United Nations / Germany Workshop on the International Space Weather Initiative: Preparing for the Solar Maximum

ISWI-2024
13/6/2024

Space Weather prediction

USING VARIOUS TECHNIQUES, INCLUDING MACHINE LEARNING

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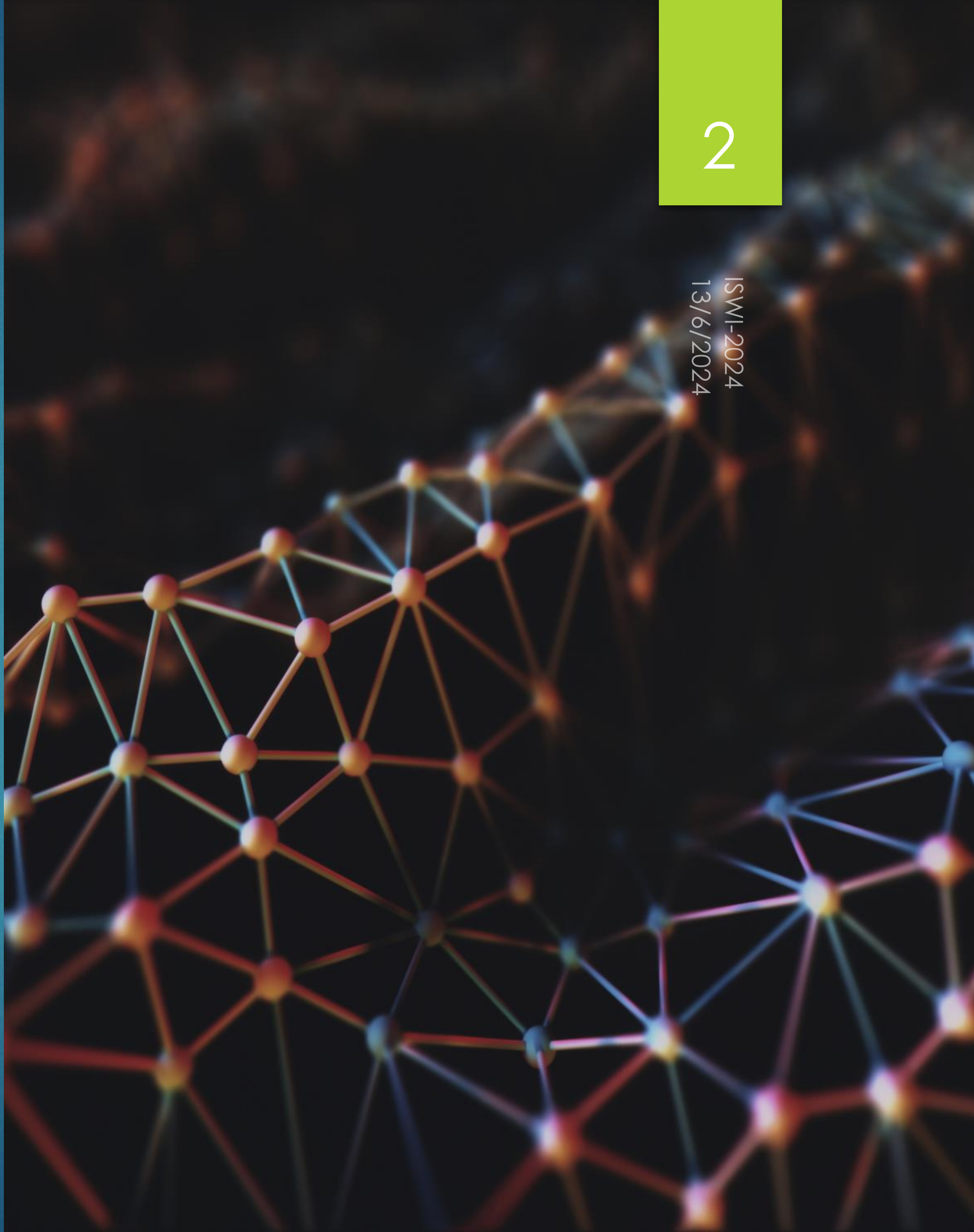
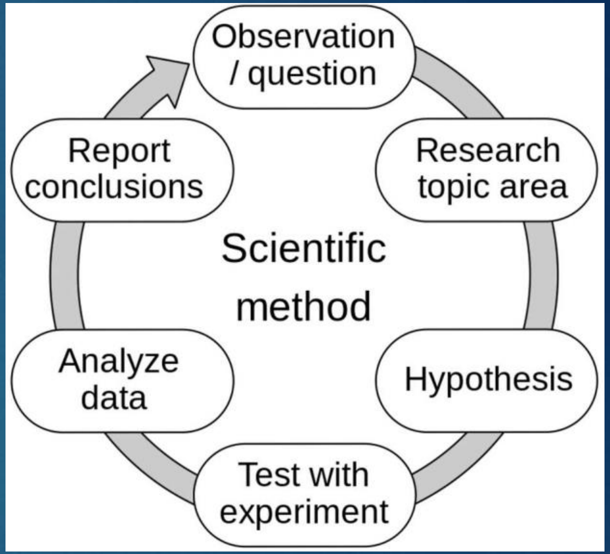
Outline

- Forecasting has always been a powerful tool
- High efficiency vs Loss of explicability
- ML is cheap + ML evolves extremely fast
- Quick, nice results vs data limits & Deep Learning
- We need to do better + we need to understand
- The next steps



Forecasting has always been a powerful tool

We have honed this ability first in the eons of the biological evolution, then encoding it in our culture, 'recently' by applying the scientific method to our everyday life problems.



The mathematical tools to understand why some events are more difficult to forecast than others.

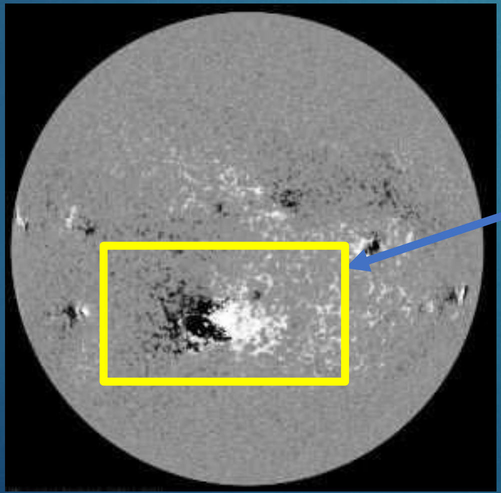
The development in the last decades in sciences of complex systems and statistics have allowed us to better define the limits of predictability and - often- to extend those limits.

BUT! The robust forecast of flare eruptions still escapes us.

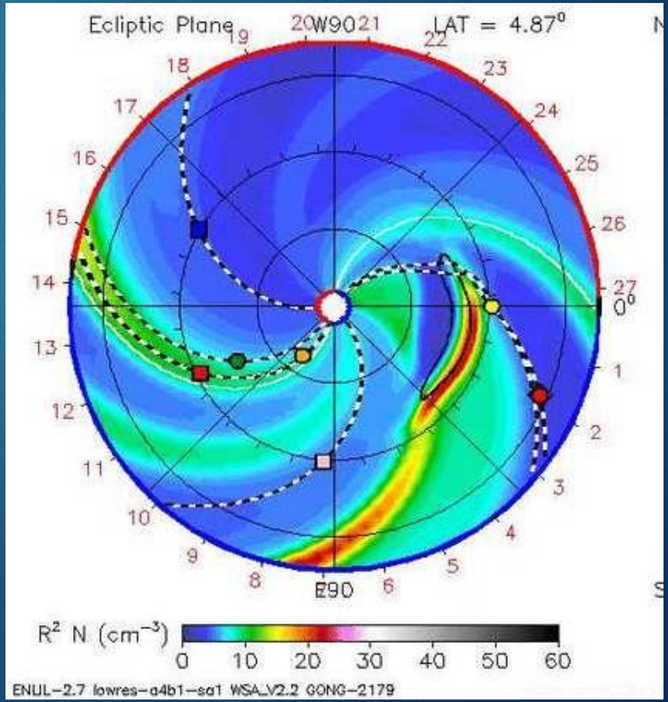
And also the apparently simpler problem of the propagation of a coronal mass ejection in the interplanetary medium has not been solved to the limit that we would like, while we fight with the uncertainties associated with the boundary conditions.

Scientific approach vs Machine Learning

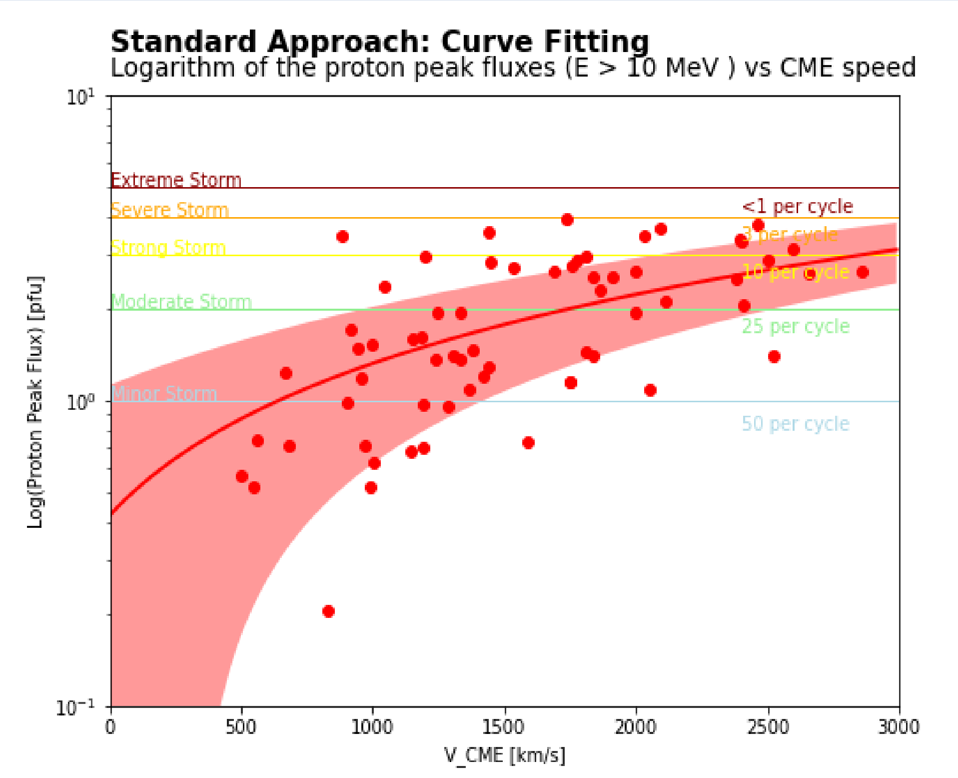
- It is now feasible to compute the trajectory of plasma and magnetic field structures under the MHD equations in domains as large as the Heliosphere.
- Or try to predict -just by analyzing full disk images or the magnetograms- whether a given solar Active Region will release part of its stored energy as high energy photons and particles, or shoot out a coronal mass ejection.



