

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

Ely Doodson, Supervisor: Cecilia Garraffo

*Additional supervision from: Pavlos Protopapas, and Jeremy J. Drake*

26 January 2020

## 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.

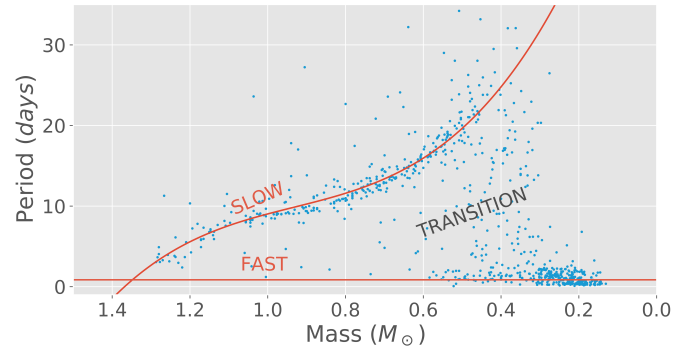
Our goal is to build a predictive probabilistic spin-down model that links the period of a star at any given mass and age. We use machine learning to predict the age at which each star transitions from fast to slow-rotation. Using a graphical model we will translate the distribution of initial periods 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. Such a cloud, though being made up of many molecules with their own random velocities, can be said to be spinning in one direction overall. Some of this angular momentum is sequestered in newly-formed stars which consequently rotate. However, their rotation rates are not static and decrease over a star's lifetime as a result of angular momentum lost through stellar winds.

Cool stars, which are those classified as having a convective envelope (a turbulent layer in which convection carries a significant fraction of the outward energy flow) and a mass  $\lesssim 1.3M_{\odot}$ , have an interior magnetic dynamo powered by rotation which drives a magnetized wind. Ejected stellar material travels along magnetic field lines, effectively co-rotating with the star out to several stellar radii and carrying away much more angular momentum (AM) than if the material was lost at the stellar surface.

The rate at which a star rotates drives the stellar strength of this magnetic braking, the faster a star rotates, the stronger its magnetic dynamo and therefore the more prominent the winds that slow the star. The resulting change in stellar rotation rate can in principle be used to estimate the age of cool stars, a technique called "gyrochronology". The self-regulating magnetic braking mechanism was expected to cause all the stars in an evolving population to converge together and is why gyrochronology works for older stars: they have had time to converge to the regime one can model. However, when observing groups of coeval stars in open clusters (OC) with ages  $< 1\text{Gyrs}$ , a branch of fast rotating stars is also observed, see Figure 1. This fast rotators branch is a mystery and is not encompassed by current gyrochronological models, leaving a gap in their predictive capabilities. This work hopes to fill this gap.



**Figure 1.** Plot of rotation period vs mass for the Praesepe young open cluster (age  $\approx 790$  Myrs), with visualisation of the slow, fast and transitional rotators.

Understanding the evolution of stellar rotation is crucial for understanding stellar magnetic activity as the magnetic dynamo generated by stellar rotation is responsible for many observed stellar characteristics such as star spots, UV/X-ray chromospheric and coronal emission, and the aforementioned magnetised winds driving stellar spin down. So far our understanding of these magnetised winds is purely derived from studies of our own Sun so our understanding of their origin is therefore incomplete; stellar spin-down provides a powerful probe of the physics of these winds. Stellar activity and wind create an energetic photon and particle radiation environment that has significant impact on the formation of planets and their subsequent atmospheric evolution. Understanding this will be crucial to the development of the rising field of exoplanet habitability.

It was shown in Garraffo et al. (2018) that, when ac-

counting for the effects of surface magnetic field complexity on AM loss, the bimodal rotation population could be reproduced in simulations of stellar spin down. This was an analytical approach to the problem, however, with a wealth of new data from Kepler, K2 and TESS, this has provided the opportunity to approach gyrochronology from a more data-driven approach and form an even greater understanding of the parameters that constrain such systems. The aim of this project is to utilize this growing database of observed stellar rotation periods and new numerical methods of machine learning to make a model capable of predicting a star's period, for a given mass and age.

