Using Bayesian Machine Learning Models To Estimate The Ages Of Stars

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Age Estimates for Young Stars:

It is generally accepted that stars form in clustered environments[1]. This leads to common environments in terms of chemical abundances in clusters of stars. Depending on a star's mass, and therefore its temperature, certain chemicals within the star's atmosphere and inner structure will show variable abundance in spectral observations across a large time period.

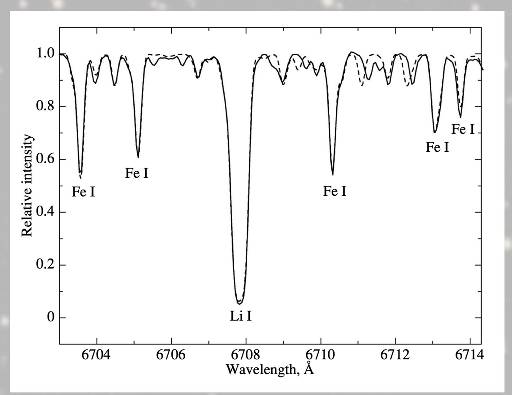

Fig 1. Spectra from a super-Li rich star, HD 77361[2] showing the Li I line at 6708Å from the star's atmosphere. Lithium within the upper layers of the star's atmosphere absorbs light of this wavelength, leading to a reduction in intensity seen on the plot.

Particularly useful is the abundance of Lithium within a star's spectral observations. Over the first ~1 billion years of main sequence life, a star's Lithium will deplete over time, mixing through its inner layers as they become convective, with the most variation seen in cooler stars.
Therefore, the abundance of Lithium within a given cluster or star can be used to give an estimate of the age of a young star.