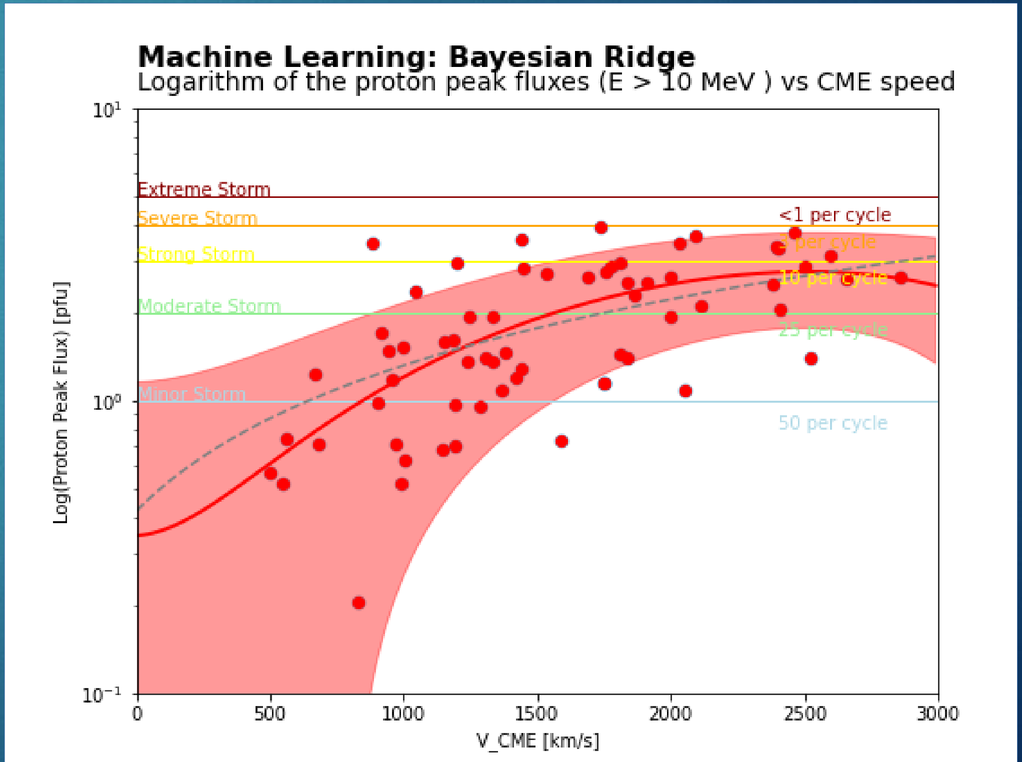
Solar flares originate from magnetically active regions (ARs)



Scientific approach vs Machine Learning



- Empirical, data-driven models and data fitting now enrolled into ML...



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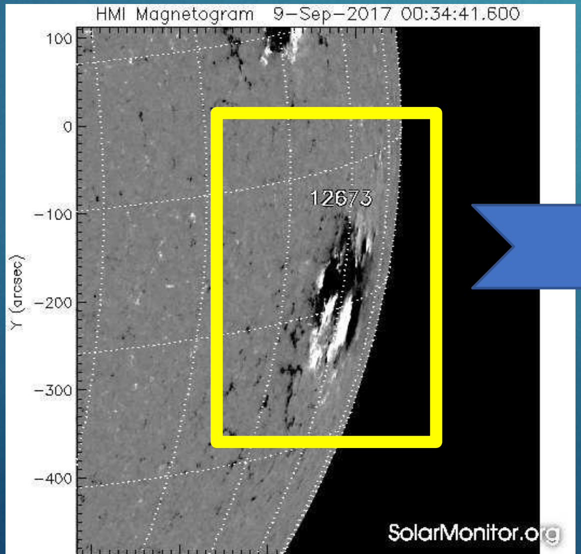
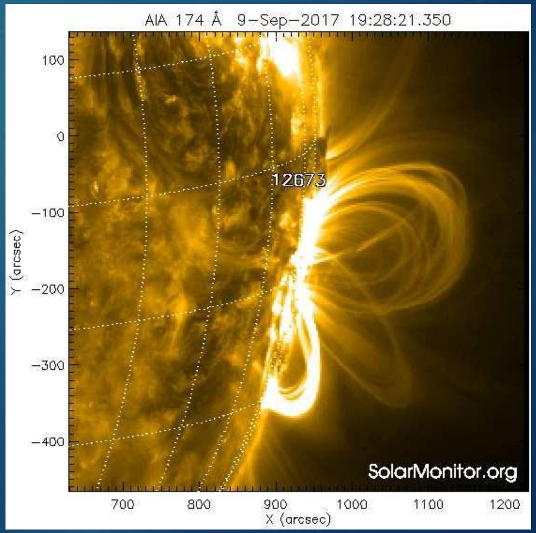
Scientific approach vs Machine Learning

- Exact space weather predictions are prevented either by intrinsic limitations or by the lack of knowledge about the present state.
- To counter these limitations, we have come up with clever and clever numerical techniques to solve the differential equations that typically describe our problems, and ensemble methods [3,4] to cope with measure errors and unknown variables. We strive to extract from remote measures all the relevant information [5], by applying our understanding of the physics of the problem, to feed this information into our forecasting algorithms.
- And we are getting better and better at this too.

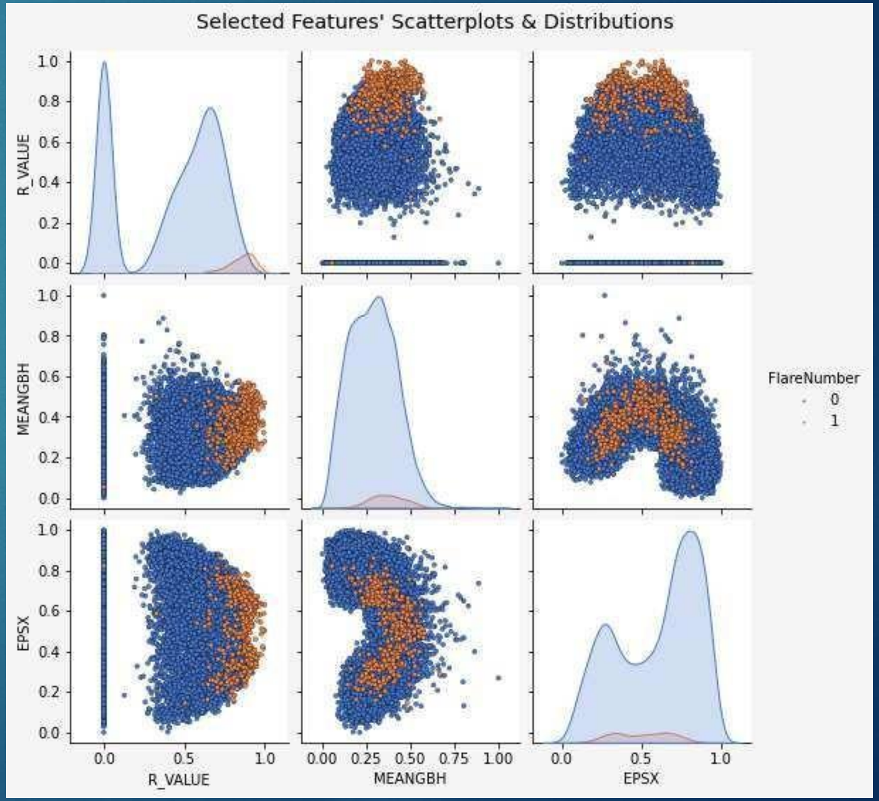


Will a solar flare of or above class **K** be generated in the next **Dt** hours?



Scientific approach vs Machine Learning

- In the absence of a definitive physical theory explaining the mechanisms of an AR, the best hope for forecasting solar eruptions lies in finding an empirical relationship between some well chosen features of ARs and the solar flares and CMEs.
- As a consequence, we have turned to the dark side and applied the methods of this hybrid of numerical methods, complex system science and statistics which is usually referred to as Machine Learning (ML).