## 2 OBSERVATIONS

### 2.1 Data Reduction

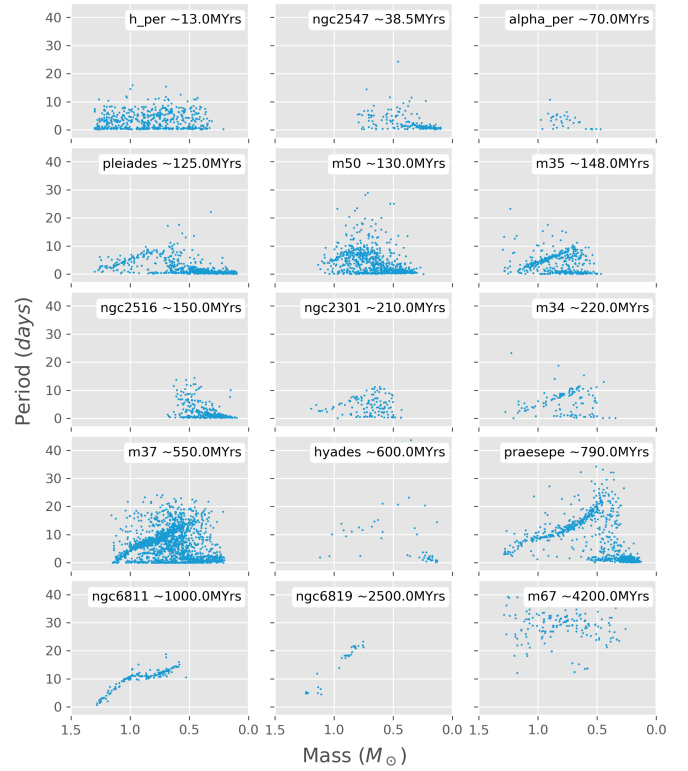
OC are coeval groups of stars and, when observed in period and mass space, two distinct populations of fast and slow rotators can be seen after  $\approx 10$  Myrs; before this time, stars are thought to be magnetically coupled with their stellar disks which modulate stellar rotation through a process known as "disk locking". In addition there are transitional stars between these two populations, which are less numerous, showing that the time to move between the populations must be rapid. This can be seen in Figure 1.

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 known ages, observed by Kepler, K2 and TESS, ideal for collecting data on period and mass.

Stellar rotation periods for OC were gathered from Beuther et al. (2014) and combined with our new additions to already existing OC measurements, such as for the M37 cluster Chang et al. (2015). Although all these catalogs contained values for period, mass was not often provided. Stellar masses were derived from catalogued multi-band photometry converted using stellar model photometric predictions.

I used the Modules for Experiments in Stellar Astrophysics (MESA) Isochrones and Stellar Tracks (MIST) tables from Choi et al. (2016), which are simulations that provide information on the properties of stars, for a range of masses, evolved through time. I have obtained masses for all OC stars in our master catalogue and display them in Figure 2.

~~These tracks start at 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 one star can have the same photometry value as another at a different age and mass, and as a consequence the conversion was not as simple as choosing the two closest photometries and interpolating. Instead I restricted the values of the various mass tracks to the closest ages of that star and from this pool, interpolated between the two closest photometries for that given age. 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. TOO MUCH DETAIL!?!?!?~~



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

## 3 ANALYSIS METHODS

The methods laid out in this section are aimed at attaining a predicted period as a function of mass and age.

### 3.1 Unsupervised Clustering

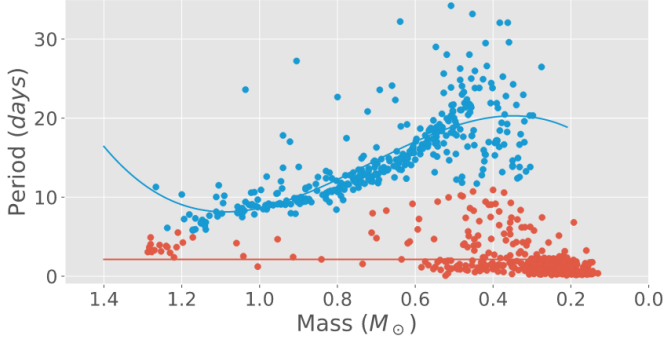
Our initial approach to the problem was to use *Unsupervised Clustering*. Clustering is the process of grouping data of similar properties together such as stars on one or the other rotation branch. The process being unsupervised means the data did not have a "correct" label telling us which group it belongs to, which one can use to reinforce and encourage certain clustering.

This clustering would split the data into "fast" and "slow" rotators and we could then fit a polynomial regression to each of these groups. A polynomial regression is like linear regression, where you fit a straight line is fitted to your data  $\hat{y} = b_0 + b_1x$ , but with a polynomial you allow  $n$  more higher order terms such as  $\dots + b_2x^2 + b_3x^3 + b_4x^4 + \dots + b_nx^n$  to be considered such that

$$\hat{y} = b_0 + \sum_{j=1}^p b_j x^j \quad (1)$$

This allows,  $\hat{y}$ , to be a closer approximation to the true value,  $y$ .

