Integrated & Interpretable AIA-HMI Imaging Analysis with Multi-Linear Tensor Gaussian Process

Hu Sun [1], Ward Manchester [2], Yang Chen [1], Meng Jin[3], Yang Liu[4]

[1]Department of Statistics, University of Michigan, Ann Arbor

[2]Climate and Space Sciences and Engineering (CLASP), University of Michigan, Ann Arbor

[3]Solar & Astrophysics Lab, Lockheed Martin

[4]Solar Observatories Group (SDO), Stanford University

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Background: ML-Based Flare Prediction

In this project, we:

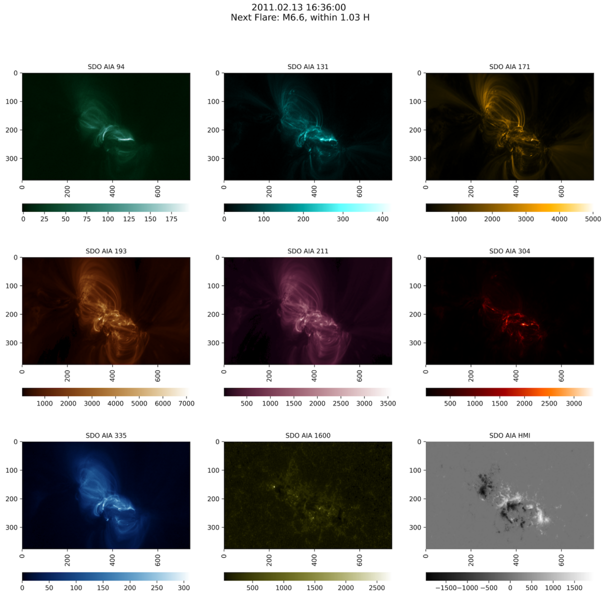
- derive a new statistical learning methodology named *Tensor Gaussian Process with Spatial Transformation* (**Tensor-GPST**) for flare intensity prediction.
- make feature extraction from AIA-HMI imaging data explicit with spatial transformation.
- analyze the AIA/HMI channel contribution to flare intensity prediction.

Data: AIA-HMI Multi-Modal Data

Our dataset has these characteristics:

- has 1205 B-class flares, 695 M-class flares spanning the period of 2010-Jun $\sim$ 2017-Sep.
- contains $\sim$ 24 hours of data, at 12-min resolution, prior to each flare's peak time.
- contains 8 AIA channels (AIA-94, 131, 171, 193, 211, 304, 335, 1600) and one HMI channel (Br) with high spatial resolution

Data: AIA-HMI Multi-Modal Data



Data: AIA-HMI Multi-Modal Data

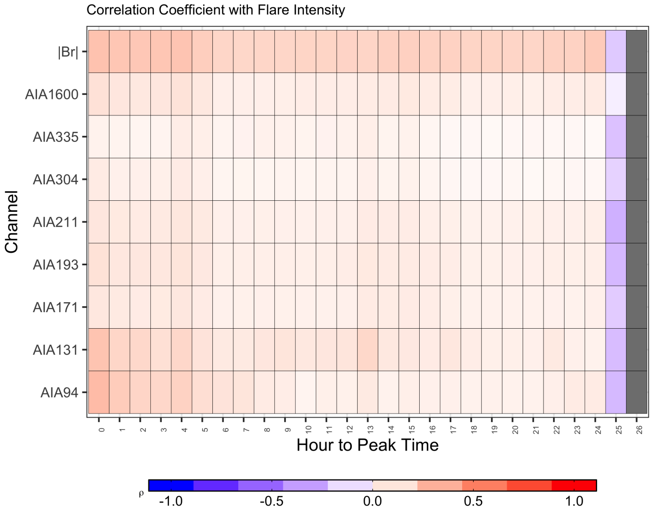


Figure: Channel (sum of all pixels) Correlation Coefficient with Flare Intensity

Method: Gaussian Process (Standard GP)

Given any dataset $\{x_i, y_i\}_{i=1}^{N}$, a canonical Gaussian Process (GP) regression model formulates relationship between y_i and x_i as:

$$y_i = f(x_i) + \epsilon_i, \quad f(.) \sim \mathcal{GP}\left(\mathbf{0}, \mathcal{K}(.,.)\right)$$

where $(f(x_1), f(x_2), \ldots, f(x_N))$ are distributed as a multivariate zero-meaned Gaussian distribution, and the covariance is defined via a *kernel* function $\mathcal{K}(.,.)$, where $\mathrm{Cov}(f(x_i), f(x_j)) = \mathcal{K}(x_i, x_j)$.

