

PHYS6013 Midterm Report: A Machine Learning Approach to Cool Star Spin-Down

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ABSTRACT

Observations of young open clusters have shown a bimodal distribution in the rotation periods of cool stars. This bi-modality stems from stars having fast or slow rotation periods. The evolution of this trend through time suggests a fast transition from fast to slow rotating. Our current understanding of cool star spin down, through magnetic braking, accounts for the slow-rotators branch, while the fast rotators remain somewhat of a mystery.

Our goal is to build a predictive probabilistic spin-down model that links the period of a star at any given mass and age. We use machine learning to predict the age at which each star transitions from fast to slow-rotation. Using a graphical model we translate the distribution of initial periods into a rotation period probability distribution for a given mass and age.

1 INTRODUCTION

Stars are born from the collapse of clouds made of dust and gas. This cloud, though being made up of many molecules with their own random velocities, can be said to have an overall spin which, when the star collapses, will be the axis of rotation when the star is born. However, this spin rate is not constant and will decrease over a star's lifetime, assuming no companion or outside influence.

Cool stars are classified as having a convective envelope, which have a mass of $\lesssim 1.3M_{\odot}$, meaning the outer-most layer of the star is moving. Due to this movement, ionic material in the star is allowed to generate massive magnetic fields which stretch in orders of stellar radii. Ejected stellar material travels along these lines, forming large arms which effectively co-rotate with the star. When material at the end of these arms breaks free, the loss in angular momentum (AM) is much greater than it would have been if the same material was lost at the star's surface. This loss in AM causes the star to lessen its rotational period and spin down. This is called *magnetic braking* and is a very efficient way for the star to spin down.

Open clusters (OC) are coeval groups of stars and, when observed in period and mass space, two distinct populations of fast and slow rotators can be seen after ≈ 10 Myrs; before this, stellar disc effects make it hard to model what is happening. In addition there are, to a lesser extent, transitional stars between these two populations, showing the time to move between the populations must be rapid. This can be seen in Figure 1. It was shown in (Garraffo et al. 2017) that, when accounting for magnetic braking and AM loss, this bimodal population could be seen with an evolved simulation of stars.

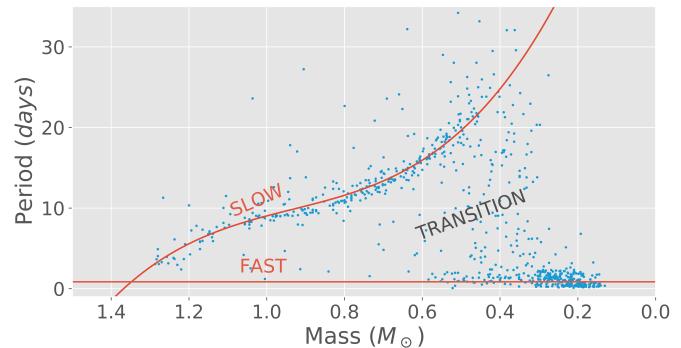


Figure 1. Plot of period vs mass(inverted) for Praesepe, with visualisation of the slow, fast and transitional rotators.

((((((())))))

Stars born spinning, Over time they spin down with a mechanism. First pointed out by Skumanich (feed-back mechanism so they converge (Faster they spin the LESS?? they lose)), however fast branch escape this for long period of time) and studied further for hopes of a gyrochronological model. Magnetic braking modeled and used as a method of spin down by Garraffo et al. 2017. Linked to magnetic field complexity. Dipole causes large arms that make for an efficient spin down. Viewing open clusters one can see the fast, slow and transitional rotators. Some evolution between the two that is UNKNOWN(?)

2 METHODS AND OBSERVATIONS

2.1 Data Reduction

Collected from various papers stated in CITE BOOK, plus personal findings and unpublished data. Each cluster in different photometry and no one fits all conversion. Used MIST tracks to interpolate a mass from the given ages of the stars. FIGURE OF ALL CLUSTERS REDUCED MERGE CLUSTERS?

Though there are lots of field stars with known masses and periods, the difficulty lies in having a correct value for their ages. This makes OC, with a known age, ideal for the data used in this modelling process if we know the period and mass of the stars contained. The vast majority of OC data for this project was gathered from ?(PLANET BOOK et al. YEAR) as well as some new additions to already existing OC M37 ?(Chang et al. 2017) and some unpublished data generously provided by Jason Curtis. Although all these catalogs contained values for period, mass was not often provided. Instead, mass was effectively given by the photometry values of each star, with each catalog providing different bands for their stars. This made it difficult to convert all the stars to mass as different conversion are needed for different bands and different mass ranges, with some conversions not stretching as low as the lowest mass.

