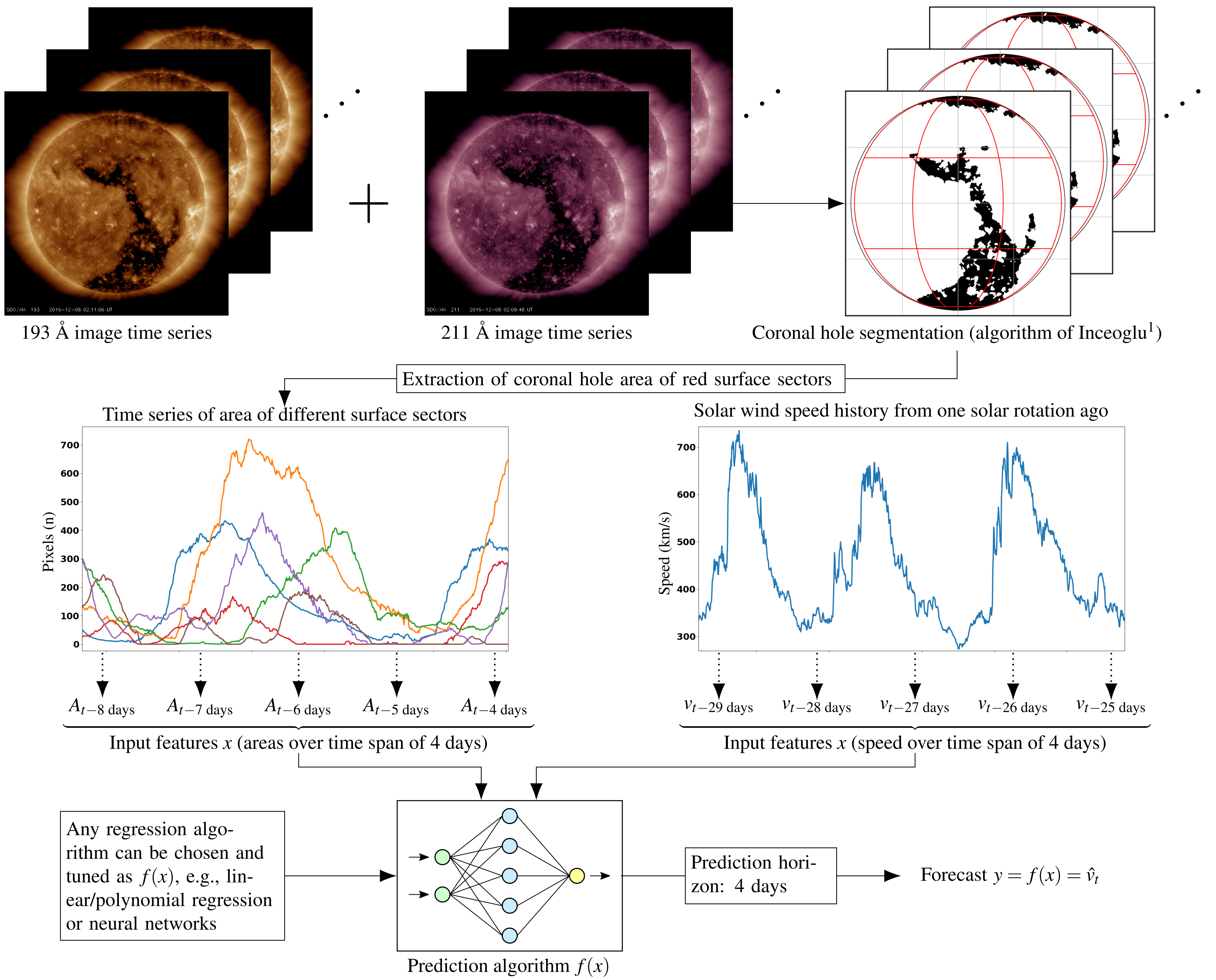

Figure: Schematic representation of model workflow. Coronal holes can be seen in solar images at the top (dark structures on surface). [1]Inceoglu et al., The Astrophysical Journal, 2022

Evaluation

5-fold cross-validation:

1. Divide data set into contiguous sections of 20 days.
2. Discard 4 days between each section to ensure that they are not correlated.
3. Assign sections sequentially to cross-validation splits.