After a polynomial regression of the two groups, I cycle through each star in a cluster and assign it one or the other of the groups. After each star was assessed, a new polynomial fit was generated for each cluster and the process repeated



**Figure 3.** The results of unsupervised clustering of Praesepe in which stars are assigned to either the fast or slow rotating groups. The "fast" rotators are shown in orange, "slow" rotators are shown in orange and their respective polynomial fits.

until stars no longer changed groups. To measure the score, the mean squared error (MSE), Equation 2, was minimised and reduced.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (2)$$

and substituting in Equation 1

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n \left( y_i - \left( b_0 + \sum_{j=1}^p b_j x_i^j \right) \right)^2 \quad (3)$$

where  $y_i$  is the true value, and  $\hat{y}_i$  is the predicted value.

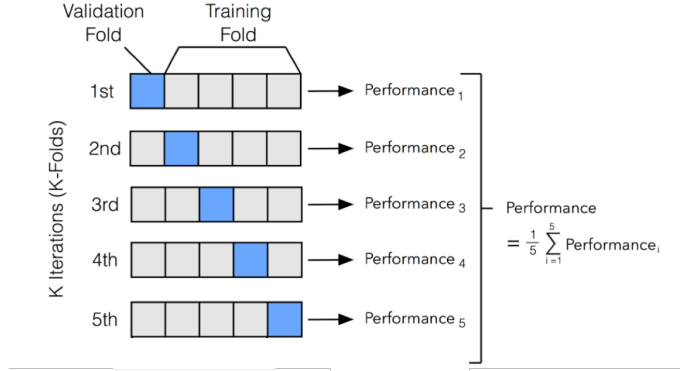
A reduction in MSE means the predicted values are closer to the true values and a good fit is being generated. We minimise this MSE then we are rewarding the model with a fit closer to the true data.

Figure 3 shows the results of this approach. The fits generated were a polynomial  $\mathcal{O}(x^3)$  for the blue "slow" rotators, and  $\mathcal{O}(x)$  for the orange "fast" rotators. As can be seen, this approach does not generate an accurate representation of the two groups. This is because the modelled transition between these two clusters is effectively instantaneous, however, in reality this is not the case. We also wanted to try to understand how these stars transitioned and since this approach would not extract this kind of information clustering was deemed an insufficient method.

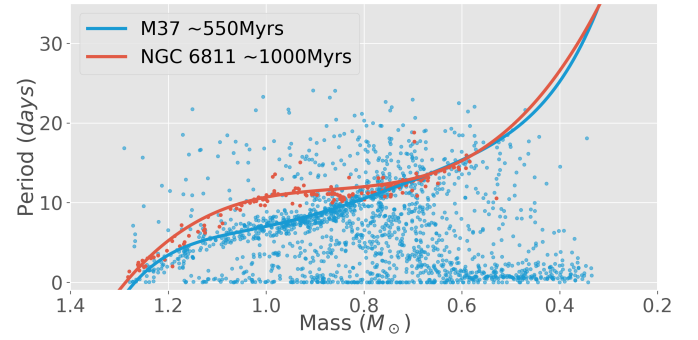
### 3.2 Polynomial Ridge Regression

Our next approach was to fit a polynomial to a portion of the "slow" rotators and combine this polynomial with a sigmoid function ( $\Phi(x)$ ), shown in Equation 6 below, to represent the transition between the fast and slow rotators. The sigmoid function maps any value of  $x$  to the range  $0 \leq \Phi(x) \leq 1$ , and can be thought of as switching between the two lines in Figure 1.

The method was to remove the "slow" and as many transitional rotators for each cluster as possible, by eye. From this subset of stars I created 10 bins according to mass and reduced this subset to the central 80% to remove outliers and remaining transitional stars. (Is a figure needed to show the reduction?) This reduced data set was then fit using *Ridge Regression*, which scores using MSE, Equation 2,



**Figure 4.** An illustration of how cross validation splits a data set and produces a score of that model, from [github.io](https://github.io) (2020).



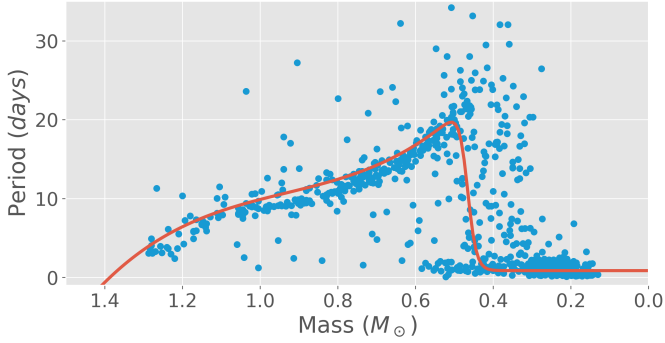
**Figure 5.** The rotation period as a function of stellar mass for stars in M37 in blue and NGC6811 in orange with their respective minimised polynomial fits.