A conversion was possible, however, it did not use conventional functions to map photometry to mass. Instead I used the MESA Isochrone and Stellar Track(MIST) tables ?(MISTTHING et al. 2004), which are simulations that provide information on the properties of stars, for a range of masses, evolved through time. The converted OC can be seen in Figure 2

These tables start with discrete mass steps(e.g 0.1, 0.15...1.35, 1.40 M_{\odot} etc). These masses, evolving at different rates, are very likely to have a degeneracy in their photometry, meaning they may cross each others "photometry path", and as a consequence the conversion was not as simple as choosing the two closest photometries and interpolating. Instead I had to restrict the available pool of photometries, based on the closest ages to that star, and from that pool choose the closest photometry to interpolate between. The discontinuity of the tracks, due to discrete time steps, means there will be an inherent error in choosing the pool of ages, this has not currently been addressed, however may be implemented into error propagation in a future model if a Bayesian network approach is used.

2.1.1 M37 shift?

Perhaps due to metalicity

2.2 Unsupervised Clustering?

Initial attempt to seperate the fast and slow rotators however problematic due to it not being a "two group" problem. Transitional stars need to be considered, otherwise subjecting the transition to a dirac delta.

Our initial approach to the problem was to cluster the data into "fast" and "slow" rotators and fit a weighted polynomial regression to each of these groups. We then cycle through each star and assign it to the opposing group, if the

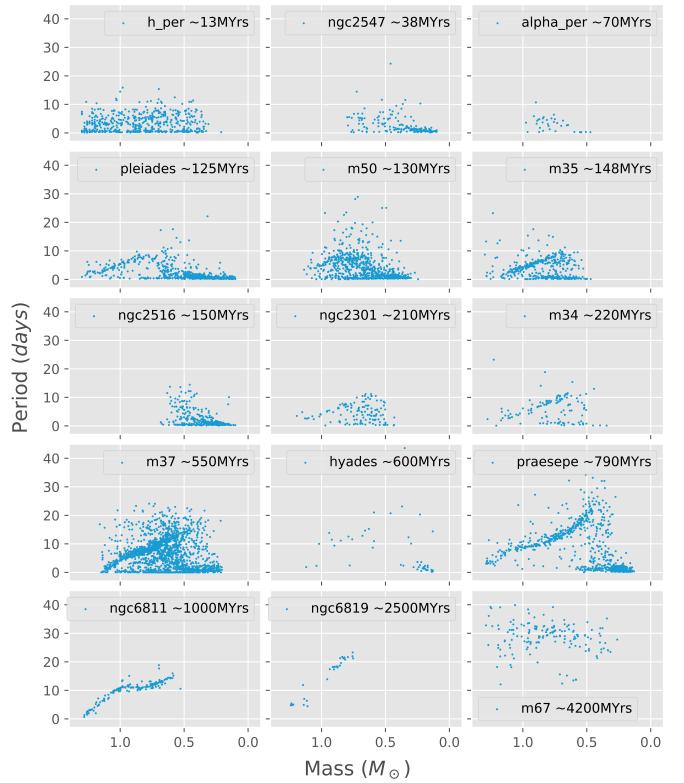


Figure 2. Plot showing all converted OC and their respective ages

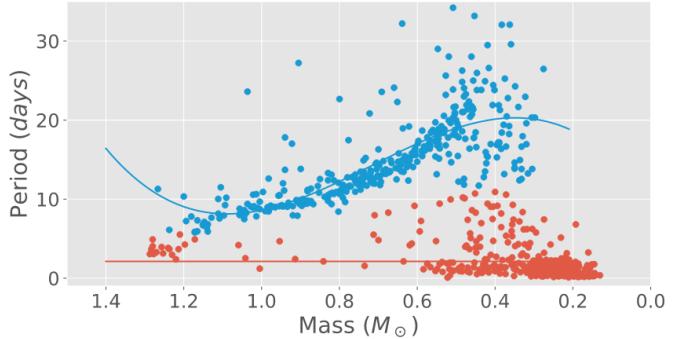


Figure 3. shows the results of unsupervised clustering of the "fast" rotators in blue, "slow" rotators in orange and their respective polynomial fits.

overall fit is better with the star in the opposing group, it remained there, otherwise it was transferred back and the next star was assessed. To measure the fit, mean squared error(MSE) was used. $MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$, where y_i is the true value, and \hat{y}_i is the predicted value. A reduction in MSE means the predicted values are close to the predicted and a good fit is being generated, if we minimise this MSE then we are rewarding the model with a better fit.