Tensor-GP

Our AIA-HMI database is a multi-channel imaging dataset. Each AIA/HMI image is denoted as $X_i^{(v)}, v = 1, 2, \ldots, V$, and we have V channels in total. The dataset can be represented as $\{X_i^{(1)}, \ldots, X_i^{(V)}, y_i\}$, where y_i is flare intensity. Tensor-GP takes similar formulation as the canonical GP:

$$y_i = f(X_i^{(1)}, \ldots, X_i^{(V)}) + \epsilon_i$$

where $f(.) \sim \mathcal{GP}\left(\mathbf{0}, \mathcal{K}(.,.)\right)$. The kernel used for tensor data (e.g. AIA-HMI images) typically is a multi-linear kernel.

Tensor-GP

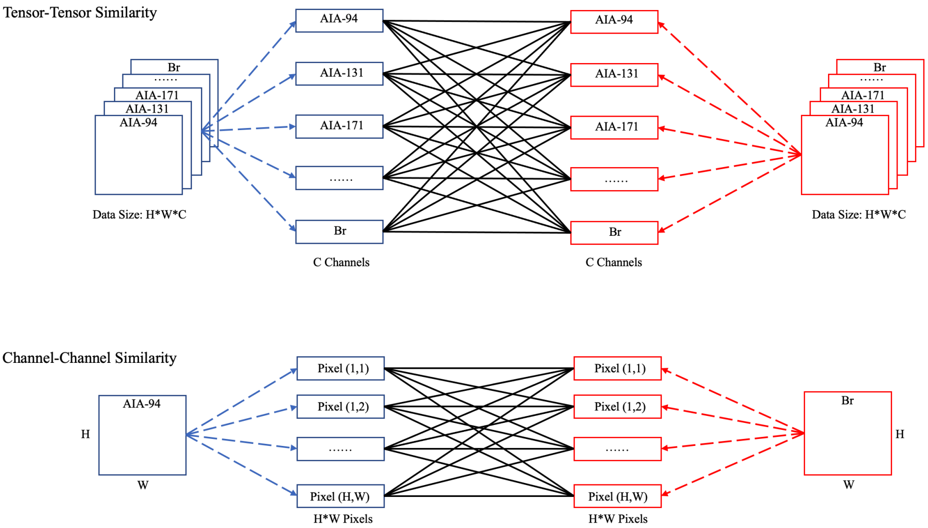


Figure: Tensor-Tensor Similarity Definition

Tensor-GP

Intuitively, between two flares' AIA-HMI imaging data,:

- we want to define a scalar quantity that depicts the similarity of the two flares' AIA-HMI data.
- we loop over all pairs of pixels between the two tensor data, and for any pair: $(\text{row}_i, \text{col}_i, \text{channel}_i)$, $(\text{row}_j, \text{col}_j, \text{channel}_j)$ for flare i and j, their pixel intensity product is weighted by:

$$K_3\left(\text{channel}_i, \text{channel}_j\right) \times K_2\left(\text{col}_i, \text{col}_j\right) \times K_1\left(\text{row}_i, \text{row}_j\right)$$

