Flare Forecasting using Deep Survival Analysis

Moritz Meyer zu Westram, Lucia Kleint
Astronomical Institute, University of Bern, Switzerland
Contact: moritz.meyerzuwestram@unibe.ch

UNIVERSITÄT BERN

Introduction

- Flare forecasting has mostly been studied in form of binary classification models (e.g. ≥ M-class flare within the next 24 hours – *yes/no*).
- Utilize **(deep) survival analysis** in order to…
  - → … increase flexibility by removing decision boundaries
  - → … increase interpretability by allowing continuous time analysis

Concepts

- ***Survival function*** of a random variable T :

Cumulative Distribution Function

$$S_T(t) = P(T > t) = 1 - F_T(t)$$

Probability to survive beyond time t

- *Instantaneous risk of the event occuring at time t* is given by the ***hazard rate*** $h_T(t) = \frac{f_{T(t)}}{S_T(t)}$.
- In our case the *event* is a **M or X flare**.
- We model the hazard rate as the product of an estimated *baseline hazard* and an *exponential risk*: $h(t|X) = h_0(t)\exp(\beta^T \cdot X)$ ***Cox model***
- Replace $\beta^T \cdot X$ by a **neural network**: $g(X|\beta)$.
- Handle *time as an additional covariate* in X.
  - → Enables modelling of interactions between time and other covariates.

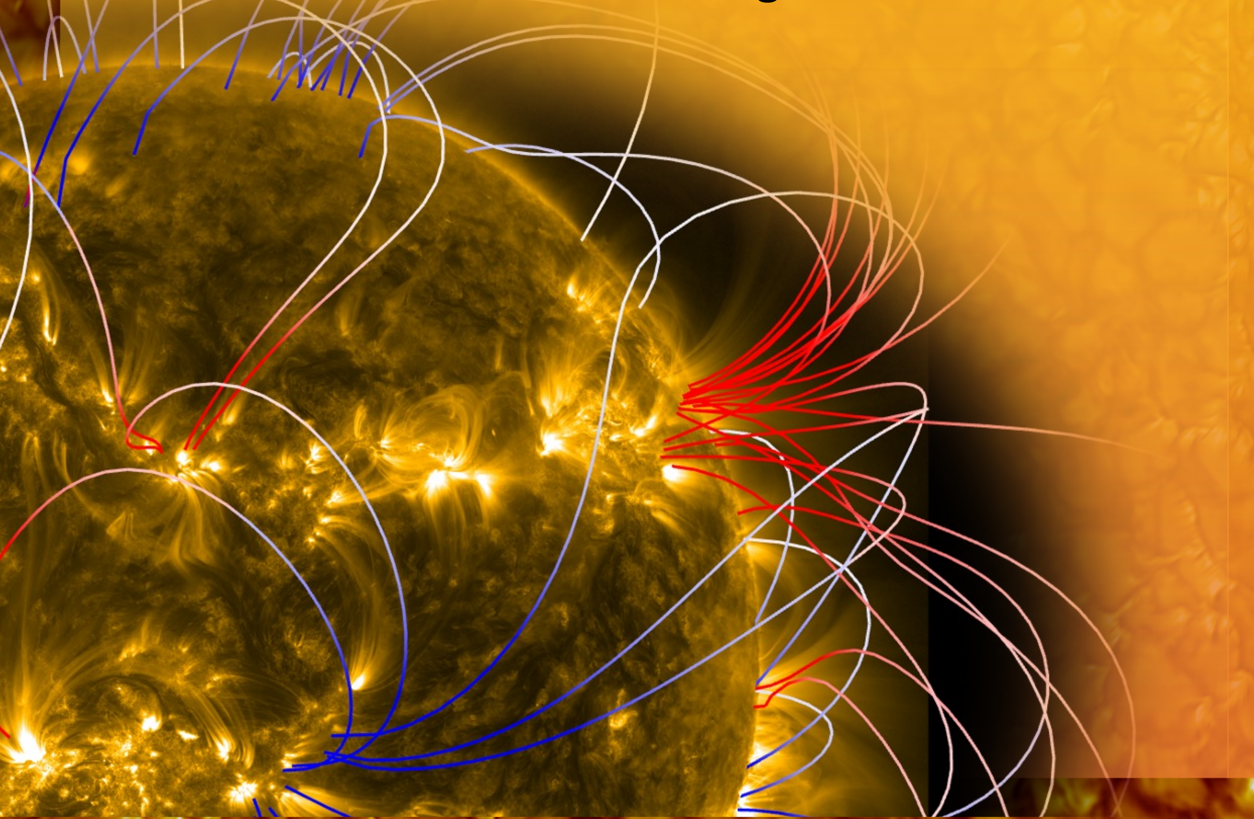
Machine Learning Evaluation Metrics

- Common metrics like accuracy, recall, TSS, etc. cannot be applied due to probabilistic nature and non-existent decision boundaries.
- Use "concordance (C-) index" and Brier Score.
  - → **C-index (0-1)**: Close relationship to accuracy. Describes the probability that, for a random pair of events, the predicted survival times of the two events have the same ordering as their true survival times. *Focuses on ordering!*
  - → **Brier Score (0-1)**: Mean square difference between the survival status ∈ **{0, 1}** and the predicted survival probability **[0, 1]**.