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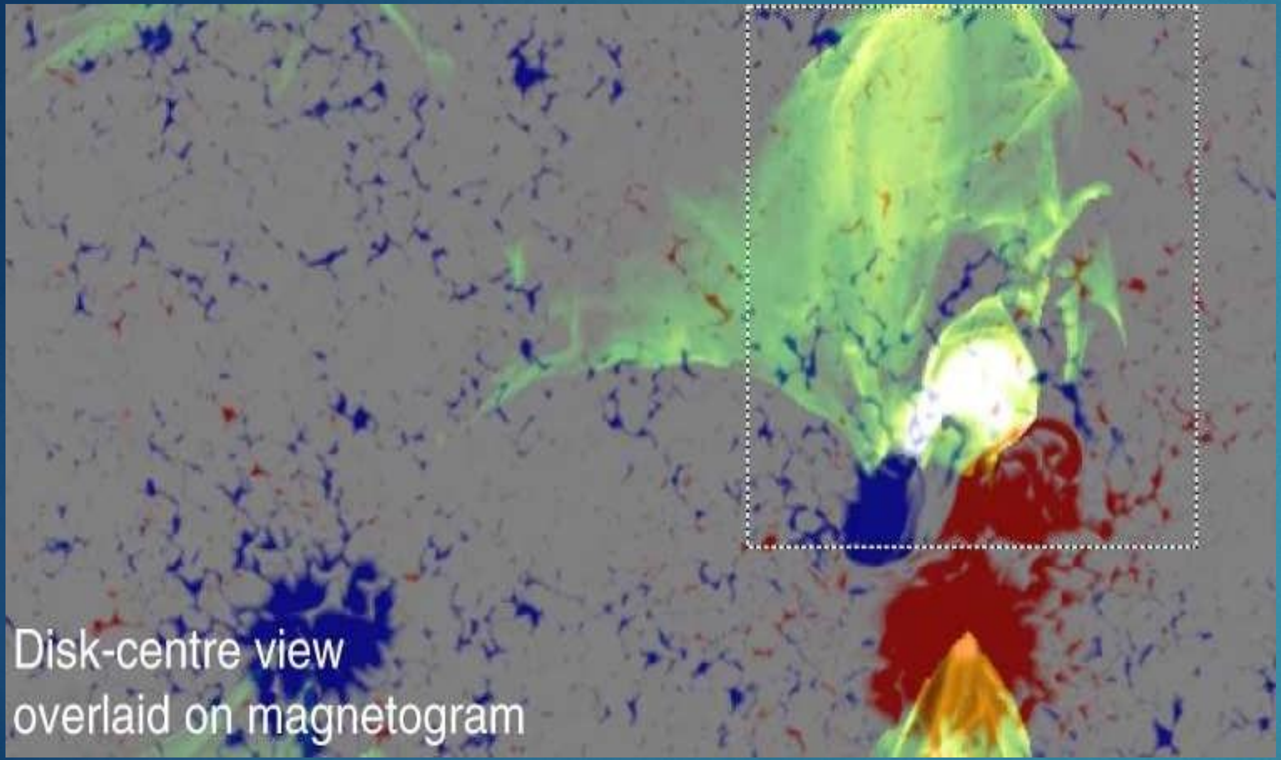
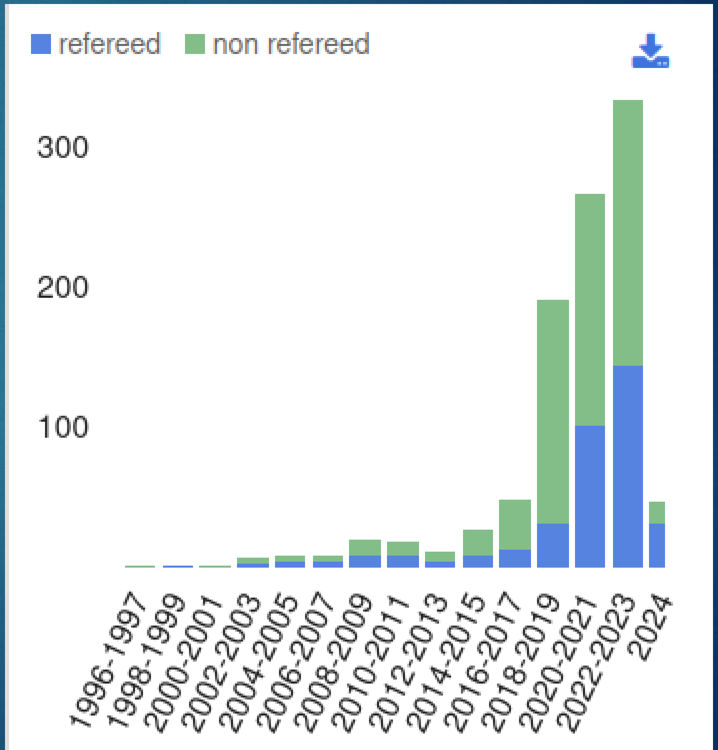
- Florios, K., Kontogiannis, I., Park, S. H., Guerra, J. A., Benvenuto, F., Bloomfield, D. S., & Georgoulis, M. K. (2018). Forecasting solar flares using magnetogram-based predictors and machine learning. Solar Physics, 293(2), 28. https://doi.org/10.1007/s11207-018-1250-4

ML is cheap + ML evolves extremely fast





- Cheung, M. C. M., Rempel, M., Chintzoglou, G., Chen, F., Testa, P., Martínez-Sykora, J., ... & McIntosh, S. W. (2019). A comprehensive three-dimensional radiative magnetohydrodynamic simulation of a solar flare. Nature Astronomy, 3(2), 160-166. https://doi.org/10.1038/s41550-018-0629-3
- Camporeale, E. (2019). The challenge of machine learning in space weather: Nowcasting and forecasting. Space weather, 17(8), 1166-1207. https://doi.org/10.1029/2018SW002061

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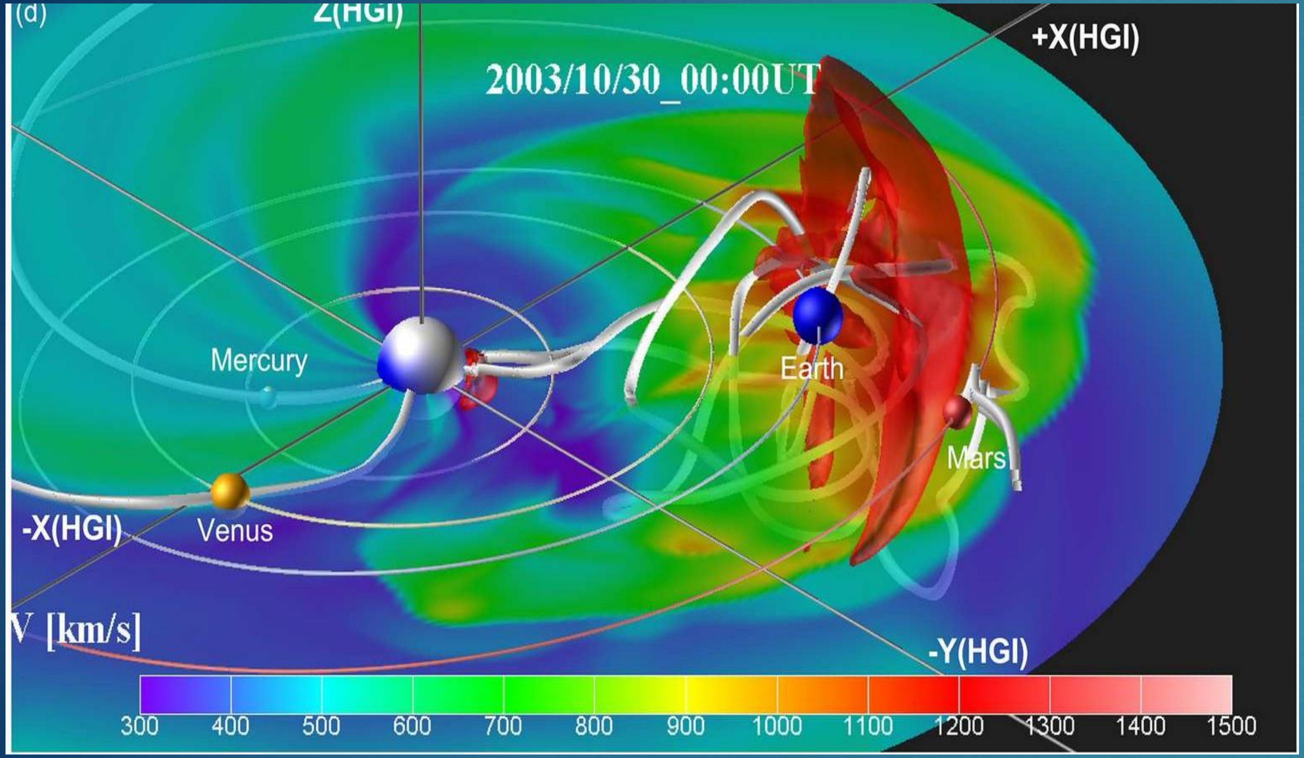

