Stellar Age Estimation via Machine Learning

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Abstract

Stellar age is an important evolutionary parameter which is difficult to estimate. Our group used machine learning (ML) as a stellar age estimation technique, a task which has been demonstrated by recent studies [1]. Using the GAIA Data Release 3 (DR3) dataset [2], we constructed a deep neural network (DNN) stellar age estimation model with TensorFlow. The model produces accurate (mean absolute error = 0.8 Gyr) age estimates during testing, demonstrating the efficacy and feasibility of an computationally inexpensive stellar age estimation technique.

Introduction

Accurate stellar ages are crucial to understand the evolution and structure of stars and galaxies. Traditional estimation methods include isochrone fitting, gyrochronology, and asteroseismology. Selecting the appropriate method depends on the availability and cost of the different types of data required for each method. Using a combination of several different methods can improve the accuracy of age estimation if all required data is obtainable [3]. The GAIA DR3 dataset uses FLAME, a stellar age and mass estimation model based on an enhanced version of isochrone fitting using luminosity, metallicity, etc. in its estimate [4].

Machine learning has long been used for pattern recognition, including, recently, as a tool to estimate stellar age. Deep neural networks are the most commonly used type of model in ML, using layers of neurons with both linear and nonlinear activations to capture a wide range of possible behavior. They use gradient descent to minimize a loss function, which typically represent the error or utility of a model. TensorFlow/Keras is a widely used ML library which contains efficient utilities for building and training DNNs.