with the addition of a regularisation term,  $\lambda$ , which stops the coefficients becoming too large, shown in Equation 4. This regularisation coefficient,  $\lambda$ , and the degree of polynomial,  $p$ , was chosen via *Cross Validation*.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n \left( y_i - b_0 - \sum_{j=1}^p b_j x_i^j \right)^2 + \lambda \sum_{j=1}^p b_j^2 \quad (4)$$

Cross validation is a method to choose the best model from a selection, such as we have here with varying polynomial degree and regularisation term. For each model, your data is split into a number of random subsets which maintain the original data distribution. One of these subsets is chosen as the validation set, and used to score your current model. The remaining subsets are then used to train your model on. The validation set used is then changed and the same process repeated until every subset has been a validation set. This ensures that all data has been used to train and validate the models. All these scores are then averaged to give a performance for your model. Figure 4 shows this for 5 subsets.

In Figure 5 I show the results of only the polynomial ridge regression for two clusters of different ages. It can be seen from the data and fits that the 450 Myr difference has allowed the stars on the "slow" branch to reduce their spin fur-



**Figure 6.** The result of polynomial ridge regression minimised on Praesepe.

ther. 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( $\Phi(x)$ ), as seen in Equation 5, and minimised to produce our current model shown in Figure 6

$$\text{Period} = (b_0 + b_1 m + b_2 m^2 \dots b_i m^i) * \Phi(x) \quad (5)$$

$$\Phi(x) = \frac{1}{1 + \exp^{-x}} \quad (6)$$

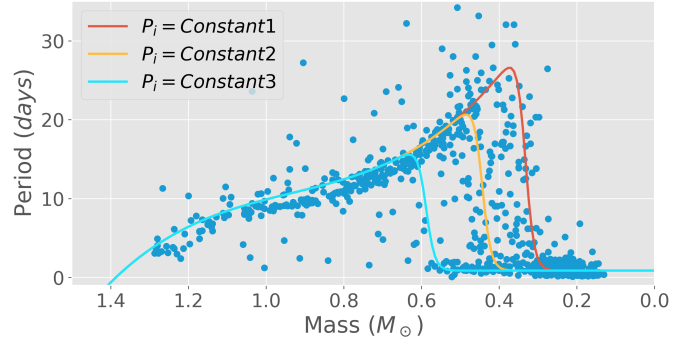
The coefficients of these polynomials were thought to be the key to understanding the progression of the system. However, it was found that there was no obvious trend to these coefficients through time. The fit in Figure 6 is able to predict the majority of the "slow" and "fast" rotator branch, however, it becomes problematic for the region in which they overlap, which varies in size for different OC. We think this degeneracy is caused by a spread of initial periods and is discussed further in Section 3.3.

A potential solution to this would be to calculate an error associated with each point of the fit. A region of uncertainty around the prediction would be produced, which would be low if the data spread was minimal and high when approaching the overlapped area.

### 3.3 The Importance of Initial Period, $P_i$

We think 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 with the same constant initial rotation period, we think the stellar distribution would follow one of the lines in Figure 7. However, in reality these observed OC are made up of a range of masses and initial periods, of which only the former can be measured. When taking an average of all these initial periods, we will get a distribution which looks like an observed OC, which has the degeneracy between the two branches due to the distribution of initial periods when the stellar population formed.

To try and address this, an estimate for initial period distribution can be made from the youngest cluster's distribution, that is no longer under the influence of disc effects, such as H Persei (h\_per) in Figure 2.



**Figure 7.** Theoretical lines that Praesepe data would follow if it was born with an initial period equal to a constant e.g. Constant1/Constant2/Constant3

## 4 FUTURE WORK?

The degeneracy discussed in previous sections is a large motivator to approach this model probabilistically. Instead of generating a polynomial regression and modelling its evolution as a function of cluster age, a heat map of the likelihood of a star being in that spot for a given age and mass could be generated. One could then sample stars of random masses for a given age to generate a synthetic population of stars, whose distribution looks like that of an observed OC.

## REFERENCES

- Beuther H., Klessen R. S., Dullemond C. P., Henning T. K., 2014, *Protostars and planets VI*. University of Arizona Press  
 Chang S. W., Byun Y. I., Hartman J. D., 2015, *AJ*, **150**, 27  
 Choi J., Dotter A., Conroy C., Cantiello M., Paxton B., Johnson B. D., 2016, *The Astrophysical Journal*, 823, 102  
 Garraffo C., et al., 2018, *The Astrophysical Journal*, 862, 90  
 github.io E., 2020, K-fold Cross Validation Visual Description, [http://ethen8181.github.io/machine-learning/model\\_selection/model\\_selection.html](http://ethen8181.github.io/machine-learning/model_selection/model_selection.html)

This paper has been typeset from a  $\text{\TeX}/\text{\LaTeX}$  file prepared by the author.