Dataset

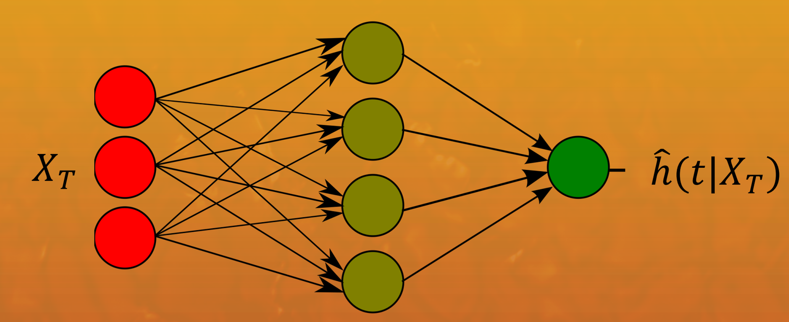
- Multivariate time series from photosperic vector magnetograms in SHARP series (SWAN-SF)
- Data between May 2010 and Dec. 2018
- Cadence: 12-minutes
- Preprocessing: Incorporate the maximum of 1-minute averaged GOES X-ray flux data during the 12 minutes.
- Instead of running on raw data, I use statistics of the data in 4-hour running windows!

Magnetic Field Parameter	Description	Formula
TOTUSJH	Total unsigned current helicity	$\propto \sum \lvert B_z \cdot J_z \rvert$
TOTBSQ	Total magnitude of Lorentz force	$\propto \sum B^2$
TOTUSJZ	Total unsigned vertical current	$\sum \lvert J_z \rvert dA$
USFLUX	Total unsigned flux	$\sum \lvert B_z \rvert dA$
TOTPOT	Total photospheric magnetic free energy density	$\propto \sum (\boldsymbol{B}^{Obs} - \boldsymbol{B}^{Pot})^2 dA$
…	…	…



The Model

- Application of a ***mixed-input multi-layer perceptron***
  - → Includes categorical features (flare type + B/C flare occurences)
- On test set: First use a ***random forest classifier to estimate the flare type***!