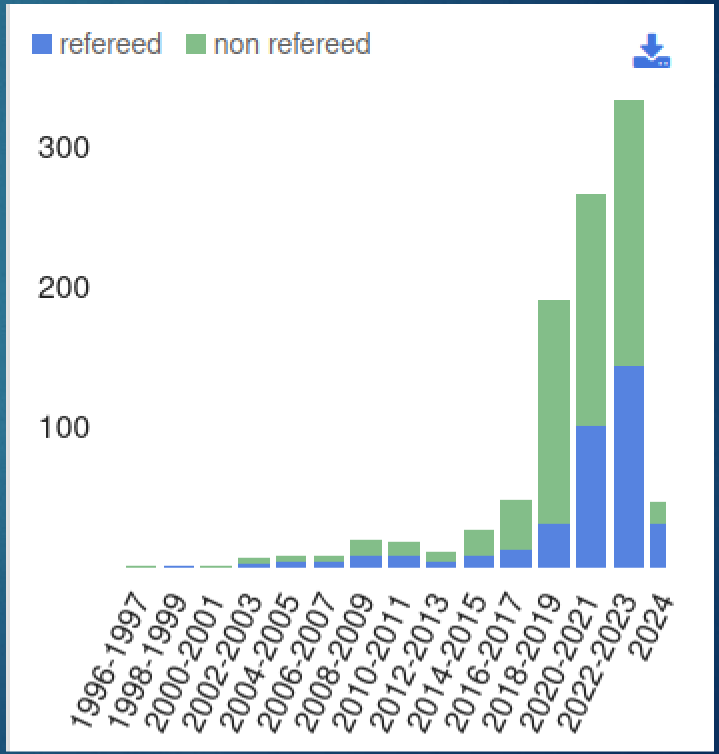

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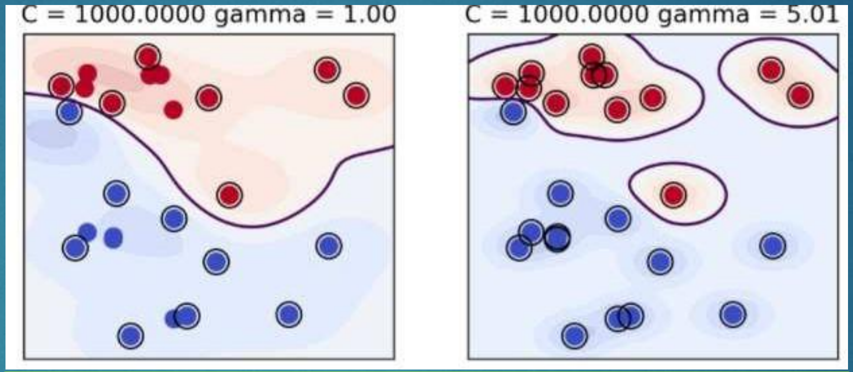
- Chierichini, S., Liu, J., Korsós, M. B., Del Moro, D., & Erdélyi, R. (2024). CME Arrival Modeling with Machine Learning. The Astrophysical Journal, 963(2), 121. DOI 10.3847/1538-4357/ad1cee
- Camporeale, E. (2019). The challenge of machine learning in space weather: Nowcasting and forecasting. Space weather, 17(8), 1166-1207. https://doi.org/10.1029/2018SW002061

ML: Quick, Nice results vs Correct Dataset use

- Neural Networks
- SVM
- Random Forest
- Gaussian models
- Convolutional NN
- ….



Flare Forecast
True Skill Score evolution:

- Barnes 2008: 0.24
- Florios 2018: 0.77
- Sun 2022: 0.90
- Deshmukh 2022: 0.90

BEWARE: sometimes there are errors in:

The hyperparameter tuning process

How the samples are used

How the cross-validation is used

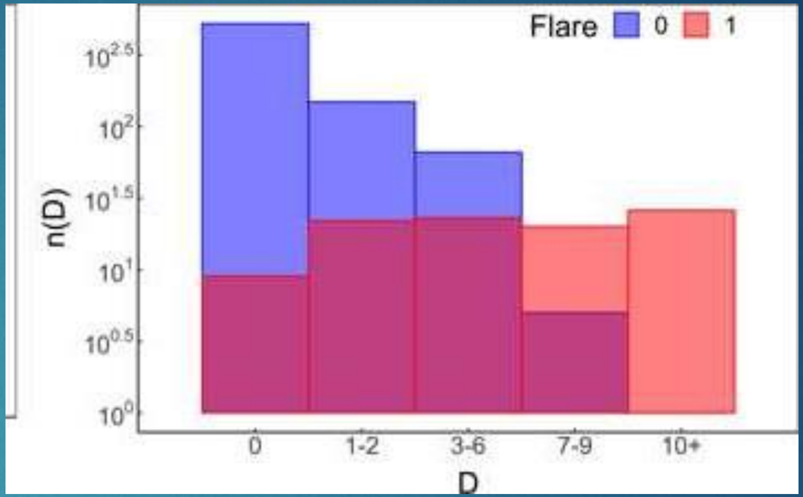
- Barnes, G., & Leka, K. D. (2008). Evaluating the performance of solar flare forecasting methods. The Astrophysical Journal, 688(2), L107. DOI 10.1086/595550
- Florios, K., Kontogiannis, I., Park, S. H., Guerra, J. A., Benvenuto, F., Bloomfield, D. S., & Georgoulis, M. K. (2018). Forecasting solar flares using magnetogram-based predictors and machine learning. Solar Physics, 293(2), 28. https://doi.org/10.1007/s11207-018-1250-4
- Sun, Z., Bobra, M. G., Wang, X., Wang, Y., Sun, H., Gombosi, T., ... & Hero, A. (2022). Predicting solar flares using CNN and LSTM on two solar cycles of active region data. The Astrophysical Journal, 931(2), 163. DOI 10.3847/1538-4357/ac64a6
- Deshmukh, V., Flyer, N., Van der Sande, K., & Berger, T. (2022). Decreasing false-alarm rates in CNN-based solar flare prediction using SDO/HMI data. The Astrophysical Journal Supplement Series, 260(1), 9. DOI 10.3847/1538-4365/ac5b0c

Flares: Next steps?

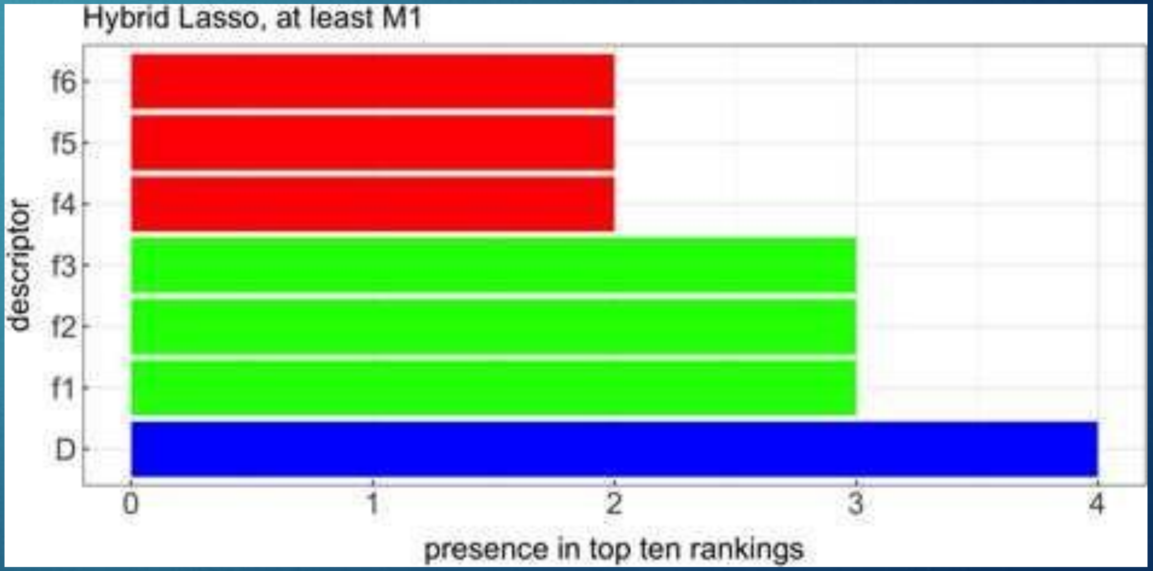
- More info from B → by using topological describers
- Add the Time dimension → use B movies
- Higher layers info → use B + chromosphere + corona
- Adapt the Loss Functions → redefine error types
- Explicability of Deep Learning → analysis of attention frames
- Change of paradigm (e.g. Physics-Informed ML, ...)

Use of topological describers

YET another parameter from magnetic polarity inversion lines (PILs)



- Topologically complex ARs are strongly correlated to flare emissions.
- Therefore a topological descriptor that counts the number of separated **PIL**s fragments in the ARs.
- **Feature ranking** analysis tells us it is extremely relevant to reach high skill scores → it brings relevant information on the AR flaring potential.



- Cicogna, D., Berrilli, F., Calchetti, D., Del Moro, D., Giovannelli, L., Benvenuto, F., ... & Piana, M. (2021). Flare-forecasting algorithms based on high-gradient polarity inversion lines in active regions. The Astrophysical Journal, 915(1), 38. https://iopscience.iop.org/article/10.3847/1538-4357/abfafb

Analysis of time sequences

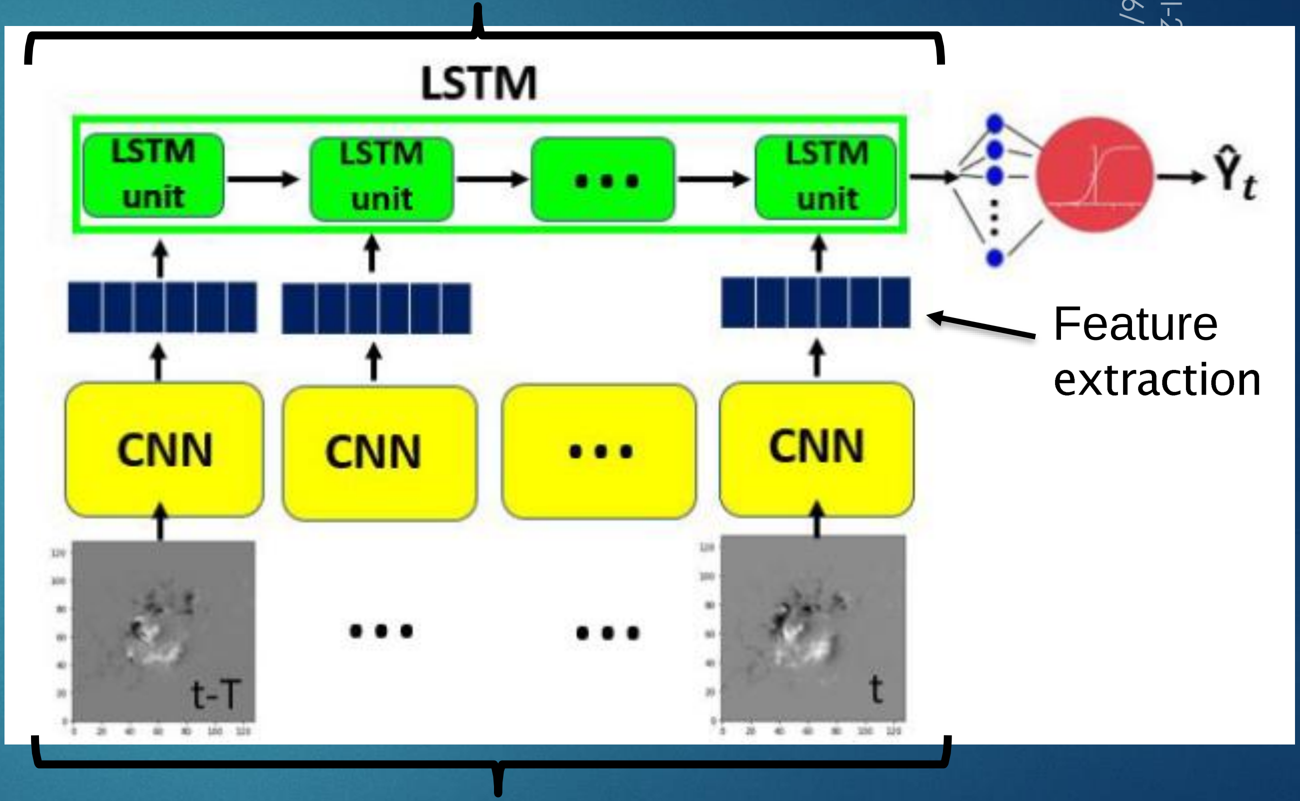
Long-term Recurrent Neural Network
LRCN = CNN + LSTM

BUT they get **similar TSS** values as more standard methods

→ HMI data do not contain enough information?