Tensor-GP with Spatial Transformation

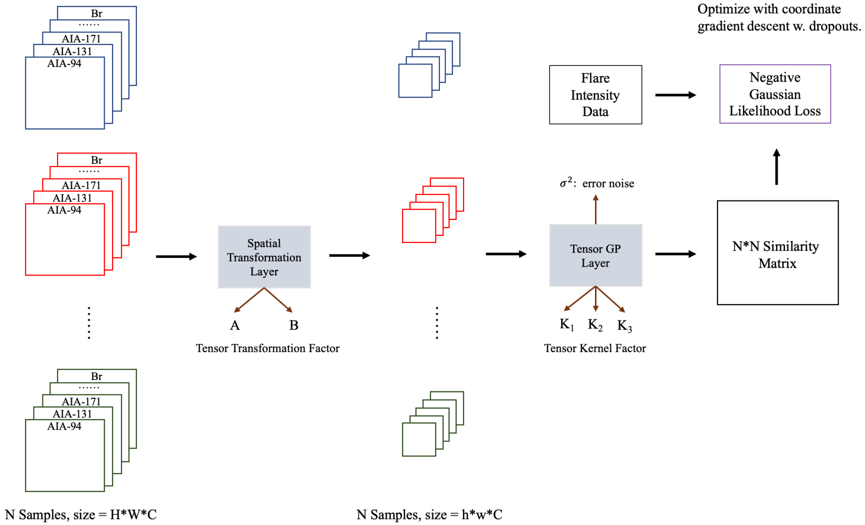
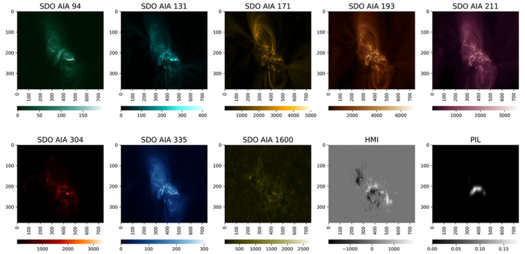
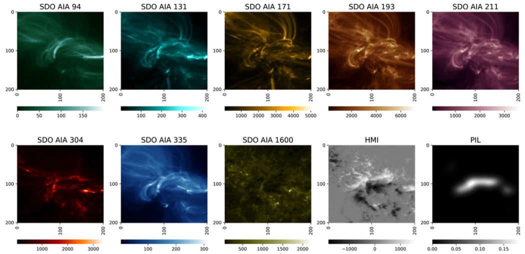


Figure: Overview of the Tensor-GPST Model

Results: Data Preprocessing

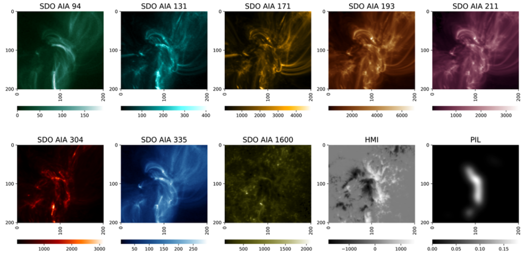


Step I: Generate Polarity Inversion Line (PIL) Mask.

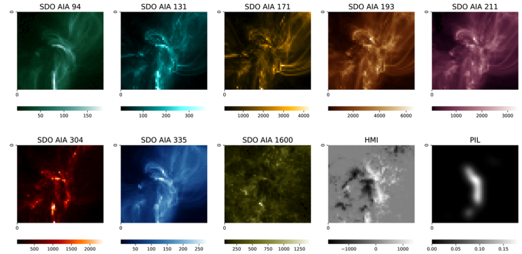


Step II: Find a shared 200*200 cropping window with the maximum PIL coverage.

Results: Data Preprocessing



Step III: Use PCA to rotate the PIL to make it vertical.



Step IV: Reduce the resolution to 50*50.

Results: Model Estimates

To train the model, we:

- use 60% of the data ($N = 1140$) for training, and 40% ($N = 760$) for testing, and B vs. M/X ratio is balanced for both training and testing set.
- do flare intensity regression, where B-flare has intensity from $[2.0, 3.0]$, and M/X-flare has intensity above 4.0 (i.e. quiet is normalized at 1.0 and scale with log scale).
- transform every 50×50 image to 1×1.

Results: Model Estimates

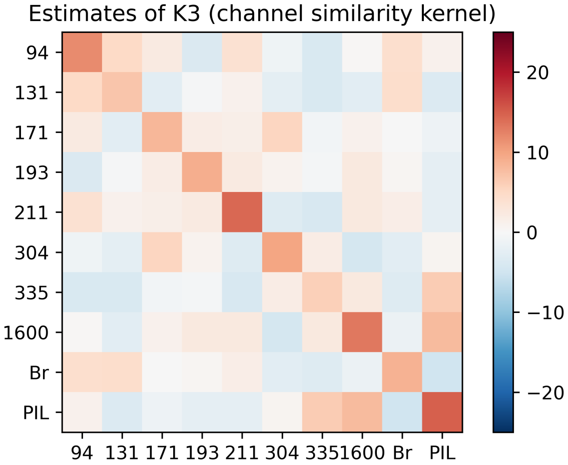


Figure: Kernel Estimates for the Tensor-GPST Model. Most important channels in the similarity metric are: AIA-94, AIA-211, AIA-1600, PIL.