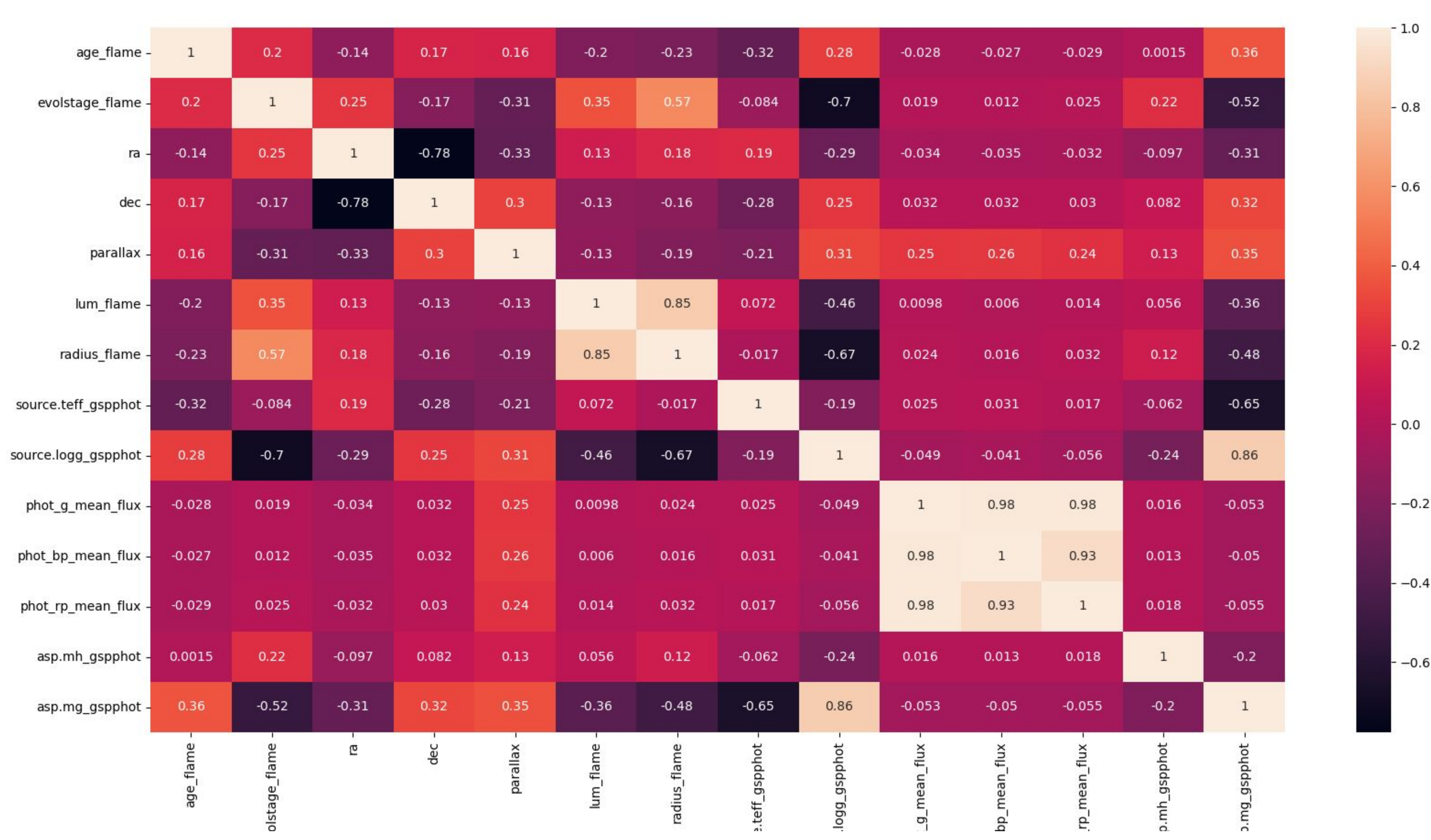

Figure 1: Correlation matrix of stellar age and training variables

Data Acquisition

All of our data was sourced from GAIA DR3 and accessed via Astroquery API. From this data, we retrieved the parameters listed in Figure 1 for 200,000 stars. The age column became the labels for our model. The rest of the data was normalized and we replaced all NaN values in our dataset with -99. The resulting array was then shuffled and partitioned into training, validation, and test datasets.

Algorithm & Performance Metric

Our predictive model was built with 4 dense layers with RELU activations (shapes 128, 100, 64, 1) and compiled using the Keras framework. We used the Adam optimizer with the mean absolute error (MAE) loss function. We trained the model for 500 epochs with early stopping with an initial learning rate of 1e-3 and reduced learning rate on plateau. The model's accuracy during training was evaluated by plotting the loss. After training, error analysis on the test split data's ages versus the model-predicted ages was performed to check against overfitting and assess the quality of our model.

