Updated High-Temperature Opacities for The Dartmouth Stellar Evolution Program and their E

High Point University

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Abstract

The Jao Gap, a 17 percent decrease in stellar density at $M_G \sim 10$ identified in both Gaia DR2 and EDR3 data, presents a new method to probe the interior structure of stars near the fully convective transition mass. The Gap is believed to originate from convective kissing instability wherein asymmetric production of 3He causes the core convective zone of a star to periodically expand and contract and consequently the stars luminosity to vary. Modeling of the Gap has revealed a sensitivity in its magnitude to a populations metallicity and consequently opacity. Thus far, models of the Jao Gap have relied on OPAL high-temperature radiative opacities. Here we present updated synthetic population models tracing the Gap location modeled with the Dartmouth stellar evolution code using the OPLIB high-temperature radiative opacities. Use of these updated opacities changes the predicted location of the Jao Gap by 0.05 mag as compared to models which use the OPAL opacities.

Updating Opacities

The OPAL opacity tables are very widely used by current generation stellar evolution programs (in addition to current generation stellar model and isochrone grids). However, they are no longer the most up date or highest presicion elemental opacities. Moreover, the generation mechanism for these tables, a webform, is no longer reliably online. Consequently, it makes sense to transition to more modern opacity tables with a more stable generation mechanism, OPLIB from the T-1 group at Los Alamos.

The most up to date OPLIB tables include monochromatic Rosseland mean opacities for elements hydrogen through zinc over temperatures 0.5eV to 100 keV and for mass densities from approximately 10^{-8} g cm^{-3} up to approximately 10^{4} g cm^{-3} (though the exact mass density range varies as a function of temperature).

Opacity Validation

An evolution of the perceptron (Rosenblatt 1958), the artificial neural network (ANN) was an early kind of neural network that gained widespread usage. ANNs generally take a one dimensional input vector of a predefined size, perform a number of matrix multiplications against weight matrices, and apply non-linear "activation" functions to the results of these multiplications. Like all forms of supervised machine learning, ANNs must be trained. This takes the form of modifying the values of the weight matrices. Once training is complete, the network can be used for its intended purpose.

Modeling the Gap

Artificial Neural Networks, presented above, are well suited for the analysis of one-dimensional data; however, because observations of real targets often involve data with large time gaps, these observations can be re-factored into two–dimensional data.

Identifying the Gap

Recurrent Neural Networks (RNNs), which have generated significant excitement in machine learning literature recently, may provide a way to analyze time series data **directly**. We have built a set of recurrent networks to analyze our synthetic data in time space; however, even with significant hyperparameter tuning (Figure 4) we are unable to approach the classification accuracy seen with either the ANN or CNN.

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References

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