Elite Athletes Refine Their Internal Clocks: A Bayesian Analysis

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Abstract

This paper carries out a full Bayesian analysis for a data set examined in Chen & Cesari (2014). These data were collected for assessing people's ability in evaluating short intervals of time. Chen & Cesari (2014) showed evidence of the existence of two independent internal clocks for evaluating time intervals below and above the second. We re-examine here, the same question by performing a complete statistical Bayesian analysis of the data. The Bayesian approach can be used to analyze these data thanks to the specific trial design. Data were obtained from evaluation of time ranges from two groups of individuals. More specifically, information gathered from a non-trained group (considered as baseline) allowed us to build a prior distribution for the parameter(s) of interest, and data from the trained group determined the likelihood function. This paper's main goals are (i) showing how the Bayesian inferential method can be used in statistical analyses and (ii) showing that the Bayesian methodology gives additional support to the findings presented in Chen & Cesari (2014) regarding the existence of two internal clocks in assessing duration of time intervals.

Keywords: Bayesian, Time Perception, Time Evaluation, Elite Athletes

Introduction

The Bayesian procedure has been used in contrast to conventional statistical methods that do not allow for eliciting a prior distribution. The specific contribution of the Bayesian inferential method consists in the possibility to produce, through the prior distribution, the likelihood function, and the posterior distribution, an evaluation of the probability of any event of interest relative to a given experiment. In this study we used this advantage of the Bayesian analysis to investigate the long-debated question regarding whether there exists two separate internal clocks for perceiving the time below and above one second, respectively.

For decades the literature in psychological research sustained the existence of one centralized internal clock for evaluating large ranges of time (e.g., Gibbon, Church, & Meck, 1984). However, more recently, this “one-clock" notion has been challenged. While the underlying neural mechanism is still under investigation, a number of reports in neuroscience suggested the presence of separate brain circuits that lead to processing time in multiple timescales (for a review see Mauk & Buonomano, 2004). More specifically, recent literature proposes that there are, at least, two distinct mechanisms for evaluating time intervals below and above a second (e.g., Ivry & Spencer, 2004; Koch et al., 2007; Matell, King, & Meck, 2004; Rammsayer, 1999). For instance, Rammsayer (1999) and Matell and colleagues (2004) endorsed the notion that pharmacological manipulation affects time perception differently in the sub- and supra-second range of time. Moreover, it is believed that short intervals of time are perceived more accurately by individuals possessing highly trained sensory-motor capacities as for professional musicians (Cicchini, Arrighi, Cecchetti, Giusti & Burr, 2012; Chen & Cesari, 2013) or videogame players (Rivero, Covre, Reyes & Buoeno, 2012). There is a widespread consensus in sustaining that, while sub-second time intervals are mainly processed at a sub-cognitive level, intervals above the second are timed with the involvement of cognition (Lewis & Miall, 2003).

Thus, in line with these notions Chen & Cesari (2014) designed a time reproduction task experiment for testing a group of elite athletes, with years of sport training and currently active at high level national and international competitions, and a group of individuals without any experience in competitive sports (non-athletes). The experiment consisted in presenting each individual with a picture of scrambled pixels. The stimulus was presented for a given temporal interval and then participants were asked to reproduce the duration of the time interval as precisely as possible by pressing and releasing the spacebar of a computer keyboard with the index finger of their dominant hand. The time intervals ranged from few hundred milliseconds to more than one second. One of the questions in Chen & Cesari's paper was to investigate whether the interval of time reproduced by the participants could be better described with two separate linear regressions, one for sub- and the other for supra-second time intervals. This would indeed suggest the presence of two distinct mechanisms for estimating time flow. Moreover, for getting a deeper insight about the working rate of the two clocks, Chen & Cesari (2014) used multiple time intervals to be detected, from 300 to 1800 microseconds (ms) in step of 100 ms. The 16 time intervals were presented in a randomized order, each of them tested for eight repetitions for a total of 128 trials for each individual. It was also of interest to investigate whether the hypothesized internal clocks might be refined through sport training.

The main goal of this paper is to carry out a Bayesian statistical analysis for the data collected by Chen & Cesari (2014), thus illustrating the value and the importance of the Bayesian method for conducting alternative statistical analyses of experiments. The two-phase procedure used for acquiring the data supports the adoption of the Bayesian method. Phase one tested each individual in a group of 23 non-athletes. Phase two tested a group of 27 elite athletes. This procedural design allows us to obtain prior information from the group of non-athletes. This prior information, together with the data from athletes in phase two, can be used to derive a posterior probability distribution that gives a probabilistic evaluation of the questions related to time perception. We expected to confirm qualitatively the findings of Chen & Cesari (2014) regarding the existence of two internal clocks to evaluate time below and above the second.

