Double Trouble II: Applying Deep Learning to EBS Systems

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Overview

Motivation: Current methods to predict stellar characteristics in EBs systems take considerable time. A speedup would allow astronomers to derive stellar properties effectively.

Goal: Predict characteristics of EBS and the uncertainty of the predictions.

Approach: Use various deep learning techniques to approximate predictions.

Background

Astronomy:

- Eclipsing binaries (EBs) systems: two stars revolve around each other
- Each star has characteristics such as a radius, temperature, mass, etc.
- The stars emit observable, periodically varying light curves

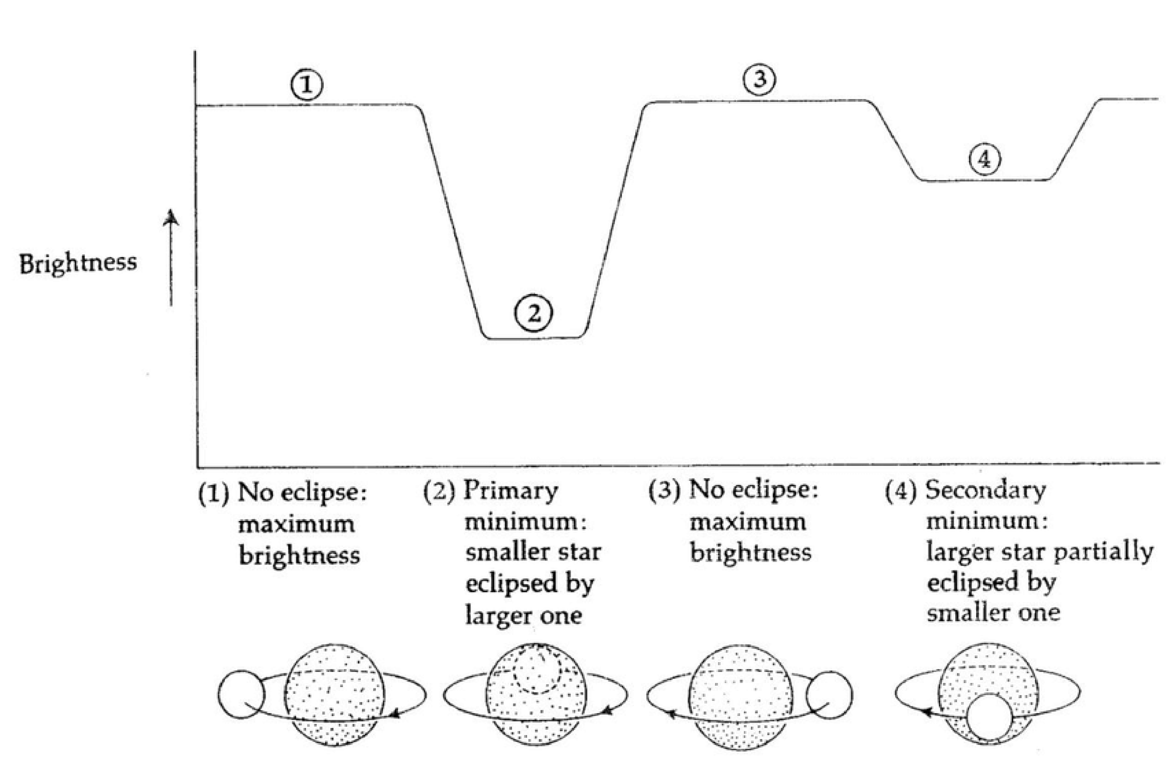

Figure: Binary Star System and Light Curves

www.researchgate.net/figure/Figure-8-Light-curve-of-eclipsing-Binary-Stars$_{fig6_3}$20346142

Dataset

Inputs:

- $\sim 100,000$ observations
- 50 light curves and 2 radial velocities, each with 512 steps
- 31 metadata features

Targets:

- 18 predicted targets
  - phase of the system, effective temperature, and radii

Model

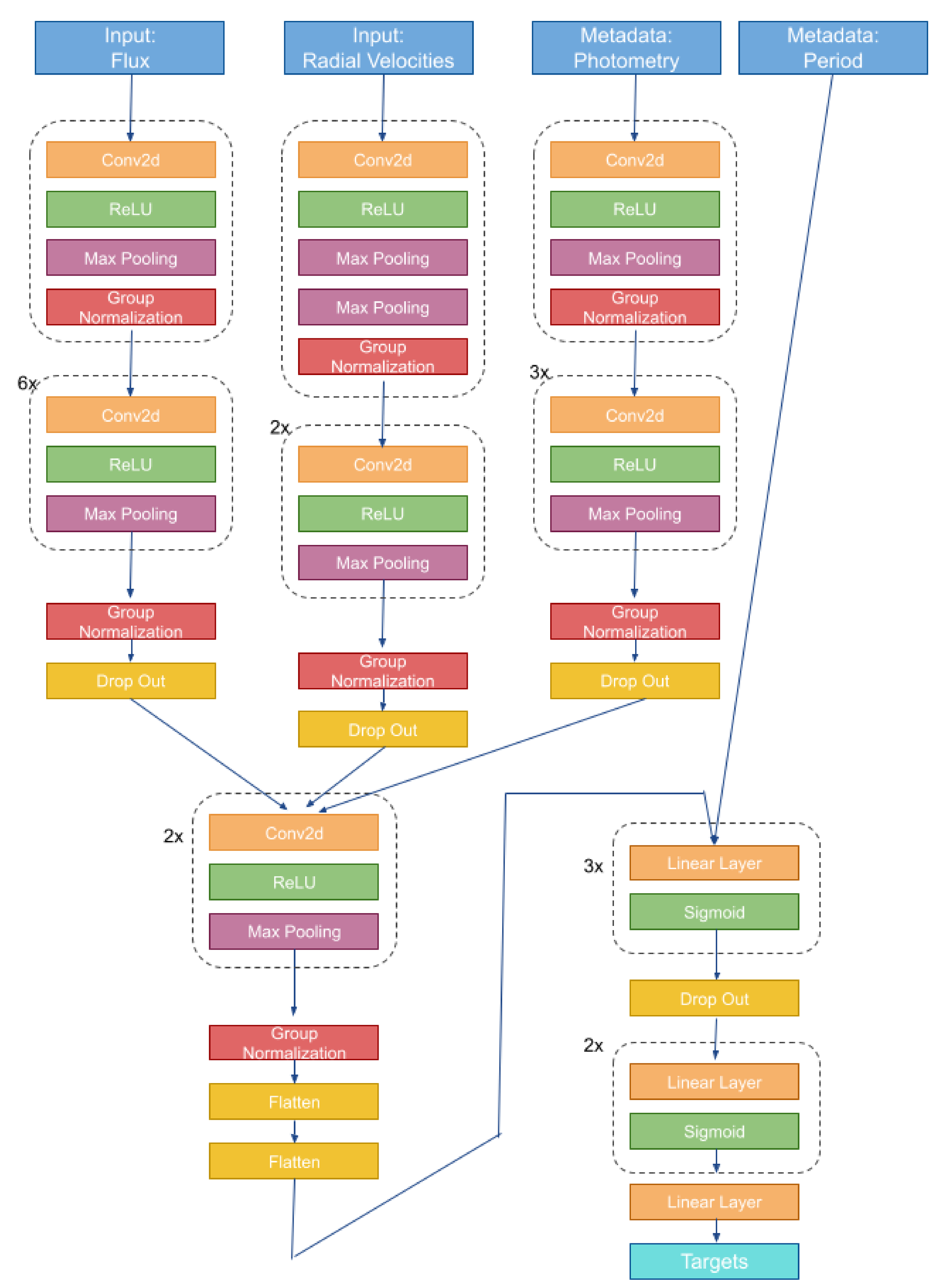

Figure: Model architecture of our current model

Custom Loss Function

- Allows prediction of Standard Deviations of estimates
- Alternative to MSE

$$\frac{1}{N}\sum_{(x,y)}\left(\sum_{i=1}^{k}\log\sigma_\theta(x)_i + A\right)$$

where,

$$A = \sum_{i=1}^{k}(y_i - \mu_\theta(x)_i)^2/\sigma_\theta(x)_i$$

Data Dropping

- Input in the field is often incomplete
- Model is trained on sparse and muted data
- The model can then generalize to situations with incomplete data

Results and Analysis

Model Comparison:

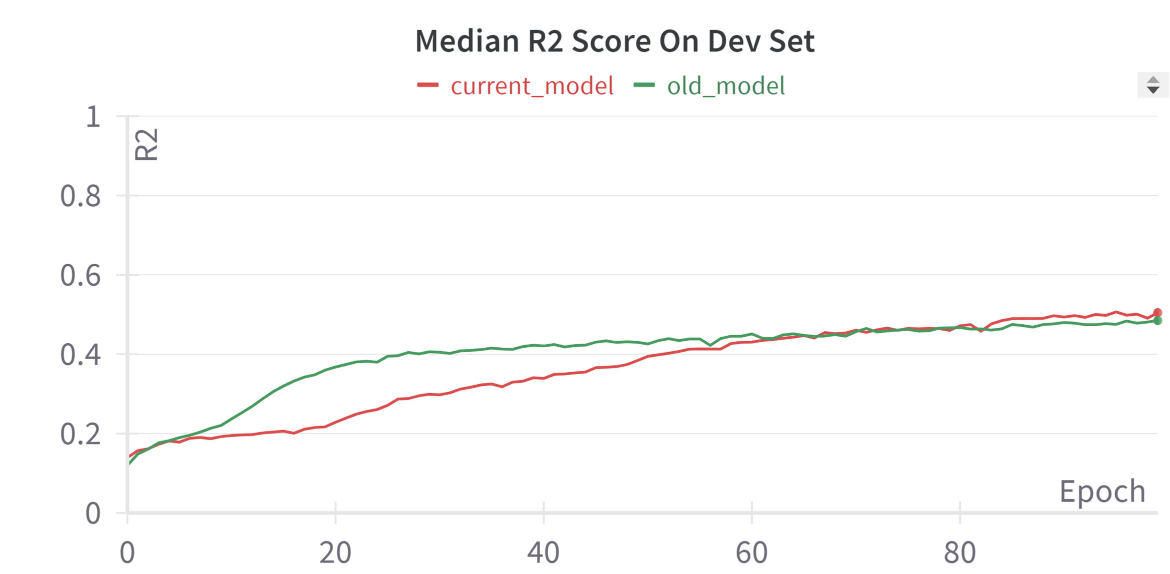

Figure: Model performance comparison

- New model works slightly better
- Struggles to predict complex parameters such as the effective temperature of the stars

Model Predictions:

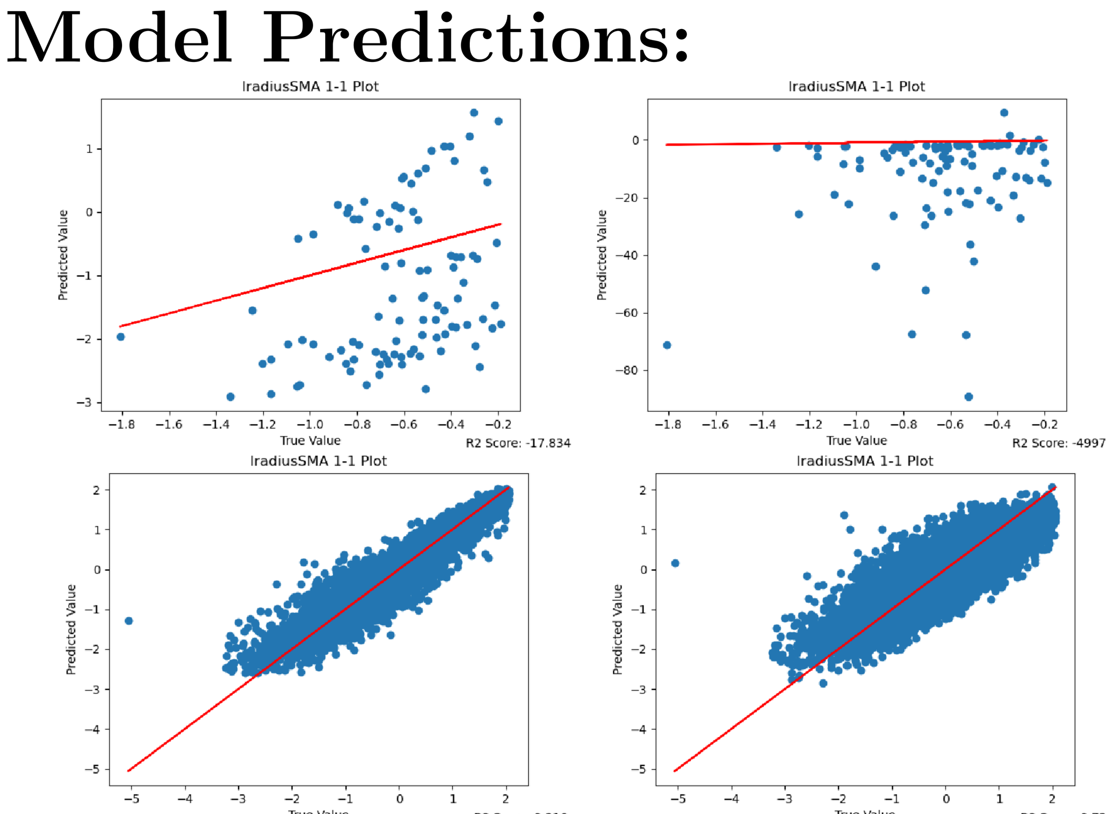

Figure: Predictions on lRadiusSMA from current model (top left) and old model (top right) on real data, current model (bottom left) and old model (bottom right) on synthetic data

- Models generalize to synthetic EBs, but struggle to generalize to true EBs

Conclusion

- Data masking and noising can approximate real EBs
- More complex model architectures provide better predictions

Future Work

- Train with new and more data
- Experiment with different model architectures