Figure 3 shows the results off this approach. The fits generated were a polynomial of 3rd order for the blue "slow" rotators, and 1st order for the orange "fast" rotators. As it can be seen, this approach does not generate an accurate

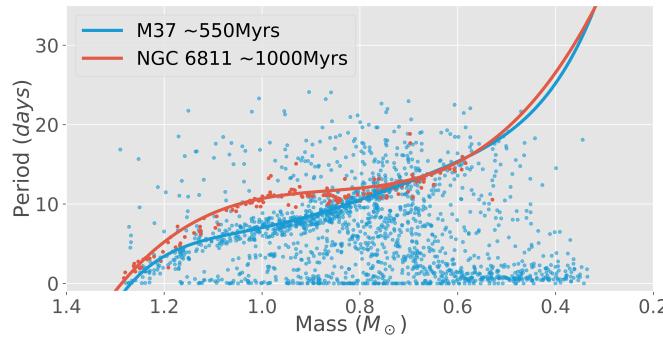


Figure 4. shows M37 in blue and NGC6811 in orange with their respective best fits.

representation of the two groups. This is because the transition between these two groups is effectively instantaneous, however, in reality this is not the case. As we also wanted to try understand how these stars transitioned throughout their lifetime, this approach would not extract this kind of information and so clustering was deemed an inappropriate method.

2.3 Polynomial Ridge Regression

slow rotators fit using a polynomial fit of order 4. Sigmoid function overlapped and optimised to change poly term on and off at switch point. FIGURE OF CURRENT FIT

Our next approach was to fit a polynomial to some of the fast rotators and combine this polynomial with a sigmoid function to have the transition between the fast and slow rotators. The method was to remove the "slow" and as many transitional rotators for each cluster as possible. From this subset of stars I created 10 bins according to mass and reduced this subset to the central 80% to remove outliers and any remaining transitional stars. This data set was then optimised using ridge regression, which is a form of polynomial regression, with the addition of regularisation term, which stops the coefficients becoming too large.

In Figure 4 I show this for two clusters of different ages. It can be seen from the data and fits that the 450Myrs has allowed the stars on "slow" branch to reduce their spin further. It can also be seen that there is a lack of a "fast" population for NGC6811 in the region $0.5 M_{\odot} \leq m \leq 1.3 M_{\odot}$. This is because all these stars have had time to transition.

This optimised polynomial can then be combined with the sigmoid function, see Equation 1, and minimised to produce our current model shown in Figure ??

$$\Phi(x) = \frac{1}{1 + \exp^{-x}} \quad (1)$$

Through the coefficients, it was thought that the progression of this transition from one population to the other could be understood, however, so far this time evolution has not been assessed. Though polynomial fits have been generated from the coefficients, the problem of degeneracy still presents itself with this method. A potential model to address this could have an error associated with it, where this line is the mean. This model would have confidence intervals as a function of mass and age. The closer to the "overlap

area" the prediction was, the larger the uncertainty becomes, then subsequently dropping after the lone fast rotators have been reached.

This spread/overlap of the data can be explained in the next section.

2.4 Initial Period and other parameters

Expand of the effect initial period and perhaps metalicity. Other parameters could allow for deeper understanding of the "overlap" sections of the open clusters FIGURE OF HOW INITIAL PERIOD CAUSES MULTIPLE LINES TO OVERLAP AND MAKE THE TRANSITION "BLURRY"

The difficulty in these predictions of period, for a given age and mass, stem from the lack of information on the initial period distribution. In a hypothetical OC, whose stars are born of a single initial rotation period, we think the distribution would look like figure XXXXX.

INSERT FIGURE HERE

However, an OC produces a range of masses and initial periods, only the former of which can be measured. Therefore the best estimates for initial period of the system can be assumed to be the youngest clusters distribution that is no longer under the influence of disc effects, such as H Persei(NGC 869).

3 FUTURE WORK?

Since there is overlap, 1 polynomial fit will give poor predictive results and without initial period is not purely deterministic to the degree we want. To remedy this a probabilistic model will be built that can be used to sample and generate a synthetic population of stars at a given age and a range of masses.

ACKNOWLEDGEMENTS

The Acknowledgements section is not numbered. Here you can thank helpful colleagues, acknowledge funding agencies, telescopes and facilities used etc. Try to keep it short.

APPENDIX A: SOME EXTRA MATERIAL

If you want to present additional material which would interrupt the flow of the main paper, it can be placed in an Appendix which appears after the list of references.

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