Methods

Task, participants, and procedure

We used a version of time reproduction task previously considered by other authors (cf. Brown, 1995). Participants were presented with a visual stimulus (an image of scrambled pixels) for a certain time interval (from 300 to 1,800 ms in steps of 100 ms) and they were asked to reproduce these time intervals. We refer to Chen & Cesari study (2014) for a detailed illustration of methods and materials of the experiment. Also an accurate description of participants and of the apparatus and stimuli can be found in that paper.

Data analysis

Chen & Cesari (2014) modeled the relationship between reproduced times and sample times by fitting the reproduced times with two linear regression lines (bi-linear regression), one for the sub-second range (8 levels, from 300 to 1,000 ms) and one for the supra-second range (8 levels, from 1,100 to 1,800 ms). The data were also fitted with a single regression line. They compared the sum of squares of the residuals (SSR) to the fitting line(s) and found a better fitting for the bi-linear model versus the single linear regression model. They conducted an evaluation of goodness of fit of the two models using the Bayesian Information Criterion (BIC) procedure and the Akaike information criterion (AIC). They also considered two-way repeated measures ANOVA. The within-subjects factor being the time range (sub- and supra-second) and the between-subjects factor being the group of individuals tested (athletes and non-athletes). The difference between the slopes of the bi-linear regression was found significant ($p < .001$).

More specifically, the athletes' estimates of the slopes in the bi-linear regression were 0.83 in the sub-second range and 0.64 in the supra-second. In this paper we show that the use of prior information from the non-athletes group, will allow us to reach a conclusion sustained with a strong probabilistic evaluation, thus confirming the conjecture regarding the existence of two different internal clocks for timing sub- and supra-second time intervals.

Before carrying out the Bayesian data analysis procedure we list briefly the main steps of a Bayesian statistical inference procedure.

1. Let data y be obtained from a given experiment, designed for investigating some characteristic of a phenomenon. We denote such characteristic as the "unknown quantity of interest" and refer to it as a parameter θ, say.

2. Before the experiment is performed, gather any existing prior information about the quantity θ, and represent this information in the form of a prior probability distribution for θ, denoted as $p\ (\theta)$.

3. Consider the data y, obtained from the experiment, and synthetize all information carried from the data about θ, through the likelihood function, $f\,(y|\ \theta)$.

4. Compute the posterior distribution for θ; $p\ (\theta\ |y)$, using the following formula, known as the Bayes theorem.

$$p\ (\theta\ |y) = \frac{p(\theta)f(y|\theta)}{\int p(\theta)f(y|\theta)d\theta} \quad (1)$$

The posterior distribution includes all available information about θ. It does involve both the prior information $p\ (\theta)$ and the information extracted from the data, through the likelihood function $f\,(y|\ \theta\,)$.

5. Use the posterior distribution for obtaining estimates for θ, for testing hypotheses about θ, and for obtaining probability evaluation of events involving θ. Details regarding the Bayesian procedure are in the Appendix.

Results

The bi-linear model is given by the following two regression lines:

$$\mathrm{y}_{i,j} = \alpha_i + \beta_i x_{i,j} + \epsilon_{i,j}; \quad i = 1,2; \;\; j = 1, \ldots 8; \;\; (2)$$

where i = 1 refers to the sub-second line and i = 2 to the supra-second. The regressors $x_{i,j}$ are the exposure times: $x_{1,j}$ = (300, 400, …1,000) and $x_{2,j}$ = (1,100, …1,800). Normal noise random variables $\epsilon_{i,j}$ with unknown variances, are added to complete the standard regression models and, as usual, they represent the errors in measurements.

The data from non-athletes, to be used as prior information about the slope parameters β_i, give us the two following estimated regressions:

$$\begin{cases} \mathrm{y}^*_{1.j} = \hat{\alpha}^*_1 + \hat{\beta}^*_1 x^*_{1,j} = 203.13 + 0.76 x^*_{1,j} \\ \mathrm{y}^*_{2.j} = \hat{\alpha}^*_2 + \hat{\beta}^*_2 x^*_{2,j} = 302.03 + 0.65 x^*_{2,j} \end{cases}$$

where * denotes quantities referred to non-athletes. Thus the estimates of the slopes for the bi-linear model fitted to non-athletes data are: $\hat{\beta}^*_1 \approx 0.76$ and $\hat{\beta}^*_2 \approx 0.65$. A t-test on these values produced an observed t(26) = 2.77 (p < .01). Note that the difference between the estimated slopes of bi-linear regression in non-athletes group is statistically significant, even if it is smaller than the same measure in the athletes group. Since the interest regards the estimated difference between slopes of the bi-linear regression, let us denote the difference by $\theta = \beta_1 - \beta_2$, the parameter of interest of the study.

