**RotNet**: Fast and Scalable Estimation of Stellar Rotation Periods Using Convolutional Neural Networks

J. Emmanuel Johnson¹, Sairam Sundaresan², Taneu Daylan³, Liseth Gavilan⁴, Daniel K. Giles⁵, Steila Ishihani Silva⁶, Anna Jungbluth⁷, Brett Morris⁸, Andrés Muñoz-Jaramillo⁹

¹University of Valencia, ²Intel Labs, ³MIT, ⁴NASA ARC, ⁵IIT, ⁶Catholic University, ⁷Oxford University, ⁸University of Bern, ⁹SwRI

**INTRODUCTION**

The magnetic field of stars strongly affects the habitability of nearby planets. Currently, very little is known about the magnetic activity of stars other than the Sun. Magnetically active stars can show dark spots on their surface (starspots). Distant stars are imaged as a set of pixels whose brightness changes are monitored with time. Several stellar parameters can be inferred from these light curves including the number of spots, sizes and rotation characteristics. The most critical parameter is the rotation period, $P_\text{rot}$, which is correlated to stellar age and size.

**TIME SERIES TO IMAGE TRANSFORMATIONS**

To take advantage of transfer learning with SOTA pre-trained ResNet-18 convolutional neural networks, we used geometry preserving transformations [1] of our time series to images. We create a 3-channel image using the Grammian Angular Field (GAF), Markov Transition Field (MTF), and the Recurrence Plot (RP).

**RESULTS**

- 2D Histograms for 3,700 stars in our test said versus benchmark McQuillan periods (cite)
- Time is measured on a single CPU
- Violin Plots display residual errors

**NEXT STEPS**

- Evaluate the uncertainty of our predictions.
- Evaluate other time-series to image transformations.
- Compare our ML results to inference methods.

**CHALLENGES**

Can we use 1-D time series of the changing photon flux (light curves due to starspots on the surface) to estimate a star's rotation period?

- Redundant: Many parameters describe the data equally well.
- Few-labels: Lack of ground-truth on large-data scales.
- Physics SOTA: computationally expensive and time consuming.

**BASELINE METHODS**

- AutoCorrelation Function (Physics Community SOTA)[2]
- Random Forest Regressor
- 1D Convolutional NN

**DATA & PREPROCESSING**

- ~100K light curves in the catalog from Kepler mission
- 18,472 light curves with McQuillan rotation period estimates
- Each light curve is a time series, with ~60k data points which were rebinned to 1,080 time steps.

**RESU LTS**

- Evaluation of uncertainty of our predictions.
- Evaluation of other time-series to image transformations.
- Comparison of our ML results to inference methods.

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**REFERENCES**