Results:

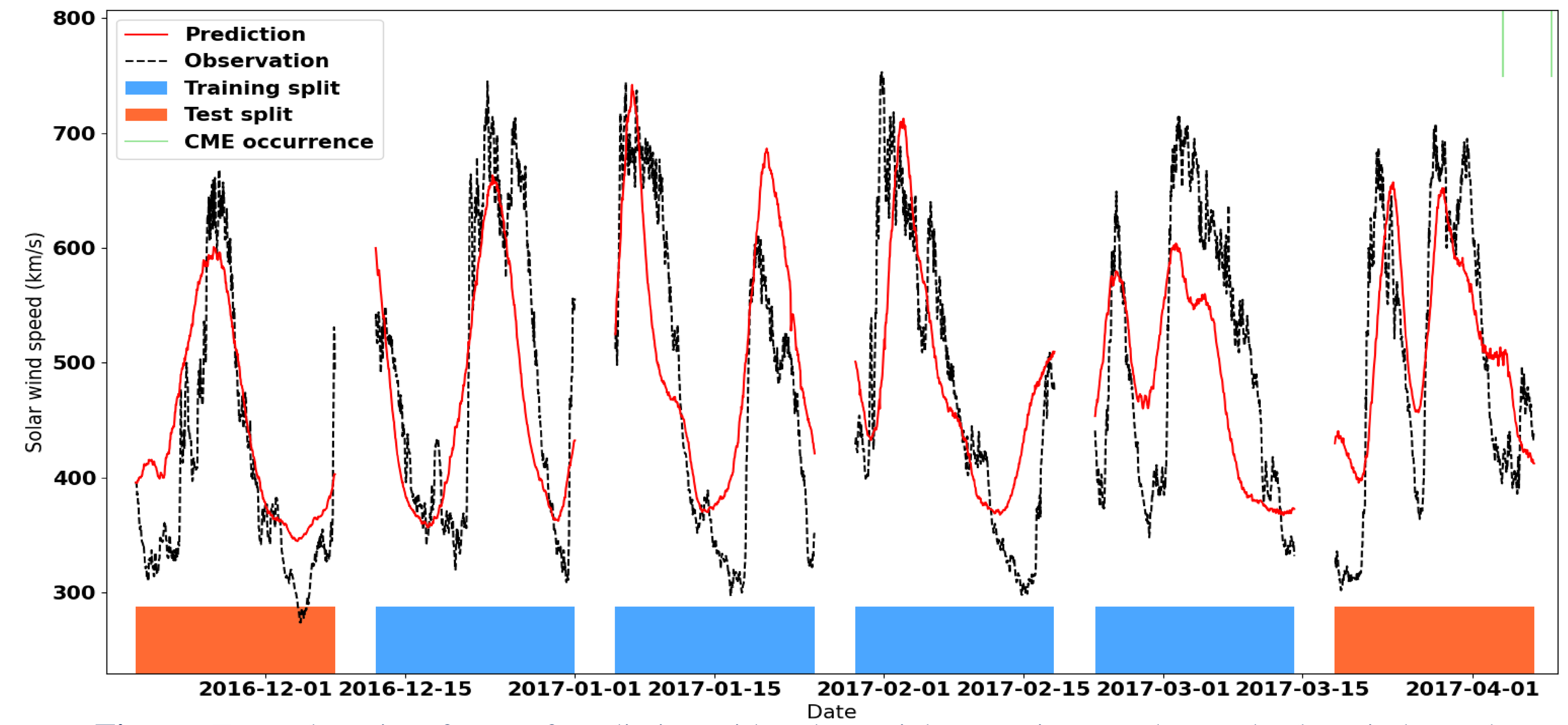

Figure: Exemplary time frame of prediction with polynomial regression vs. observed solar wind speed.

Model	Prediction algorithm $f(x)$	RMSE (km/s)	CC (Pearson)
Upendran et al. (2020)[1]	Convolutional NN & LSTM	80.3	0.55
Raju et al. (2021)[2]	Convolutional neural network	76.3	0.57
Brown et al. (2022)[1]	Vision Transformer	**72.2**	**0.63**
Our model	Linear regression	**74.1**	0.59
	Polynomial regression	74.4	**0.61**
	Fully connected neural network	74.8	0.58
Our model (Coronal mass ejections excluded from data)	Linear regression	70.7	**0.68**
	Polynomial regression	**70.6**	**0.68**
	Fully connected neural network	70.7	0.67

Table: Comparison of our model (for different prediction algorithms $f(x)$) to state-of-the-art image-based models. Thick numbers: best result. [1]Space Weather, [2]Solar Physics.

Model characteristics

- **Simple yet informative features:** Area, location of coronal holes and solar wind history capture most solar wind variations
- **Feature history:** Incorporation of temporal component improves prediction
- **Explainability:** Linear/polynomial regression is easy to interpret
- **Performance:** Our model is competitive with more complex models

Conclusion and Outlook

- The model is a simple and physically explainable but competitive forecasting tool for the solar wind emitted by coronal holes.
- However, coronal hole contours provide no information about CMEs. We plan to extend the model to capture CME effects.
- Furthermore, we want to feed images directly into a machine learning model to make use of the greater amount of information.