When considering a full Bayesian analysis we can use the least squares estimates $\hat{\beta}^*_i$ and their variability for obtaining the prior distribution for the difference in slopes $\theta = \beta_1 - \beta_2$.

From the normality assumption in model (2), the distributions of the least squares estimators, $\hat{\beta}_1^*$and$\hat{\beta}_2^*$, are normal. Their means β_1^* and β_2^* are the true (but unknown) values of the bilinear slopes, and their standard error is estimated from fitting the two regression lines. The values obtained for these standard errors are, respectively,$\hat{\sigma}\beta_1^* \approx 0.026$ and $\hat{\sigma}\beta_2^* \approx 0.031$. The computed values of $\hat{\beta}_i^*$ and $\hat{\sigma}\beta_i^*$ are used as means and standard deviations for building the prior distributions for the slope parameters. These distributions are plotted on the left panel of Figure 1. The right panel of Figure 1 shows, instead, the prior distribution of θ, the difference between the slopes of the bi-linear regression. The prior distribution for θ is derived from the priors for β_1^* and β_2^*, as described in the appendix. In this way, the information from the group of non-athletes can be utilized for building the prior distribution for the quantity of interest θ. The question about the equality of β_1 and β_2 is replaced by the evaluation of the probability that $\theta > 0$, in the athletes group, or, more precisely, by the evaluation of the value of posterior probability $\mathbb{p}\left(\theta > 0 \,\middle|\, y^{Ath}\right)$ obtained after observing the athletes data $\mathbf{y}^{Ath}$.

The likelihood function for θ, from the reproduced times of the athletes' data $\mathbf{y}^{Ath}$, is derived by fitting a bi-linear regression to these data, using the model specified in (2). The two estimated regression lines are:

$$\begin{cases} y_{1.j}^{Ath} = \hat{\alpha}_1^{Ath} + \hat{\beta}_1^{Ath} x_{1,j}^{Ath} = 112.49 + 0.83 x_{1,j}^{Ath} \\ y_{2.j}^{Ath} = \hat{\alpha}_2^{Ath} + \hat{\beta}_2^{Ath} x_{2,j}^{Ath} = 319.88 + 0.64 x_{2,j}^{Ath} \end{cases}$$

The values of the estimates $\hat{\beta}_1^{Ath}$ and $\hat{\beta}_2^{Ath}$ together with their standard errors $\hat{\sigma}\hat{\beta}_1^{Ath}$ and $\hat{\sigma}\hat{\beta}_2^{Ath}$ are used for building the likelihood function for θ, with the same procedure used for obtaining its prior distribution. We then use the Bayes theorem (1) to combine the prior distribution and the likelihood into the posterior distribution for θ. Figure 2, shows the prior, the likelihood function and the posterior distribution for $\theta = \beta_1 - \beta_2$.

Figure 3 shows, in more detail, the posterior distribution for θ. Note the cross on the x-axis at 0.072. That point is the smallest value of the difference in slopes with posterior probability greater than 0. This suggests that the posterior probability that the difference in slopes is greater than 0 is close to 1. In fact Figure 3 shows that the posterior probability that $\theta > 0.1 \,|\, y^{Ath}$ is equal to .99. Results from the Bayesian analysis sustain the proposed use of a bi-linear regression for estimating the response to sub- and supra-second exposition times, thus confirming the conjecture regarding the existence of two internal clocks for evaluating time intervals below and above one second.

Discussion

The aim of this study was investigating, from a Bayesian point of view, the evidence of the existence of two independent internal clocks for evaluating the passage of time for intervals below and above one second as suggested in a previous study by Chen & Cesari (2014). These authors' suggestion turns out to be further endorsed by the Bayesian analysis conducted here.