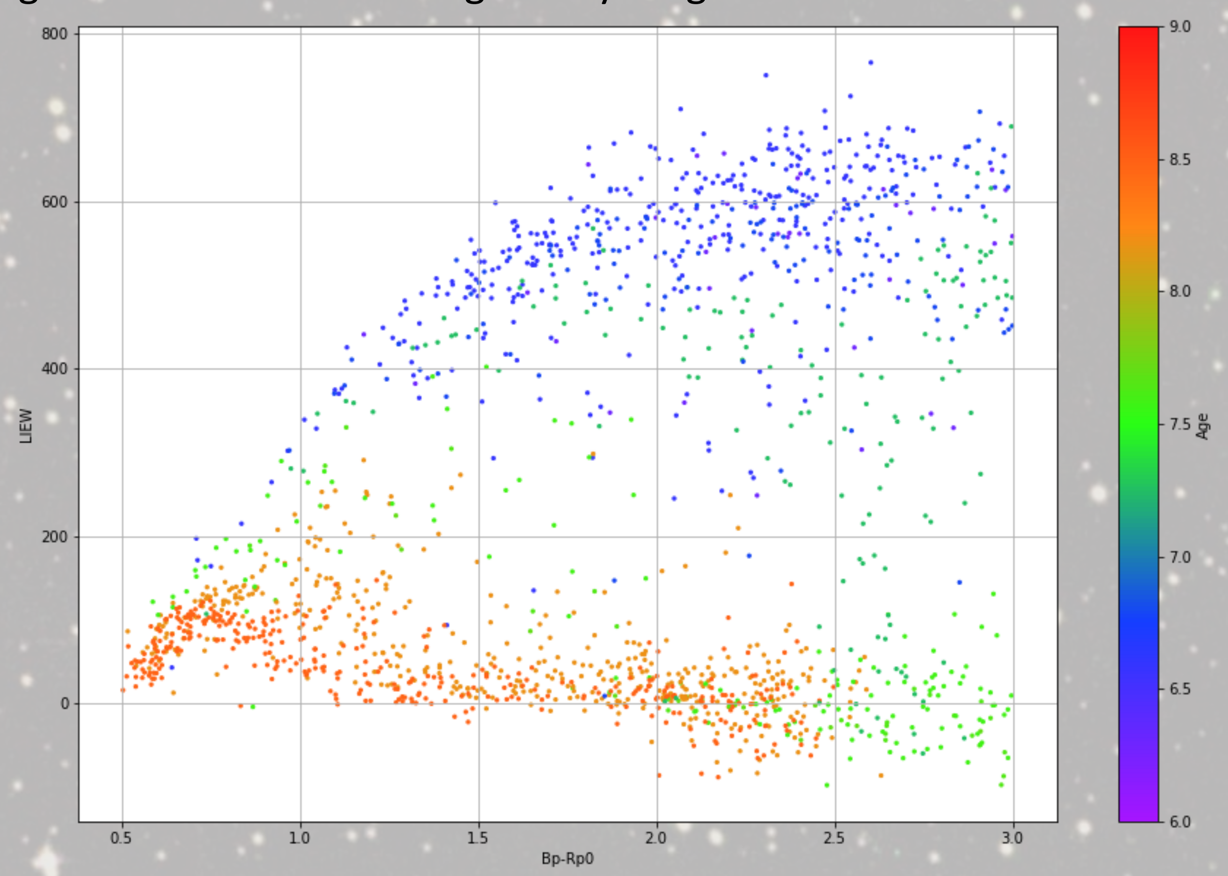

Fig 2. A plot of Lithium abundance vs Colour (a measure of stellar surface temperature) for stars from 9 clusters. Visible on this plot are two main features, firstly, hotter stars (those further left) show significantly lower Li abundances than some cooler stars. Secondly, younger stars (blue/purple) show greater Li abundances than older stars (red/orange).

Utilising a Neural Network to Model Relationships

A neural network consists of several neurons within a model, each of which have an associated weight and bias value, which can be adjusted during the learning process to provide a better outcome.

Known data, as inputs (features) and desired outputs (labels) are passed through the network of neurons in order to train the model. The model applies changes to the weights and biases associated to each neuron over the course of several learning runs (epochs), each change aiming to reduce the difference between the model's output and the desired output data.

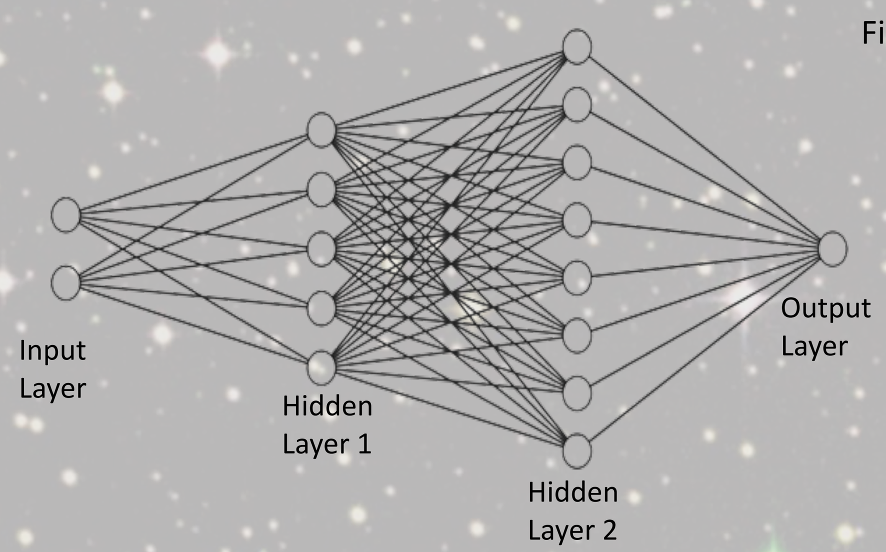

Fig 3. The neural network architecture utilised for modelling the relationship between Lithium abundance, surface temperature and age in its current configuration.
Li and temp data are entered in the input layer, and the model changes the weights and biases associated with each neuron in the hidden layers to produce an output estimate closer to the true value.

The trained model can then be used to estimate outputs from any given input data in the same configuration as the training data. In the case of this work, Lithium abundance (equivalent width) and surface temperature (intrinsic colour) data.
As the network utilises a Bayesian approach with variable distribution layers, the output is a probability distribution of adjustable format, currently a Gaussian distribution.

Results and Data:

Utilising a training dataset of 1641 stars within 9 clusters from the GAIA-ESO survey, the network in Fig 3. has been trained to give probability distribution estimates for both single stars and clusters of stars. The results show Gaussian distributions of probability for stars that, between 10 million and 1 billion years old, have a maximum likelihood estimate within ~0.2 dex of literature ages.