Results

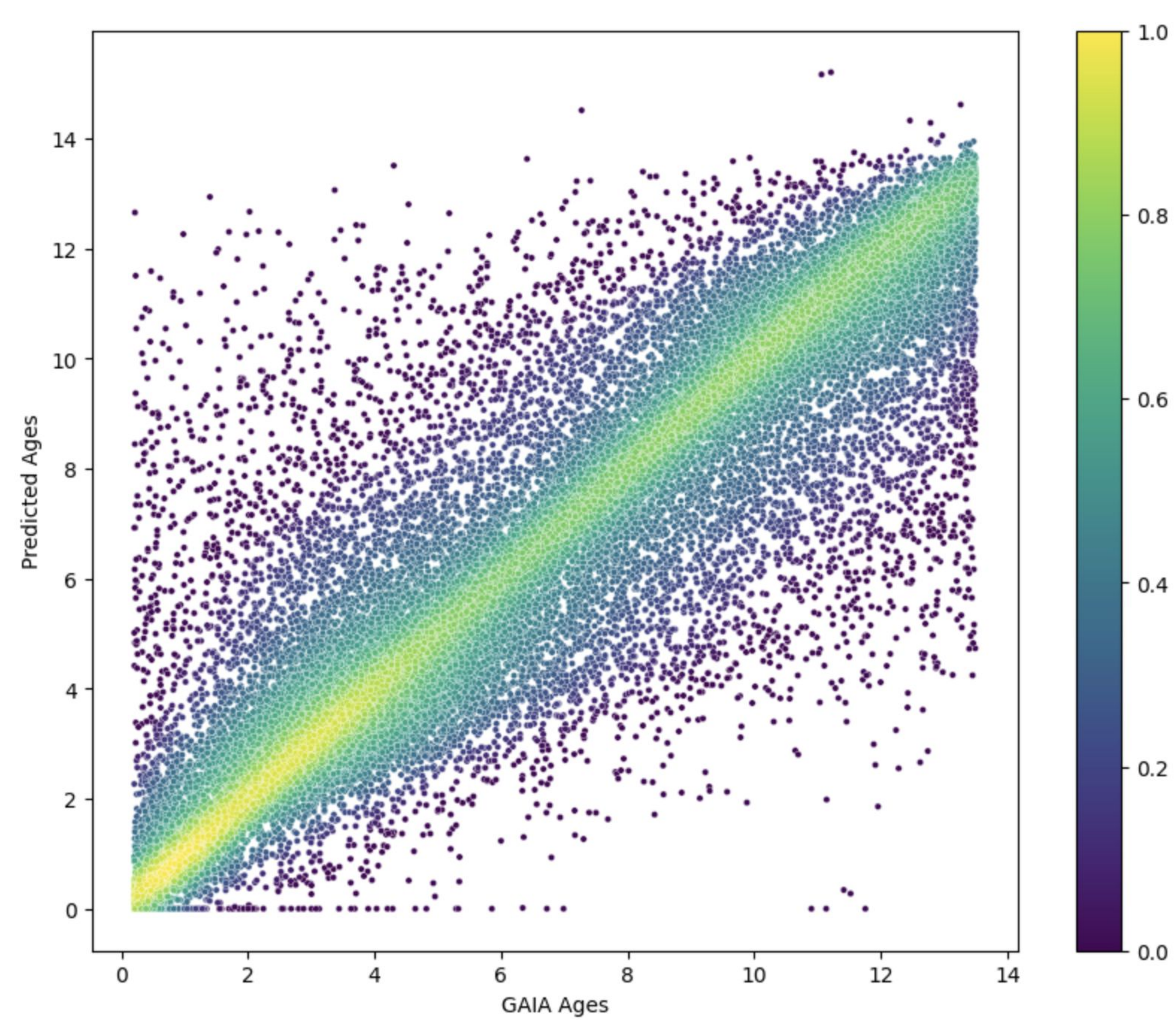

Figure 2: Scatterplot of predicted vs actual ages in test split, with color indicating probability density (scale is relative and logarithmic with floor of 1e-3)