We illustrated how a prior distribution for the difference between slopes of a bi-linear regression is obtained from non-athletes data, while athletes' data were used for deriving the likelihood function. Indeed, non-athletes data were considered to be a baseline response for estimating bi-linear slopes difference before any athletic training, while the likelihood function evaluates information about slopes difference from people with specific athletic training. The posterior distribution shows how information from the two groups is combined to offer probability evaluation for the quantity of interest. More specifically, we obtain a large posterior probability that slopes of bi-linear regression are different, thus reinforcing the suggestion in Chen & Cesari's (2014) paper regarding the existence of two different internal clocks. The ability to reproduce short intervals of time (sub-second) has been referred as related to unconscious and automatic behaviors triggered by a motor neural loop with particular relevance for the involvement of supplementary motor area (SMA), primary motor cortex and cerebellum (e.g., Ivry & Spencer, 2004; Lewis & Miall, 2003). Athletes express higher ability in understanding (e.g., Williams & Davids, 1998) and in anticipating (e.g., Aglioti et al., 2008) dynamical events occurring in the space-time domain underpinned by a specific activation of the primary motor cortex. The fact that these internal clocks can be damaged has already been demonstrated by several neurophysiology studies testing a number of pathologies (e.g., Malapani et al., 1998) or by studies investigating the effect of aging (e.g., Rammsayer, 2001). In parallel, cognitive development has been also found beneficial in improving the quality of these clocks. For example, Szelag et al, (2002) found that the two older groups of children of 6-7, 9-10, and 13-14 years were more accurate in reproducing time instants from 1 to 2.5 seconds than did the very youngest group.

Some Bayesian literature on human motor sensory system and on control of sensory motor tasks, has dealt with Bayesian procedures (e.g., Hudson et al., 2008; Jazayeri & Shadlen, 2010; Kersten et al., 2004; Körding & Wolpert; 2004; Miyazaki et al., 2005). The focus of these papers is on investigating the way in which space-time related actions in human behavior can be justified as dictated by the Bayesian paradigm as naturally occurring in human perception. In this body of work, it has been speculated that human behavior in response to some type of stimuli follows the Bayesian model. For example, in Miyazaki et al. (2005), prior distributions and likelihood functions are identified, for individuals in a trial, to produce posterior distributions that lead subjects to perform Bayesian optimal actions, such as choosing the mean, or the mode of the posterior distribution in their evaluations. The authors recur to repeated measurement ANOVA analysis for testing whether individuals actually use optimal Bayesian estimator in their responses. In the same vein, Jazayeri & Shadlen (2010) evaluated the best Bayesian estimator through trial's variability and bias.

While the issues raised by the papers mentioned above are of great interest in speculations about the nature of human learning, attention needs to be paid to the use of statistical tools, like ANOVA, hypothesis testing procedures, or evaluation of bias and variability for drawing any conclusion regarding human behavior. These inferential procedures have been designed for carrying out statistical analyses, not for showing if a certain sample of individuals follows the Bayesian mechanism. Our paper's use of the Bayesian method is motivated by what we believe is the scope of any statistical investigation: obtaining estimates of some unknown quantity, starting from data collected for this very purpose. In conclusion, this study follows the Bayesian Inferential method for confirming the existence of a bi-mechanism for estimating time intervals below and above a second.

Appendix: Bayesian computation for the normal distribution

This appendix presents some mathematical results used for the Bayesian analysis following the Bayesian Theory (Bernardo & Smith, 2000). The question of fitting a bi-linear regression to the data was examined under the normality assumption made for the model in (2):

$$y_{i,j} = \alpha_i + \beta_i x_{i,j} + \epsilon_{i,j}; \quad i = 1,2; \;\; j = 1, \ldots 8; \;\; (3)$$

where the noise variables, $\epsilon_{i,j}$, are normal with unknown variances, and represent the errors in measurements relative to the observations $y_{i,j}$. The maximum likelihood estimator for the slope parameters $\widehat{\beta_i}$ is a linear combination of the normally distributed observations. For this reasons it is common practice to assume a normal prior distribution for the slope parameters. Specifically, the prior distributions for β_i^*'s in the bi-linear regression for the non-athletes group are:

$$\beta_1^* \sim N\left(\hat{\beta}_1^*, \hat{\sigma}^2_{\beta_1^*}\right) \quad \text{and} \quad \beta_2^* \sim N\left(\hat{\beta}_2^*, \hat{\sigma}^2_{\beta_2^*}\right)$$

Since the parameter of interest is the difference θ between the slopes of the bi-linear regression, using the linear property of the normal distribution, the prior distribution for θ is normal with mean the difference of the means and variance given by the sum of the variances:

$$\theta = \beta_1 - \beta_2 \sim N(\theta_0, \sigma_0^2), \text{ where } \theta_0 = \hat{\beta}_1^* - \hat{\beta}_2^* \text{ and } \sigma_0^2 = \hat{\sigma}^2_{\beta_1^*} + \hat{\sigma}^2_{\beta_2^*}$$

By a similar argument the likelihood function $f\left(\theta \,\middle|\, y^{Ath}\right)$ is also normal with mean and variance, respectively $\theta_1 = \hat{\beta}_1^{Ath} - \hat{\beta}_2^{Ath}$ and. $\sigma_1^2 = \hat{\sigma}^2_{\beta_1^{Ath}} + \hat{\sigma}^2_{\beta_2^{Ath}}$.