→ flares' stochasticity hampers the possibility of binary predictions, in favor of a probabilistic prediction?

Considering the "memory" of the process



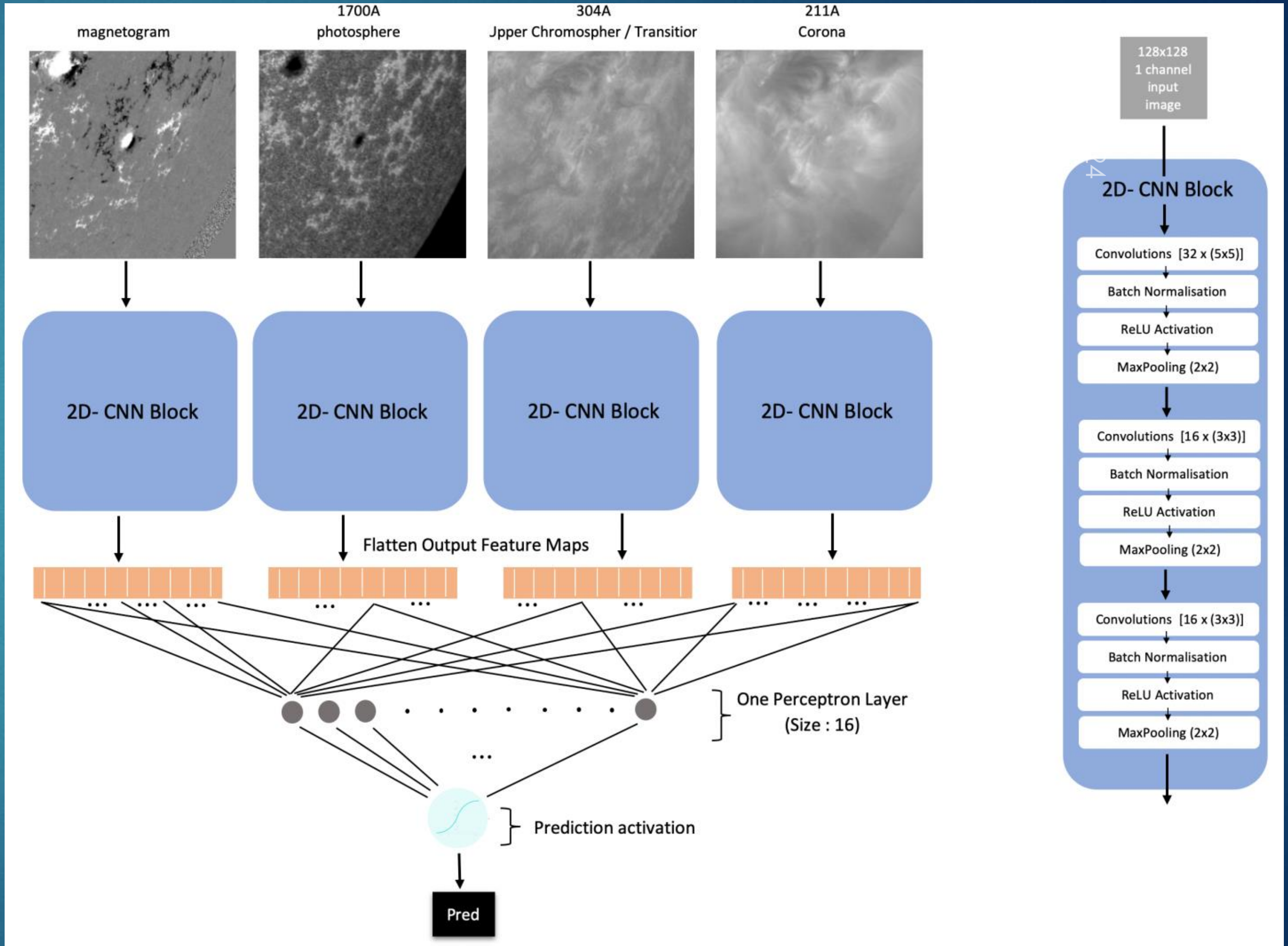
Input: videos of HMI magnetograms

Guastavino, S., Marchetti, F., Benvenuto, F., Campi, C., & Piana, M. (2022). Implementation paradigm for supervised flare forecasting studies: A deep learning application with video data. Astronomy & Astrophysics, 662, A105. https://doi.org/10.1051/0004-6361/202243617
Campi, C., Benvenuto, F., Massone, A. M., Bloomfield, D. S., Georgoulis, M. K., & Piana, M. (2019). Feature ranking of active region source properties in solar flare forecasting and the uncompromised stochasticity of flare occurrence. The Astrophysical Journal, 883(2), 150. DOI 10.3847/1538-4357/ab3c26

Use of more layers

Each layer used contributes to improved performances

Models combining SDO/AIA EUV images as inputs show improved performances compared to employing SDO/HMI photospheric magnetograms alone



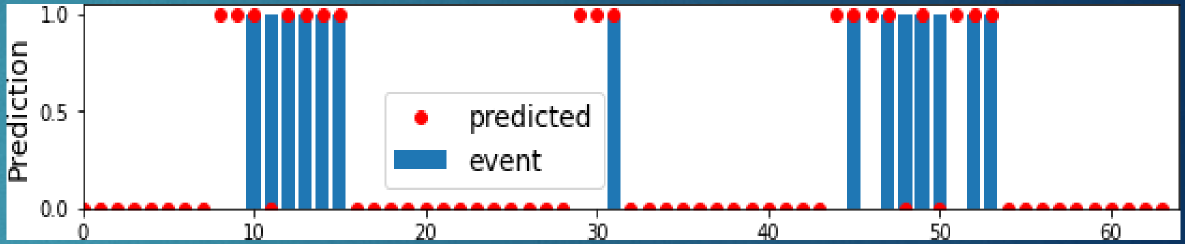
- Francisco, G., Berretti, M., Chierichini, S., Mugatwala, R., Fernandes, J. M., Barata, T., & Del Moro, D. (2024). Limits of solar flare forecasting models and new deep learning approach. Authorea Preprints. DOI: 10.22541/essoar.170688972.24631782/v2

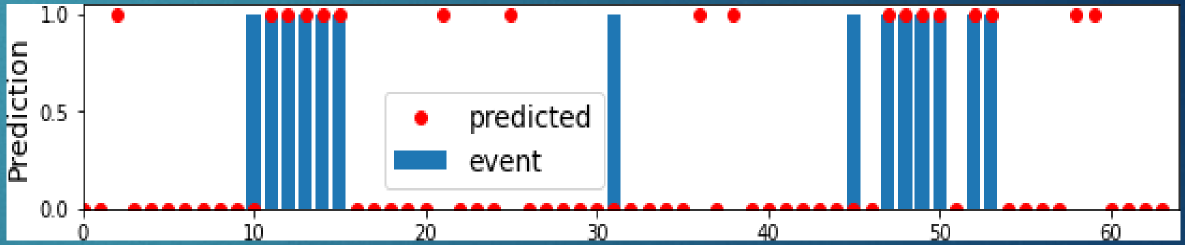
Redefine error types/Performance Scores

Classical skill scores do not take into account the temporal distribution of the prediction

A possible solution:

define new skill scores which allow ranking the prediction errors on the basis of their distribution along time



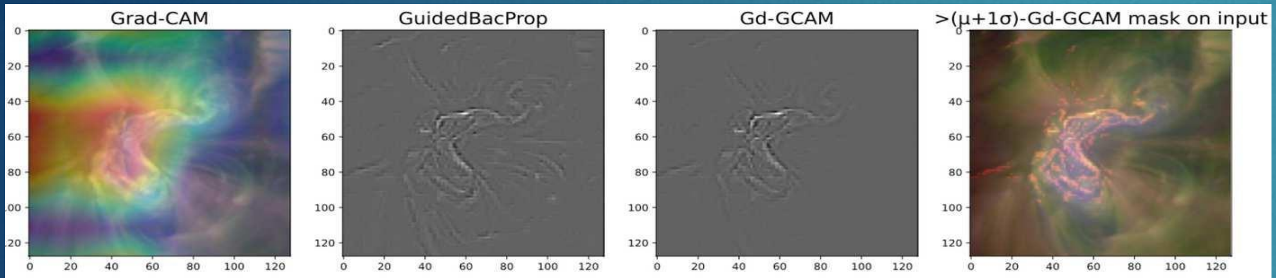


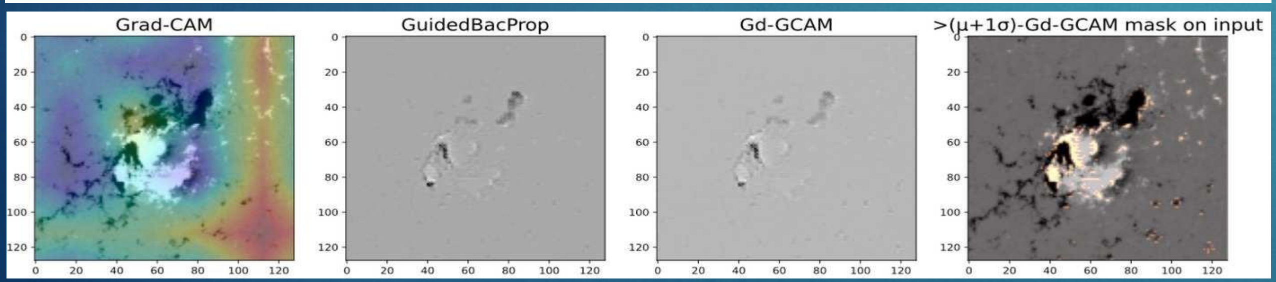
Two forecasts: same performance, but totally different predictive value.