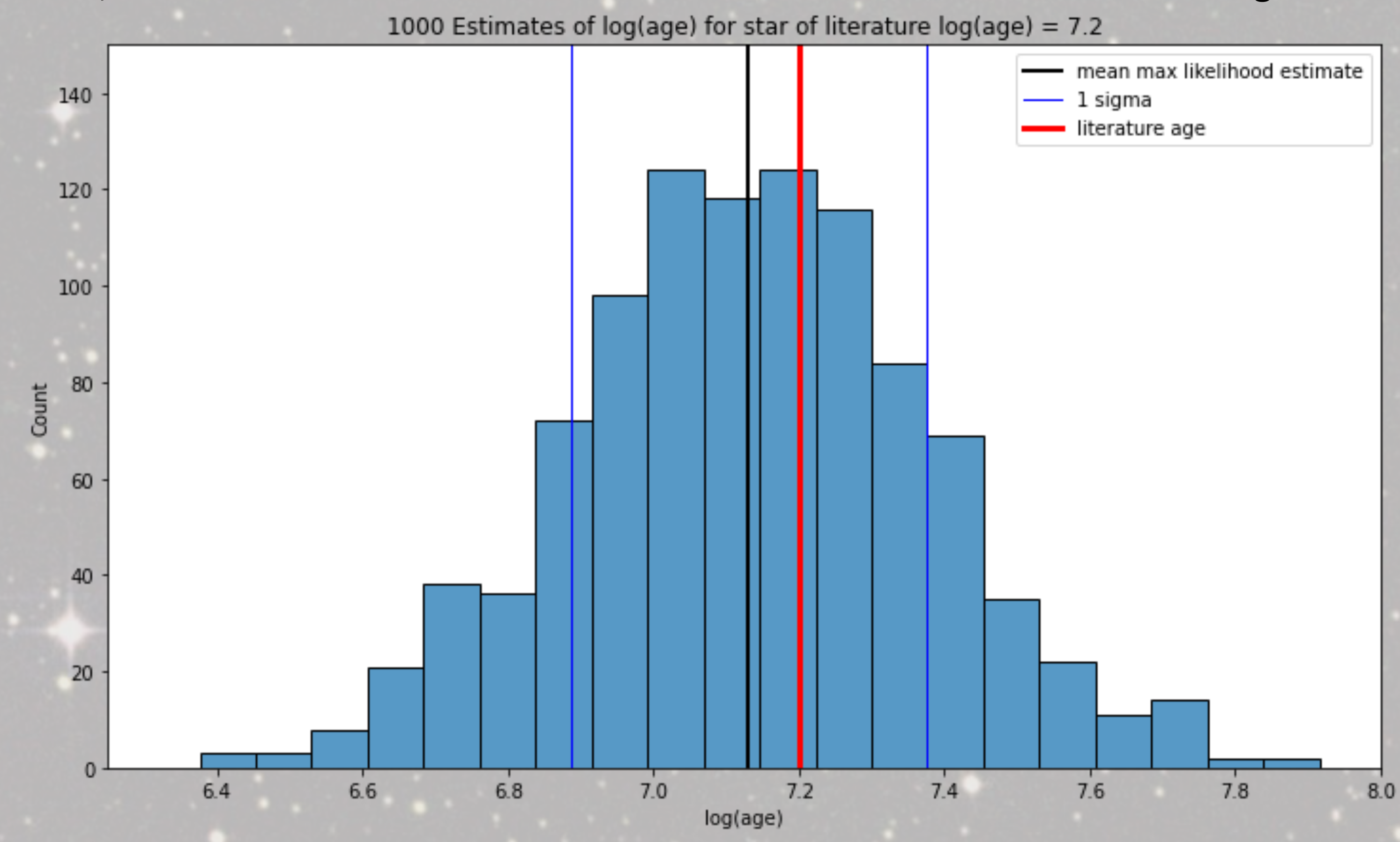

Fig 4. Estimated maximum likelihood log(ages) for 1000 model runs on a sample star, with the literature log(age) of the star shown as a red horizontal line.

The model is run over several iterations in order to account for errors within the calculated distributions of the weights and biases in the model itself.