Results: Model Estimates

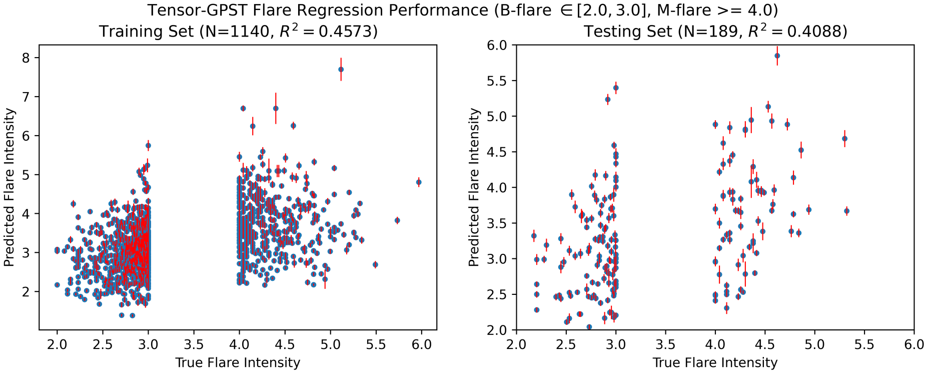
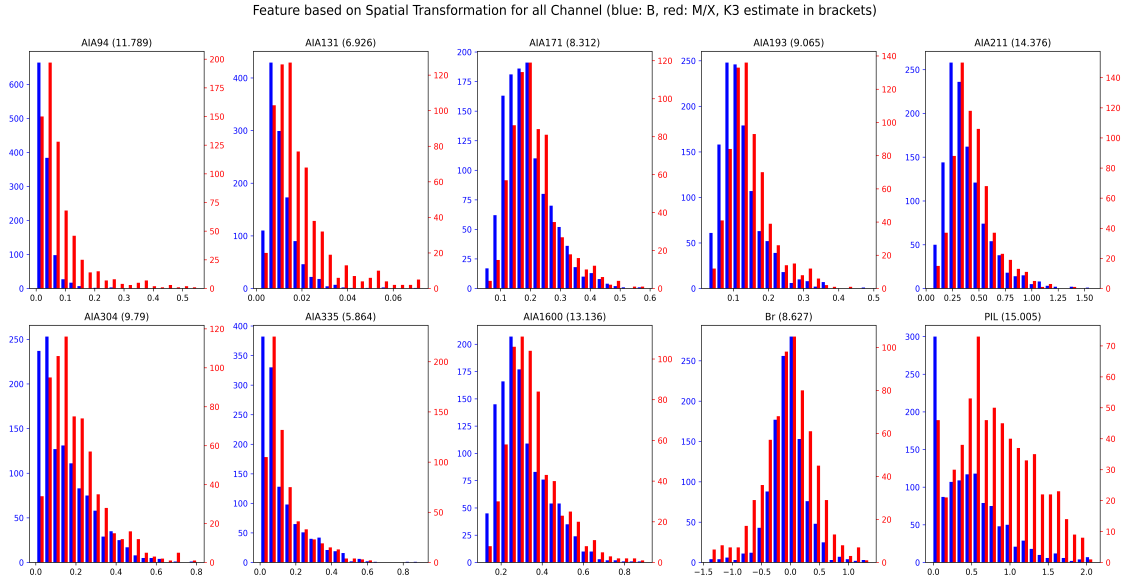
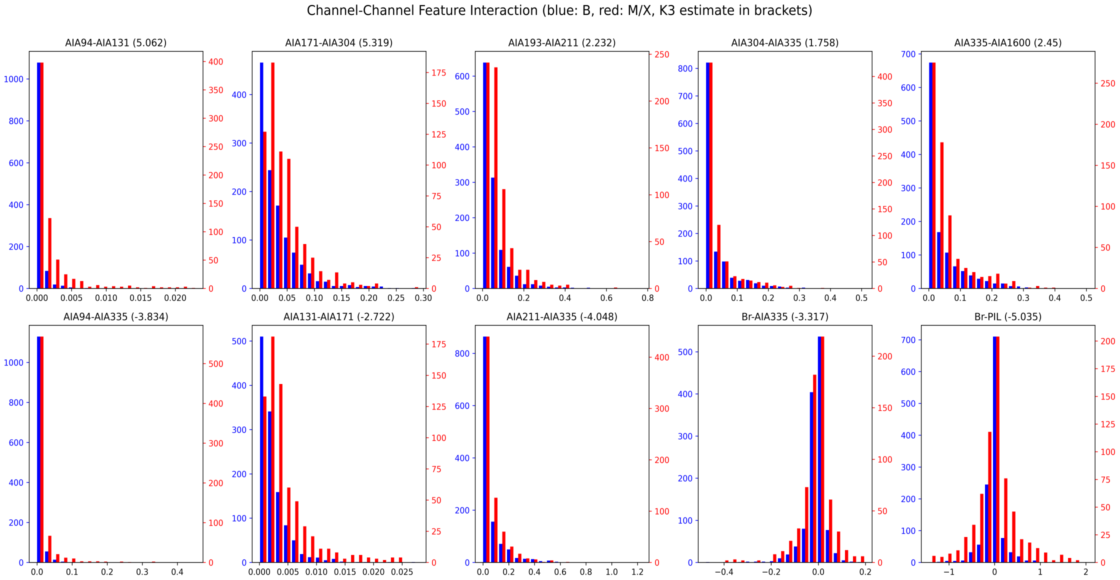