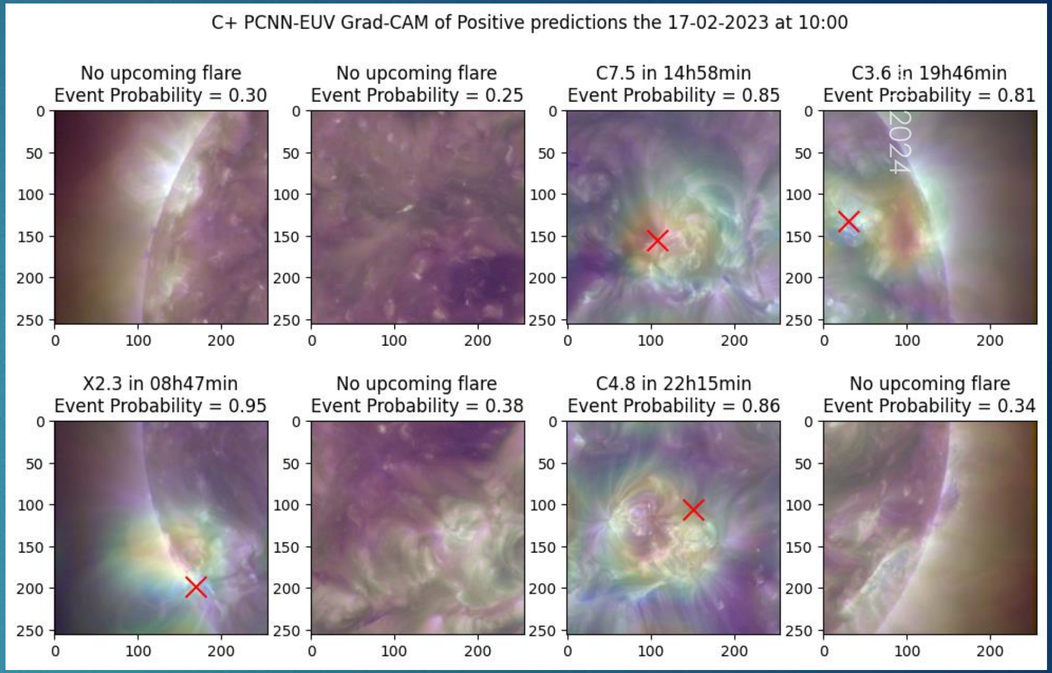
- Guastavino, S., Piana, M., & Benvenuto, F. (2022). Bad and good errors: Value-weighted skill scores in deep ensemble learning. IEEE transactions on neural networks and learning systems. DOI: 10.1109/TNNLS.2022.3186068

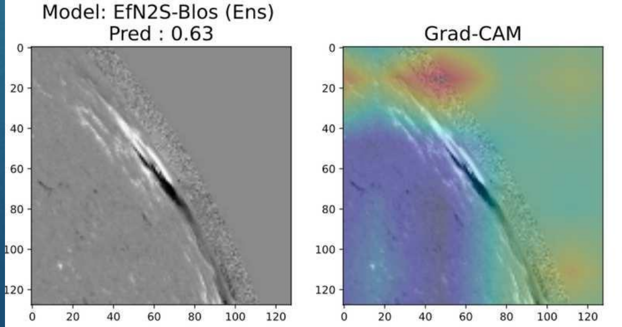
Interpretability of CNN

Identify the most class-discriminative regions
+
the pixels contributing the most to the last convolutional layer





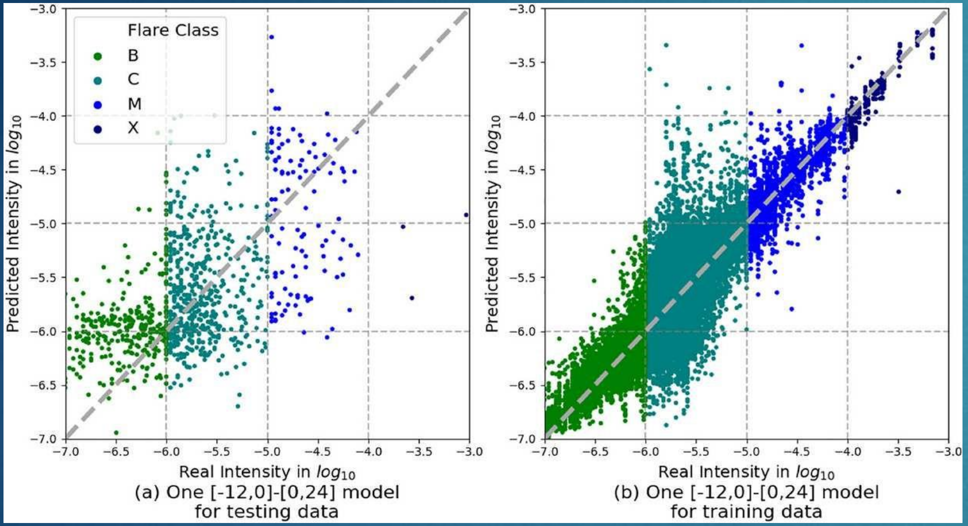


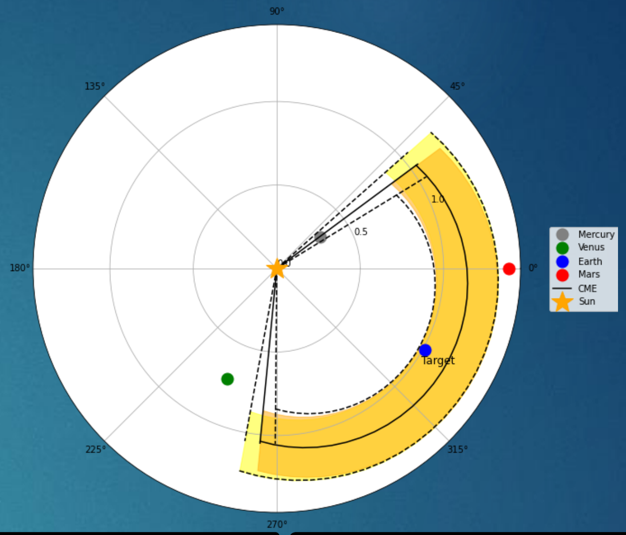


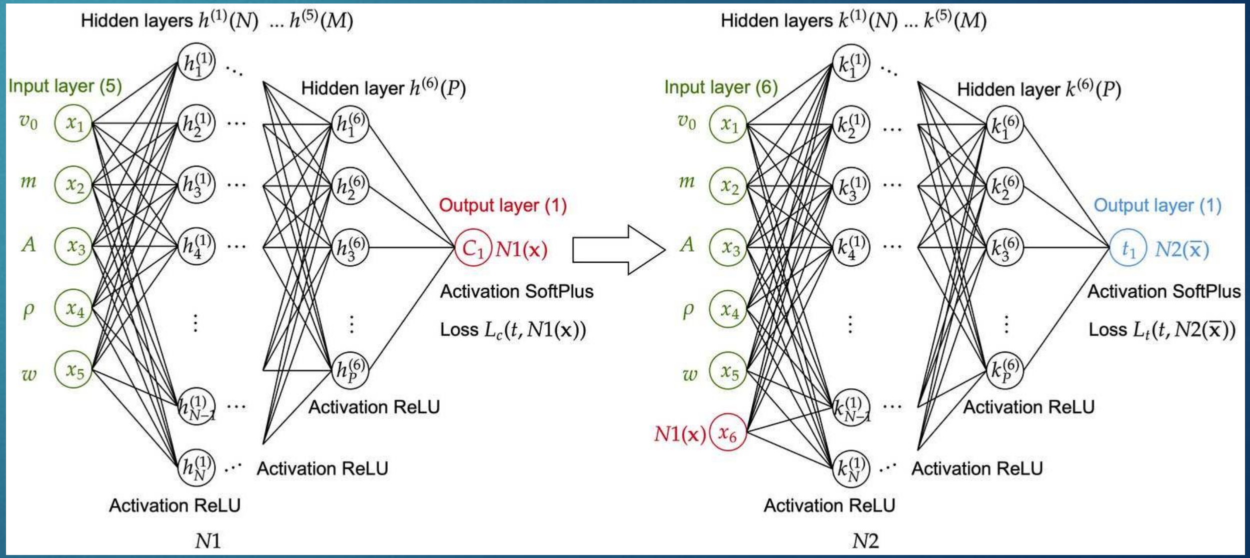
• Francisco, G., Berretti, M., Chierichini, S., Mugatwala, R., Fernandes, J. M., Barata, T., & Del Moro, D. (2024). Limits of solar flare forecasting models and new deep learning approach. Authorea Preprints. DOI: 10.22541/essoar.170688972.24631782/v2

Change of paradigm

Regression instead of Classification
+
Put the Physics in the ML model







Jiao, Z., Sun, H., Wang, X., Manchester, W., Gombosi, T., Hero, A., & Chen, Y. (2020). Solar flare intensity prediction with machine learning models. Space weather, 18(7), e2020SW002440.