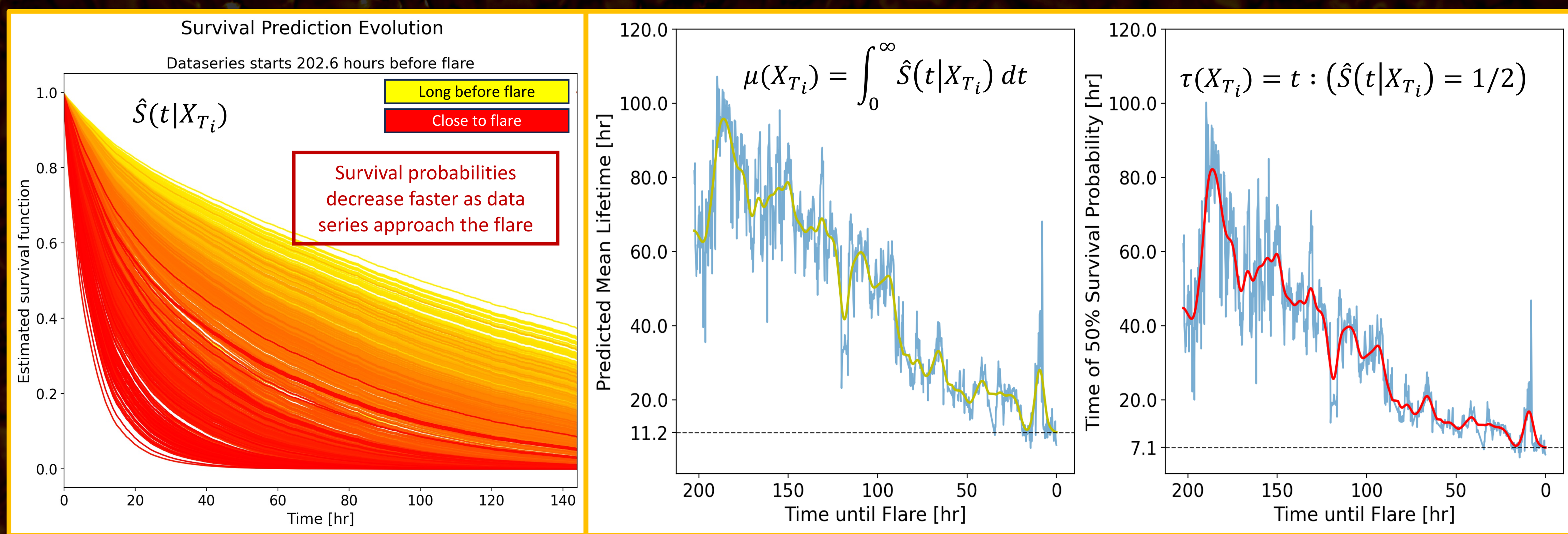


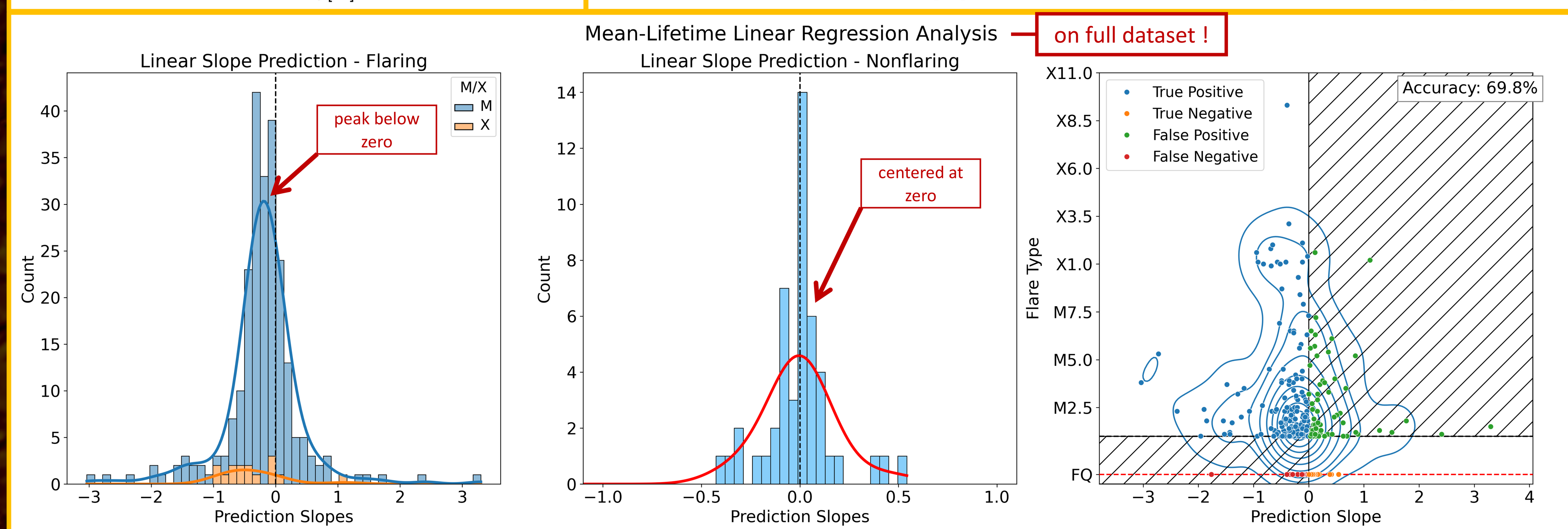
Training the Model

- Different models depending on the **separation of data between training and validation sets**
  - → Random sampling (no constraints)
  - → With flare separation (same active regions allowed – not the same flare)
  - → With active region separation (strict separation of active regions)
- With random sampling the model might just interpolate data…
- But some active regions might be too chaotic or too close to the limb…

Results

Example: SHARP 407 – M4.2 Flare : Active Region-Separated Datasets





- Evaluation metrics of (currently) best model:
  - → Random sets:
    - C-index of 0.89 (1 is best, 0 worst)
    - (Integrated) Brier Score of 0.03 (0 is best, 1 worst)
  - → Active region separated sets:
    - C-index of 0.71 (1 is best, 0 worst)
    - (Integrated) Brier Score of 0.07 (0 is best, 1 worst

Survival Analysis of a M4.2 flare at NOAA 11169

Conclusion & Outlook

- New approach to flare forecasting
  - → No decision boundaries
  - → Probabilistic

  } Predictions are not binary and allow for continuous time statements

  Also means that there are multiple prediction and warning criteria
- Current model is not yet optimized
  - → Find best hyperparameters
  - → Use other underlying neural networks instead of MLP
  - → Develop/adapt neural networks to be suited for the task
- Deep survival analysis provides new avenue for hour-precision forecasts
- Need to test on more recent data
- Find best and most robust criteria for warning systems
- Expand on features (light-curves or image data)