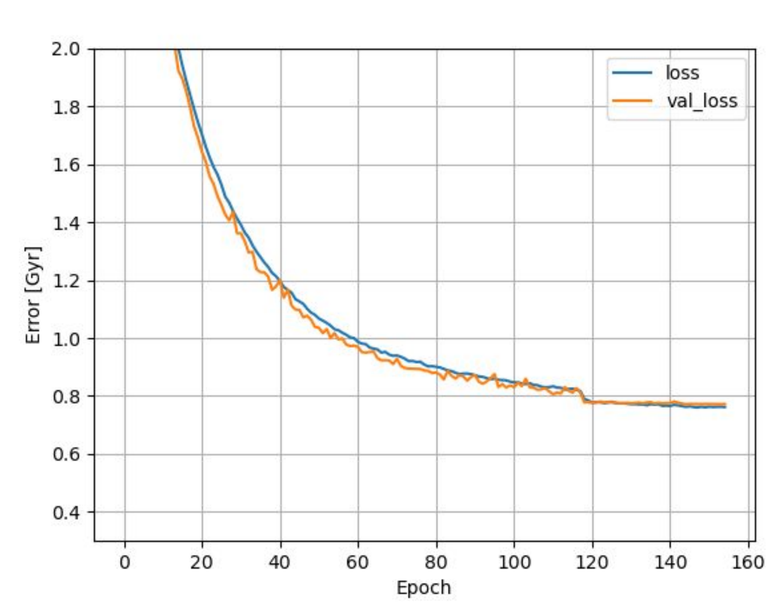

Figure 3: Loss function (mean absolute error, Gyr) during training

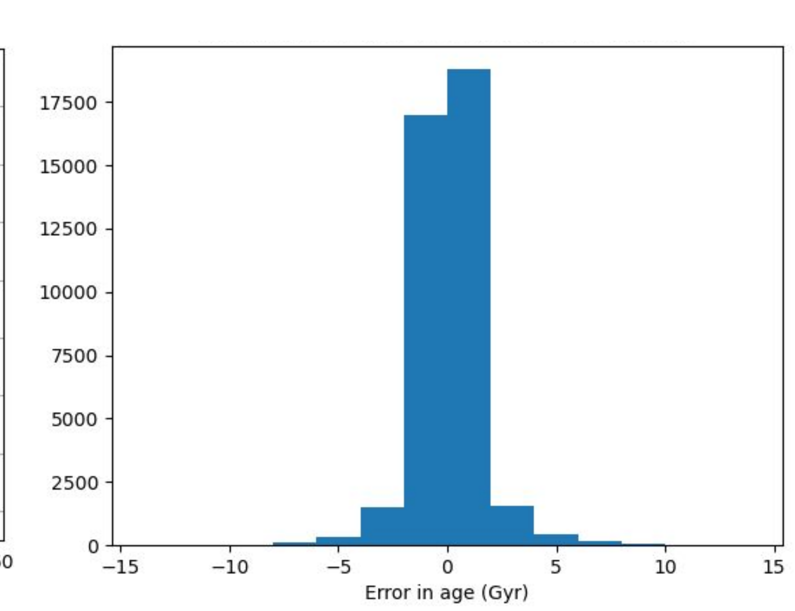

Figure 4: Error of age from our DNN to GAIA DR3

Discussion

Our mean absolute error was 0.80 Gyr, which is comparable to the results from Bu 2020 (0.16-1.60 Gyr), who used a Gaussian Process Regression technique instead. However, our mean relative error (defined as |label-predicted|/label) was much higher, at 28%, compared to 9% for Bu et al. [1]. This may be due to the large differences in age predictions at small ages, which can be seen as outliers in the heatmap, which are weighted more in mean relative error compared to mean absolute error. Changing the number of layers, the number of neurons per layer, and the parameters used in training largely did not affect the performance of the model, so changing the type of model used or performing more data preprocessing may be more effective ways to improve accuracy.

Conclusion

Our ML model proves to be a suitable method in classifying stellar age with a reasonable accuracy (MAE = 0.8). We can use the DNN model to extrapolate to larger datasets comprising varying stellar properties to extract further patterns. Our predictions could also become more accurate with simply adding more computing power, without requiring significant alteration to our training process. The use of machine learning to classify and predict stellar age shows promise for the future.

Future Work

A major area of improvement would be obtaining more accurate labels. The GAIA dataset has large uncertainties for many objects. We could preprocess the data to select only stars with reliable ages, or use other datasets with age estimates. In addition, diversifying our age sources could help avoid potential bias or overfitting from the way our labels were obtained, e.g. using the KEPLER dataset, which would lessen the chance that our model memorizes the FLAME model used by GAIA DR3.

Further work can also be done to evaluate the utility of our model, i.e. comparing the estimates obtained from our model to traditional methods. We could also evaluate the resource cost and accessibility of the data we use in our model. We could also use our model to obtain ages for stars which currently have no age estimate in GAIA DR3, which could help identify new patterns in our galaxy and beyond.

References

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3. Ruth Angus et al. (2019). Toward Precise Stellar Ages: Combining Isochrone Fitting with Empirical Gyrochronology. The Astronomical Journal, 158(5), 173.
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