Guastavino, S., Candiani, V., Bemporad, A., Marchetti, F., Benvenuto, F., Massone, A. M., ... & Michele, P. (2023). Physics-driven machine learning for the prediction of coronal mass ejections' travel times. The Astrophysical Journal, 954(2), 151.

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Beyond the Black Box: What is next?

- ML is cheap!
- ML is growing fast!
- ML is fixing its (major) drawbacks
- The data(-sets) are more and more important
- ML is here to stay ?

Thank You!

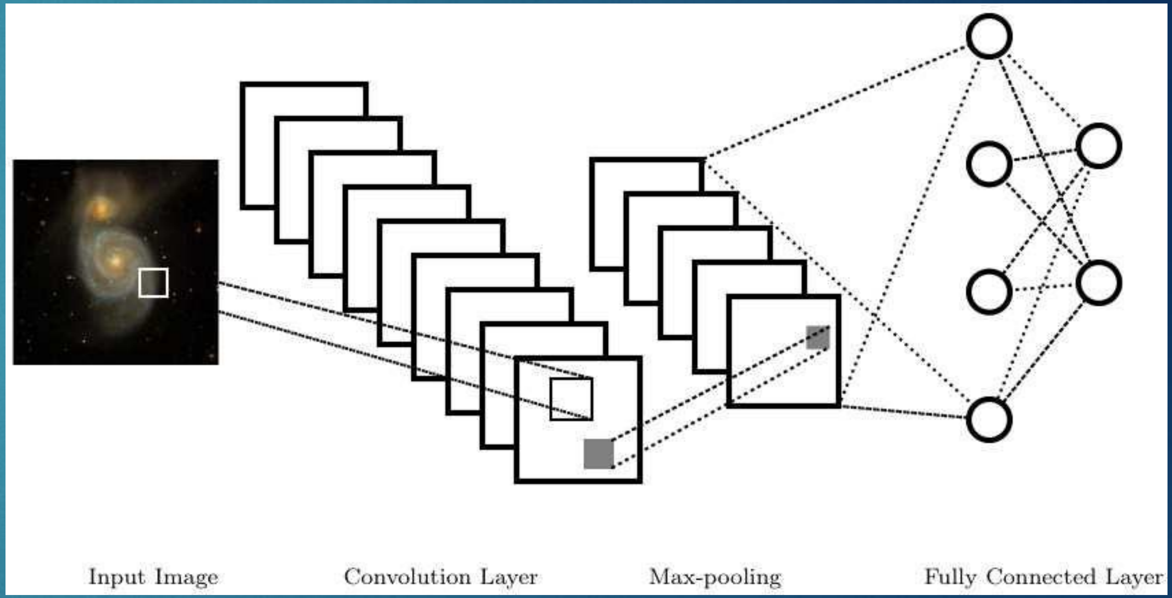
Extra Slides

CONCEPTS OF CONVOLUTIONAL NN

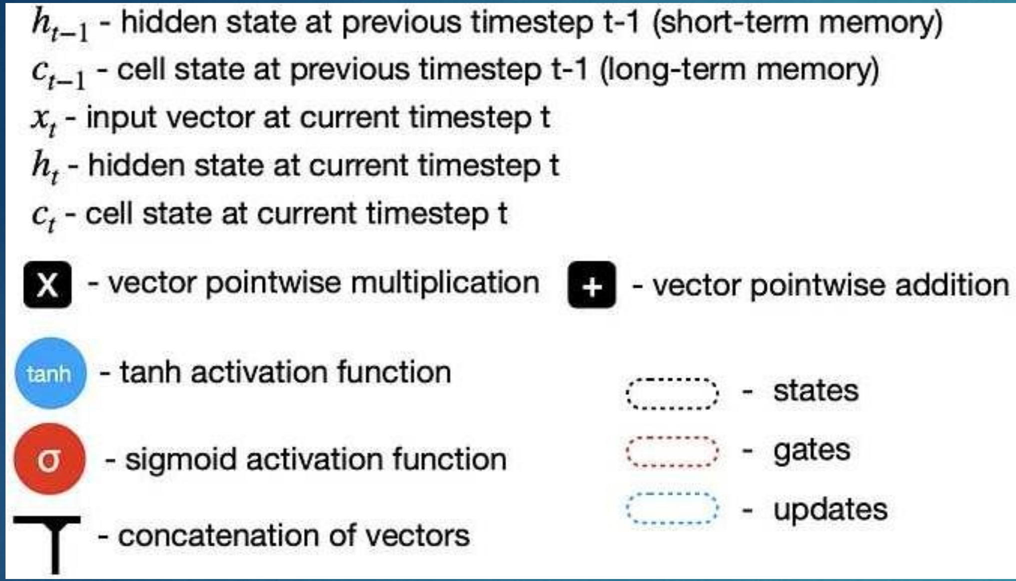
NN designed to work with images and/or regularly sampled data

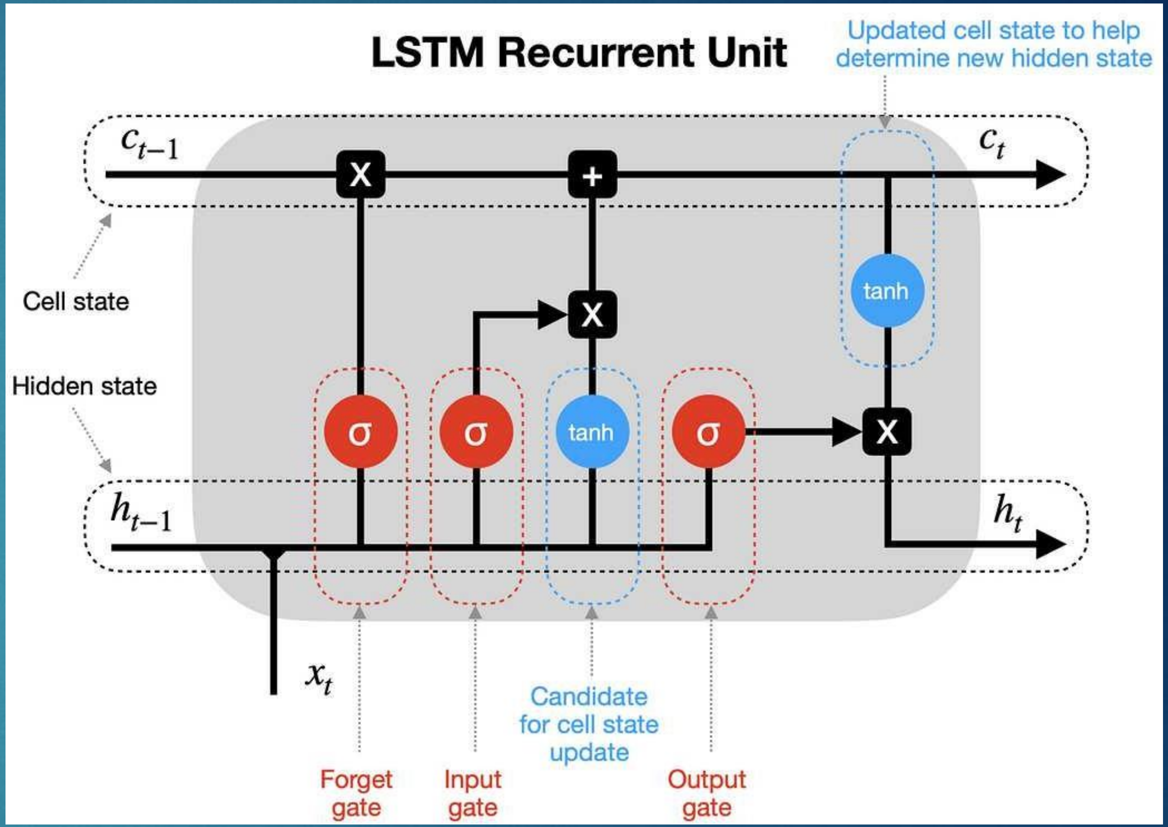
Components:

- Convolutional layer
- Non-linear activation functions
- Pooling/downsampling
- Fully connected layer for classification