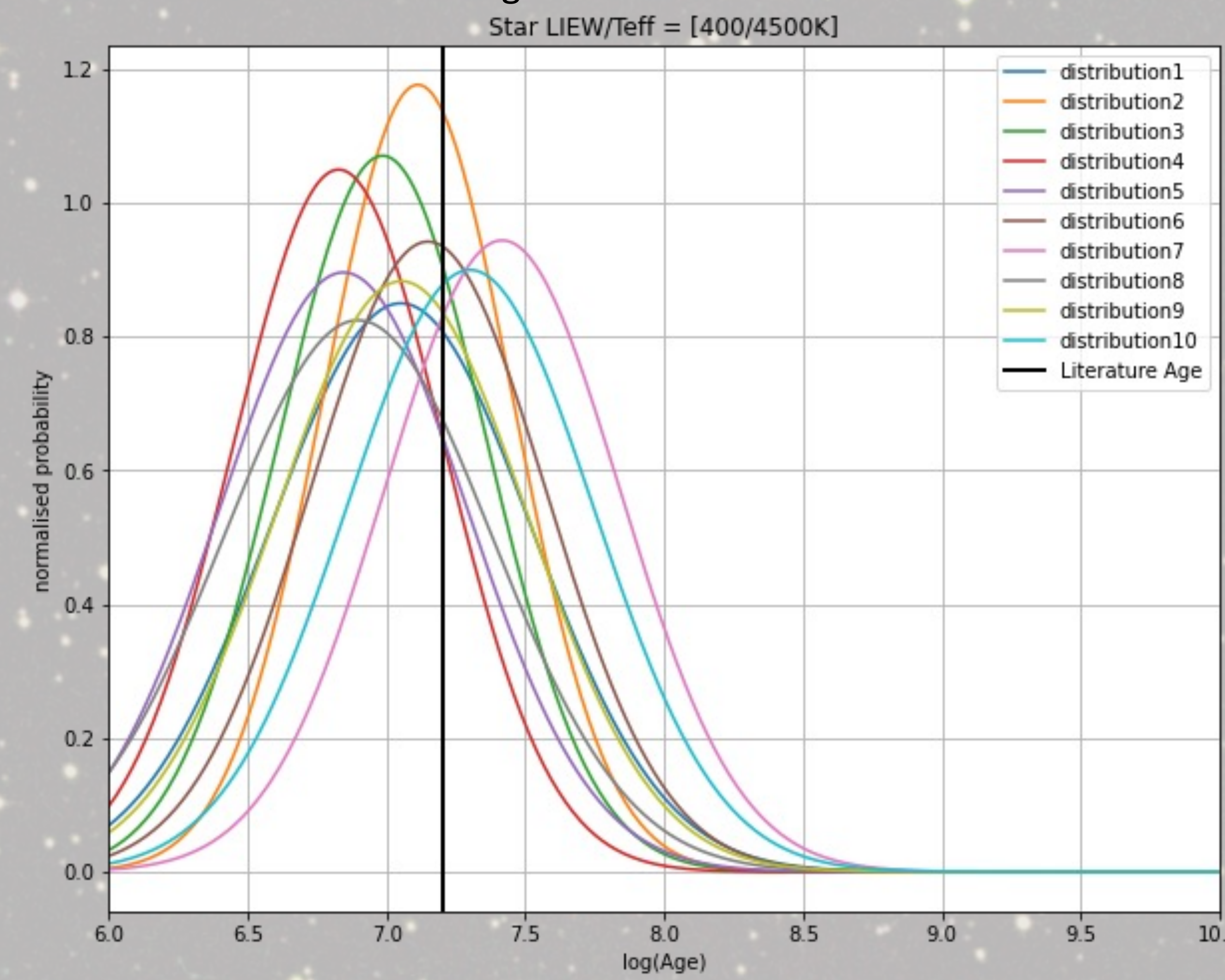

Fig 5. A sample of 10 output probability distributions from the same input star as Fig 4. demonstrating the slight change in estimations from the model between runs. The literature age of the star tested is shown in black as a vertical line.

Future Applications and Importance:

The application of this specific method of age estimation is useful in providing another model relationship between Lithium abundance, temperature and age for stars and clusters, as a comparison with other models.

Alongside this, the model can be easily adapted to accept any number of input features which are known to vary with age, such as colour-magnitude diagrams, rotation, magnetic fields, etc. This is a large part of the upcoming plans for the project, alongside training on more extensive datasets, and even from full spectral data to include as much input information as possible.

This model also provides vast possibilities for adaptation in many other aspects of statistical relationship modelling, as the model can be trained on any number of input data features to provide estimations of any output labels. This requires very little change to the model architecture, namely editing the input data dimensions.

References:

1 –Lada & Lada, 2003, ARA&A , vol. 41, pp.57-115
2 – L. S. Lyubimkov et al., 2015, Astronomy Letters, Volume 41, Issue 12, pp.809-823