Relative Age Effect in Japanese Professional Soccer

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Introduction

The Relative Age Effect (RAE) is a term used to describe how those born early in the academic year tend to have an advantage both athletically and academically. An earlier birth is typically associated with increased physical ability and this advantage may occur because those who are older are typically more physically, emotionally or cognitively developed than those who are younger. Much research has been done to look at RAE in North American and European athletes. However very little research has attempted to extend findings surrounding RAE to other parts of the world, specifically Asia. This is why we are interested in Hideaki Ishigami's work in the paper *Relative age and birthplace effect in Japanese professional sports: a quantitative evaluation using a Bayesian hierarchical Poisson model* (published in the Journal of Sports Sciences in 2016). In our paper we will replicate Ishigami's modelling process using simulated data. In order to answer the question: what is the RAE on soccer players in Japan between the ages of 23 and 25 in the 2012 season?

Our simulation and modeling process will mirror the author's study design in which he uses data sourced from the Japan Professional Football League (J. League) from the 2012 soccer season. The J. League data consist of 40 teams, representing a total of 1013 players registered in the 2012 season and since we will focus on players between the ages of 23 and 25, we have 227 observations. The author characterized "becoming a professional sports player" as an event and thus we are dealing with discrete count data. Using a poisson regression model it is possible to estimate the magnitude of the RAE on the likelihood of becoming a professional athlete. More details on the poisson model can be found below. The authors then ran an MCMC algorithm [1] using JAGS (Plummer, 2012) and confirming with Stan (Stan Development Team, 2013).

The work replicated in our paper is an important step in extending the RAE's scope of inference. Additionally this paper and our analyses allow the magnitude of relative age to be quantified. In contrast many other analyses have simply stated whether an association is statistically significant using, for example, a χ^2 test. Although it is beyond the scope of this paper, these results impact parents' decisions surrounding red shirting and informs public understanding of factors influencing success in athletics (particularly professional athletics).

Model

Our Bayesian model consists of our likelihood which describes the data generating process, an offset term which converts our "counts" into "rates", and a prior. We will go into further detail below on all the components of this model.

Data

Each of our observations is the total number of professional players born in a given month. The school year in Japan begins April and ends on March of the following calendar year, which corresponds with the competitive season of most professional sports. Since school year and competitive season both begin in April in Japan, relative age was coded as 0 (April) to 11 (March). Therefore in total we have 12 observations which sum to

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[1] The MCMC ran for 25,000 iterations with five chains where the first 5,000 samples were discarded as burn-in. Only every 100 iteration was saved for a total of 1,000 MCMC samples.

1

our total number of professional players ($\sum_{i=0}^{11} y_i = 227$). *Can say more about this dependending on whether we find data and use it or whether we generate - clarify with Katie first.*

Likelihoood

As previously mentioned becoming a soccer player can be seen as an "event", and thus a number of them can be regarded as a "count of events". To capture this data generating process the author used a poisson distribution for the likelihood with an offset term.

Poisson Distribution Our data are denoted by y_i which represents the number of professional sports players between ages 23 and 25 in the year 2012 who are born in a given month (where $\sum_{i=0}^{11} y_i = 227$). We have:

$$y_i \sim \text{Poisson}(\lambda_i) \text{ for months } i = 1, \dots, 12;$$

Where our likelihood function is:

$$L(\lambda; y_0, ...y_{11}) = \prod_{i=0}^{11} e^{-\lambda} \frac{\lambda^{y_i}}{y_i!}$$

And our log-likelihood is:

$$l(\lambda; y_0, ...y_{11}) = -11\lambda - \sum_{i=0}^{11} ln(y_i!) + ln(\lambda) \sum_{i=0}^{11} y_i$$

Offset Term The author points out that many analyses of RAE assume that births are uniformly distributed across the year (i.e. that the same number of children are born in every month of the year). However we know that this is not true. Thus we want our model to take into account the number of total births in a given month when assessing whether the number of professional players born in that same month are over-represented. One way to do this is to compare the monthly rates for becoming a professional athlete rather than comparing the number of professional athletes. We can accomplish this by using an offset term in our model. Note for a poisson regression model for counts we have $log(\lambda_i) = \alpha + \beta y_i$. However if we want a poisson regression model for rates we can use $log(\frac{\lambda_i}{\theta_i}) = \alpha + \beta y_i$, where θ_i is the number of Japanese males born in that month in the years of 1987-1989 (which corresponds to professional male athletes who are 23-25 in the year 2012). This is equivalent to $log(\lambda_i) - log(\theta_i) = \alpha + \beta y_i$ or $\lambda_i = \theta_i \times e^{\alpha + \beta y_i}$ (which is how we see the offset term represented in Ishigami's paper). To put it even more plainly, our rate $\frac{\lambda_i}{\theta_i}$ is exponential. Note that interpreting α and β is the same as for a poisson regression model for counts except we multiply the expected counts by θ_i.

Priors

Our priors on λ_i are defined by the exponential relationship below where θ_i is the total number of men born over the years during the sample in month i. θ_i is an offset term to make the months comparable since some months have different numbers of births. The intercept term α is a baseline probability of becoming a male professional soccer player after controlling for the relative age effect. RA_i is the relative age of those born in month i. The coefficient β measures the relative age effect (RAE). For example, April would be month 1, with $RA_1 = 0$. The exponential term gives the probability of becoming a professional male soccer player.

$$\lambda_i = \theta_i exp\left\{\alpha + \beta RA_i\right\}$$

The authors found the posterior estimate for $\beta|y$ to be $\beta|y \sim \text{Normal}(-0.0934, 0.0214^2)$ which we will use as our prior.

We did not see an updated posterior for α so we assume the prior in the paper, $\alpha \sim \text{Normal}(\mu, \sigma^2)$ where $\mu \sim \text{Normal}(0, 100^2)$ and $\sigma^2 \sim \text{Uniform}(0, 100)$.

References

Data

to simulate we want: - distribution for monthly birth data in Japan for males born 87-89 - distribution of birth months for our 227 observations or are we simulating alpha & beta

Results

Implementing Bayesian Model using JAGS *can include code snippets and describe our implementation*

Bayesian Model *include visual for Density of Beta* `plot(jags_out)[2]`

Assessing Convergence `plot(jags_out)[1]`

with $\hat{R}$ The authors used the Gelman-Rubin statistic (Gelman & Rubin, 1992), $\hat{R}$, which assesses convergence by comparing the estimated between-chains and within-chain variances for each model parameter. Our results for

Assessing Convergence with Geweke's Diagnostic Additionally, the authors used the Geweke's convergence diagnostic (Geweke, 1992) to check the convergence of the MCMC algorithms. The Geweke convergence diagnostic is a test for equality of the means of the first and last part of a Markov chain, typically the first 10% and the last 50%. If the samples are drawn from a stationary distribution of the chain, then the two means are equal and Geweke's statistic has a standard normal distribution. The test statistic is a standard Z-score: the difference between the two sample means divided by its estimated standard error. The standard error is estimated from the spectral density at zero, and so takes into account any autocorrelation and the Z-score is calculated under the assumption that the two parts of the chain are asymptotically independent. Both of these tests are available in the `coda` package in R.

Posterior Predictive Checks

Assessing Posterior Fit to Our Data generate plots with posterior predictive dist and have our data on it too?

Other ideas for PPCs?

Conclusion

References

Gelman, Andrew, and Cosma Rohilla Shalizi. 2012. "Philosophy and the Practice of Bayesian Statistics." *British Journal of Mathematical and Statistical Psychology* 66 (1): 8–38. https://doi.org/10.1111/j.2044-8317.2011.02037.x.

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