Stellar Age Estimation via Machine Learning

Final Project Proposal

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Certification

I certify that this project proposal is an original document that I have carried out in conjunction with only those listed here and with the assistance of my mentors and advisors. I affirm that I have properly cited all references, including journals, textbooks, figures, and other resources.

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1 Abstract

Stellar age is an important evolutionary parameter of stars which cannot be directly measured. A variety of traditional stellar age estimation methods exist, but each method has caveats. The use of machine learning as a stellar age estimation tool has been increasingly popular, and its feasibility has been demonstrated by recent studies. We will try to produce an accurate simple neural network stellar age estimation model, using the Tensorflow library in Python, on the recently released (June 2022) GAIA DR3. We will use its age estimations as the standard for our training and testing. We anticipate that an appropriate selection of input parameters will produce an accurate estimation model. If we can select a set of parameters which do not require time or money-intensive data collection, our model could demonstrate the accuracy and feasibility of an inexpensive, computationally simple stellar age estimation technique.

2 Background

Stellar age is an important evolutionary parameter of stars. Accurate stellar ages are crucial for understanding stellar and galactic evolution, including studying the behavior of star-forming regions and verifying predictions about stars' life cycles. However, there is no way to directly measure a star's age from Earth. The need for stellar age estimates has lead to a wide range of estimation methods.

Isochrone fitting is the classical method which depends on the position of the star on the H-R diagram, which can be matched to ages on theoretical isochrones with fixed initial mass. Isochrone fitting is accurate for stars near the main-sequence turnoff (at the end of the main sequence), but suffers earlier in a star's life cycle from the fact that stars maintain roughly constant luminosity and temperature during the main sequence phase [2].

Gyrochronology is an alternate method much better for stars along the main sequence, using the angular velocity and temperature of the star. Empirically, Sun-like stars with identical initial mass will start the main sequence at the same angular velocity. As stars age, their angular velocity slows due to magnetic braking, which can be observed and quantified empirically [2] This method is precise for low mass stars, but does not work for more massive stars (greater than 1.4 solar masses). In addition, the method is only reliable on isolated stars, where the star does not exchange angular momentum with planets or other nearby stars [5].

Asteroseismology is yet another method of stellar age estimation, based on the study of resonance and oscillatory modes in stars. Regular fluctuations of a star (e.g. brightness) can be understood as resonant modes, which are used to predict the internal structure of a star, giving insight on the relative abundance of different elements in its interior. Asteroseismology has allowed for more precise age estimation on more stars as longer duration data has become more available in recent years [6]. However, this kind of extended period data collection is not always feasible, especially for stars with very long pulsation periods, and the models for understanding stellar structure, especially at earlier stages in the life cycle, may be limited and thus lead to inaccurate age predictions [1].

The above methods represent only part of the vast variety of methods for stellar age estimation. Other methods exist, like tracking the relationship of stars to nearby stars in open clusters, which form at the same time and therefore share the same age. The GAIA DR3 age measurements are obtained through estimations for the mass and luminosity, which are then passed into the BaSTI model, an enhanced version of isochrone fitting that incorporates metallicity and other factors (see the GAIA website). Each of these methods can be accurate and effective tools, especially when combined with each other. However, each method has its own caveats, for example only working on certain types of stars or in certain age ranges. The need for alternate or complementary stellar age estimation techniques is still present.

Responding to this need, the popularity in machine learning techniques has lead to the use of machine learning models as stellar age estimators. Machine learning has been an increasingly popular way of analyzing large sets of data, due to its ability to use large numbers of variables and generate meaningful conclusions. The automated nature of its model generation has made it possible to reduce the amount of human labor and take into account many more factors compared to human-designed models. Its prevalence in the physical sciences is largely due to this ability to comb through large datasets and generate accurate predictions.

In machine learning, artificial neural networks (ANNs) are one of the most common and established techniques used. It shares strong parallels to biological neural networks, feeding in data through an input layer of artificial neurons and passing it through several additional layers of weighted links and neurons before arriving at a final output layer. The neural network then learns by adjusting the weights on each link to minimize a loss function, which is given by a human overseeing the learning process. This simple system is surprisingly effective at a variety of tasks, leading to its current ubiquity in the machine learning landscape.

Machine learning models for stellar age estimation often aim to fill in the gaps between traditional models. McBride et al 2020 demonstrates the utility of machine learning in this field, using a deep learning model to estimate the age of pre-main sequence stars, a difficult task with gyrochronological or asteroseismological techniques [7]. Other studies have expanded the field instead by exploring the improvement in accuracy by using more advanced models. Bu et al 2020 uses a Gaussian Process Regression (GPR) model to obtain a more accurate model than with traditional neural network models [4]. Despite these improvements, we will try to develop and demonstrate the feasibility of a conventional neural network model, only switching to more advanced techniques if the simple neural network does not meet our accuracy standards.

3 Research Question

Can neural networks be used to accurately predict the age of stars from GAIA DR3's photometric, spectroscopic, and astrometric data? We anticipate that a simple neural network model is sufficient to obtain accurate stellar age estimates, and we hope that our model will be applicable to a variety of different star types, including stars of different ages and masses.

4 Methods

We will obtain data for each of our parameters from the GAIA Data Release 3 dataset, selecting a set of stars (potentially localized in a certain area of space), and pull the data into a Jupyter environment using Python. Then, we will use the Tensorflow library, a robust and widely used machine learning library, to conduct the computation required, primarily training and testing our neural network. To visualize our results, we will use matplotlib generate relevant plots of the accuracy of successive models.

Each member of the group will select a different set of parameters to build a model on. We will compare the accuracy of each of these models to identify which parameters might be the most effective, then redo the process with different sets of parameters, selected based on which parameters were effective in the previous run. We will repeat the process until we no longer make substantial improvements by including more or different parameters.

We do not anticipate needing more complex modeling techniques than our neural network, but if our neural network model does not achieve desired levels of accuracy, we will research and try more complex machine learning models and evaluate their effectiveness.

If time permits, we will also compare our age estimates for certain stars to estimates produced by other age estimation techniques.

5 Expenses and Resources

We do not anticipate producing any expenses for our project. We will be using Tensorflow, Jupyter, and GAIA DR3, all of which are publicly available and free to use, and we plan to train the models on our personal devices.

6 Timeline

We have prepared two potential timeline pathways, one if our simple model works, and one if it doesn't. We will use the timeline that fits our results accordingly.

January: Conduct background reading related to Machine Learning and how to apply it to our topic.

February: Have a simple model completed and combining ideas to improve the model.

Timeline if the model works:

March: Compare our data to research that has been conducted previously.

April: Compile our data to create our presentation. We plan to use plotting software, such as MatPlotLib to create diagrams that showcase our findings.

May: Present our findings.

Timeline if the model doesn't work:

March: Work on model and research ways to improve accuracy.

April: If model never became feasible to use, compile our understandings of why it did not work.

References

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