Figure: Training (left) and Testing (right) set performances. We only show the test samples with longitude within $[-60°, 60°]$.

Model Interpretation: Channel Importance



Model Interpretation: Channel Interaction



Model Estimates: $50 \times 50 \to 10 \times 10$

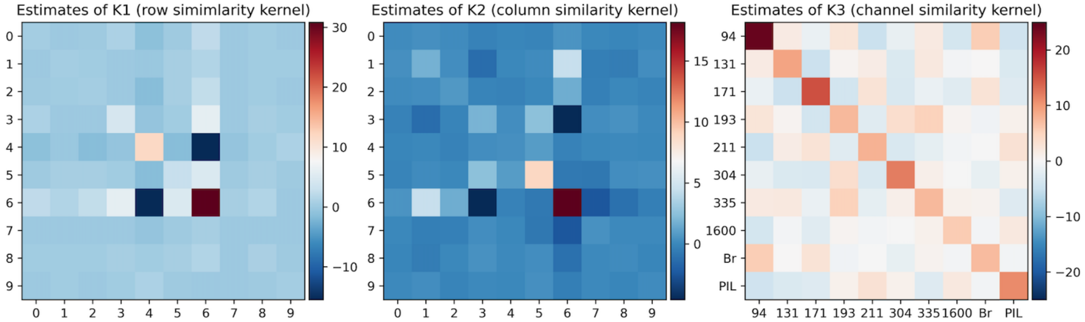


Figure: Kernel Estimates for the Tensor-GPST Model. Most important channels in the similarity metric are: AIA-94, AIA-171, AIA-304, PIL.

Model Estimates: $50 \times 50 \rightarrow 10 \times 10$

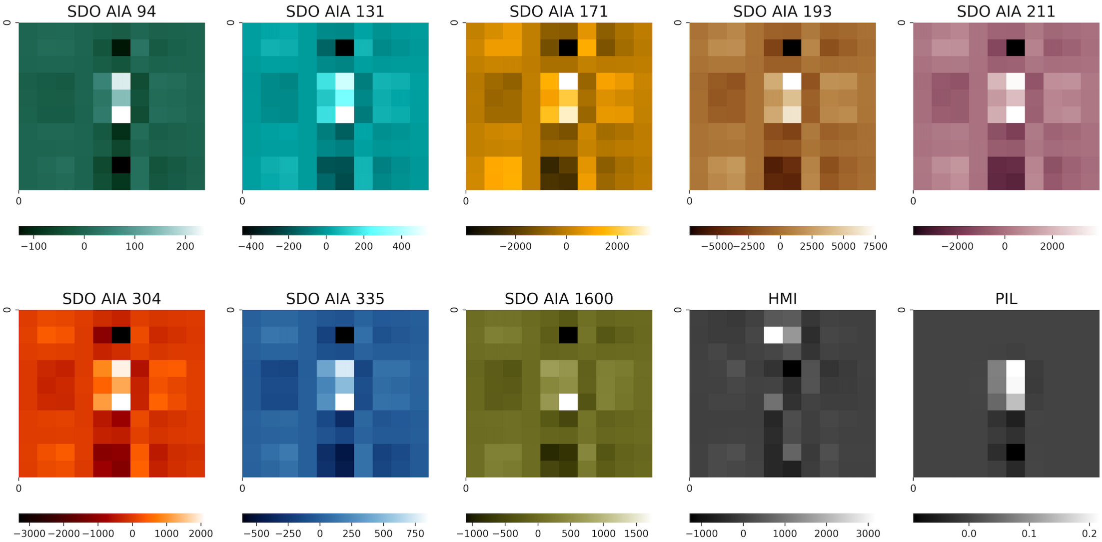


Figure: Spatially Transformed Image for AR 11158, M6.6 flare at 2011-02-13 17:38:00.