CONCEPTS OF LONG-TERM SHORT-TERM MEMORY

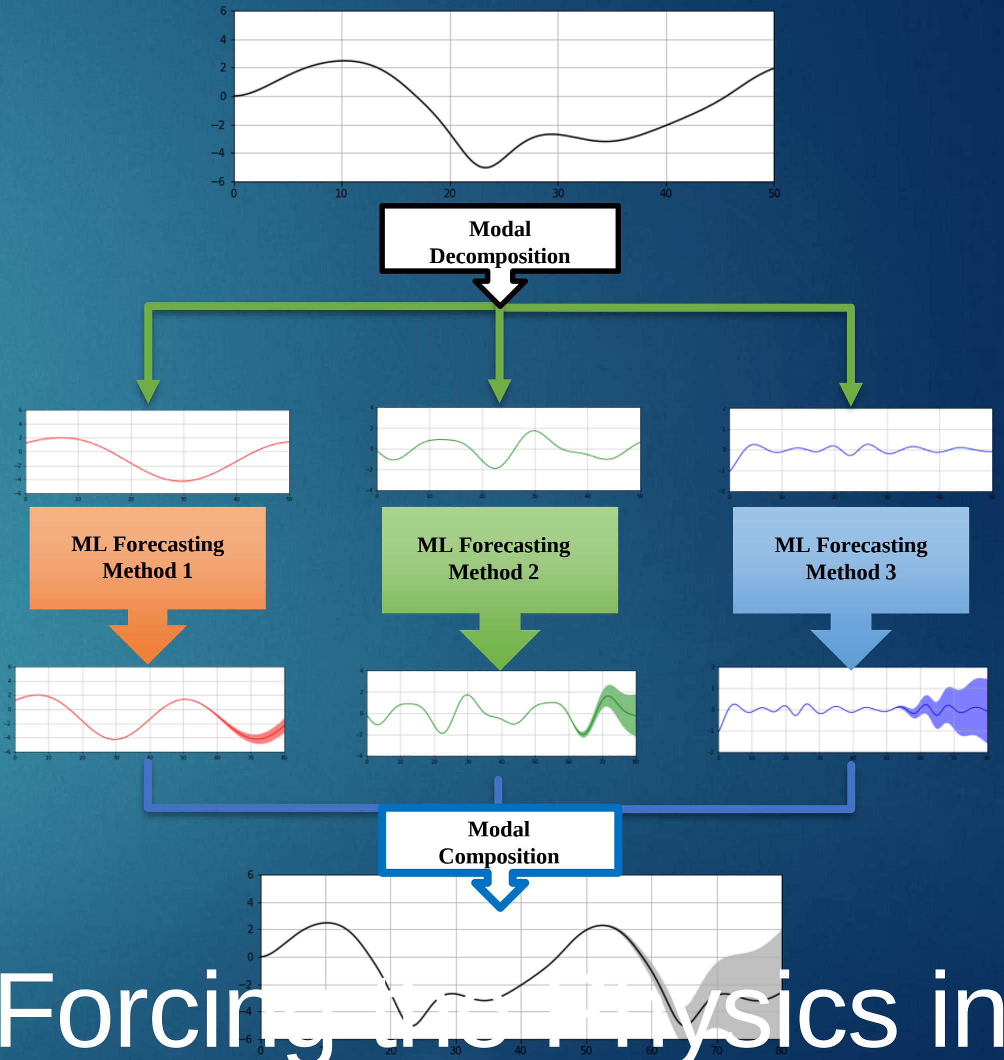




Forcing the Physics into ML approach

A complex signal, with many different timescales embedded.

→ We can try to mix different proxies to reproduce/forecast the signal.
OR:
→ We separate the signal's relevant scales into different modes, then reproduce/forecast the different modes mixing the proxies' modes (at or near the same timescales). Then, we reproduce/forecast the signal by combining the reproduced/forecast modes.



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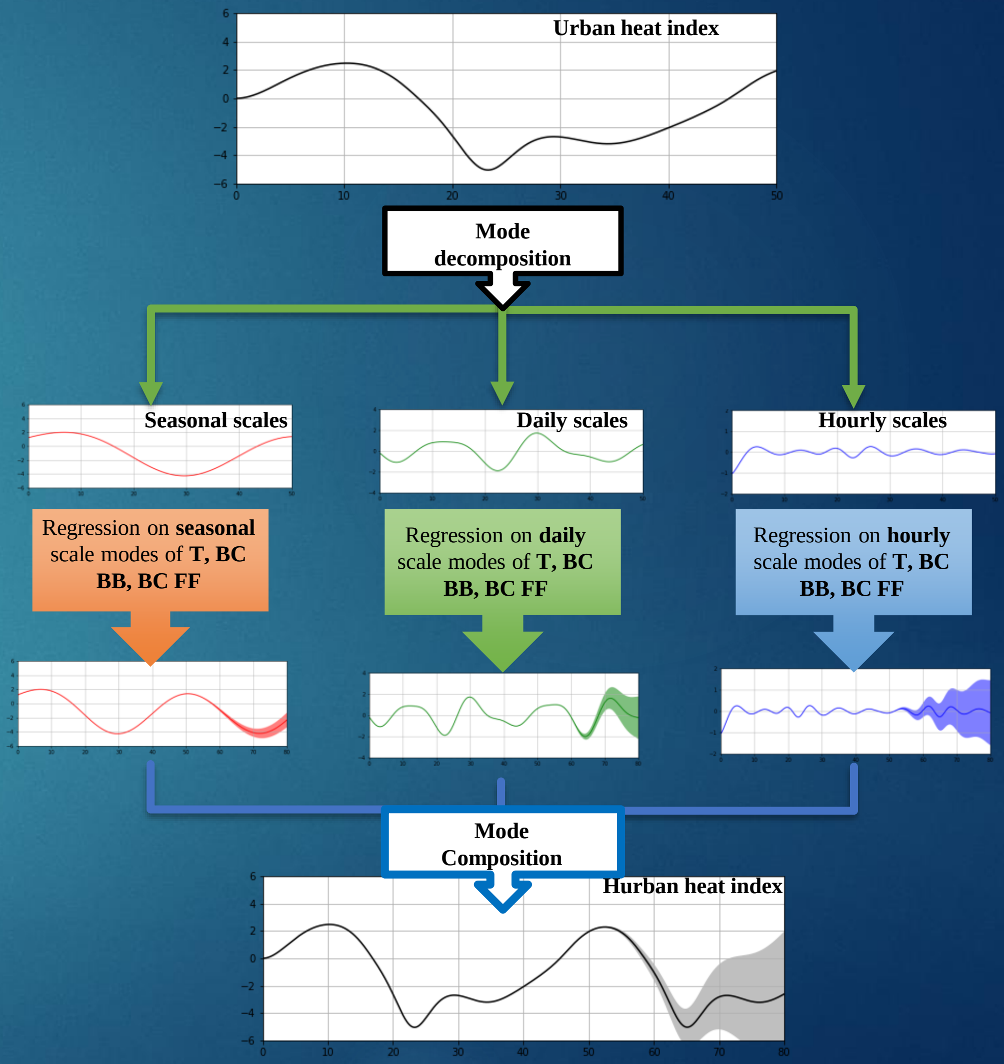
- Stumpo M, Consolini G, Alberti T et al (2020) Measuring Information Coupling between the Solar Wind and the Magnetosphere–Ionosphere System. Entropy 22(3):276. https://doi.org/10.3390/e22030276

Forcing the Physics into approach of CN

Applied to Black Carbon

An exercise: we know what we should get, we know how to interpret the results

We can verify which quantities and which modes are more relevant to reproduce the different timescales of the original signal by permutation analysis.



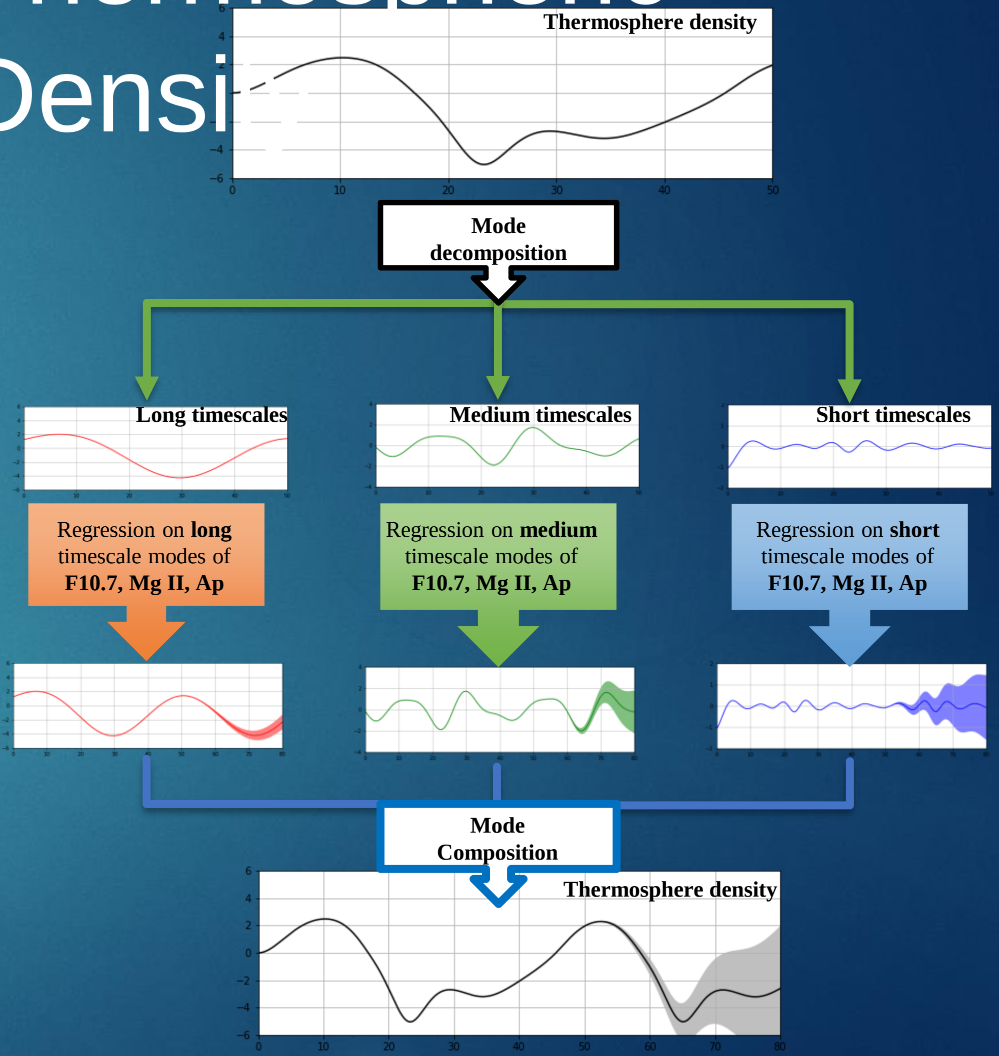
- Santinami, E. (2024, February) Does Black Carbon aerosol influence the Urban Heat Island? A data-driven approach. Master Thesis U. Rome "Tor Vergata"

Applied to Thermospheric Density

Applied to Thermospheric Density

A test: we expect the outocome and we interpret the results

We can learn which quantities and which modes are more relevant to reproduce the different timescales of the original signal by permutation analysis.



- Cafiero, D. (2024 in preparation) From solar and geomagnetic indices to thermosphere density Master Thesis U. Rome “Tor Vergata”
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