Finally, when the prior distribution and the likelihood of a parameter θ are both normal, by the conjugate family rule, the posterior distribution of θ is also normal, with mean and variance specified in the formula below:

$$\theta \mid y^{Ath} \sim N\left(\frac{\sigma_0^2\theta_1 + \sigma_1^2\theta_0}{\sigma_0^2 + \sigma_1^2}, \frac{\sigma_0^2\sigma_1^2}{\sigma_0^2 + \sigma_1^2}\right)$$

These are the mathematical formulas that we used for computing the prior and the posterior distributions of θ.

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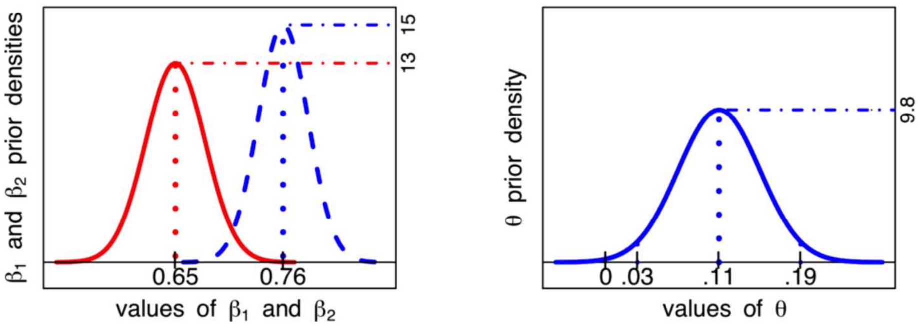
Figure captions

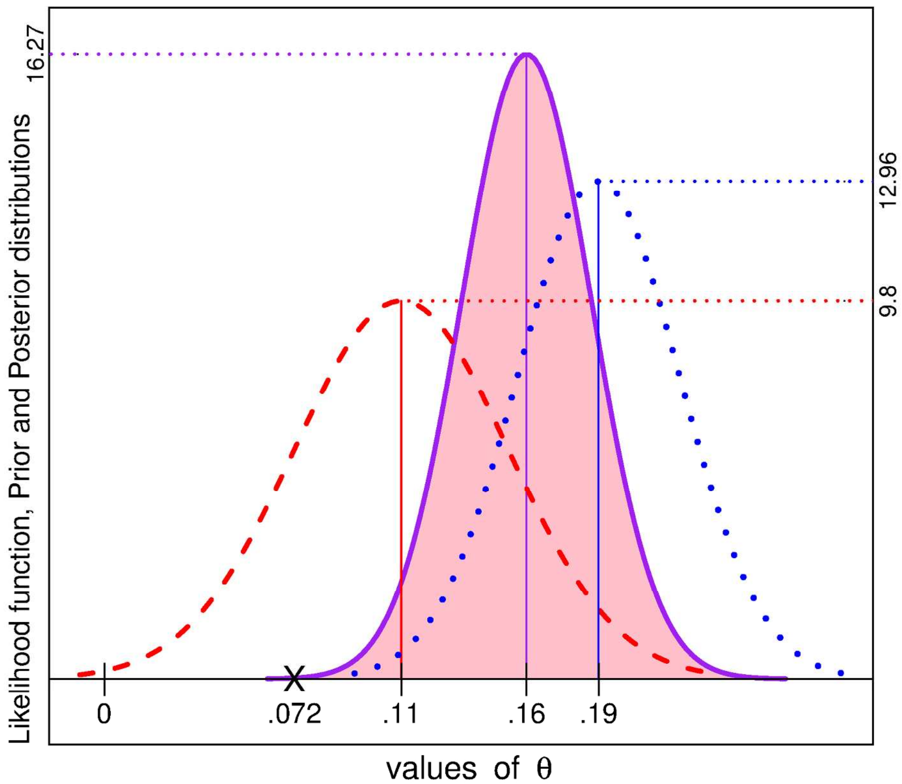
Figure. 1. Left: Prior distributions for β_1 (red/solid line) and β_2 (blue/broken line). Right: Prior distribution for $\theta = \beta_1 - \beta_2$.

Figure. 2. Prior distribution (red/broken line), likelihood function (blue/dotted line) and posterior distribution (highlighted/purple line) for $\theta = \beta_1 - \beta_2$.

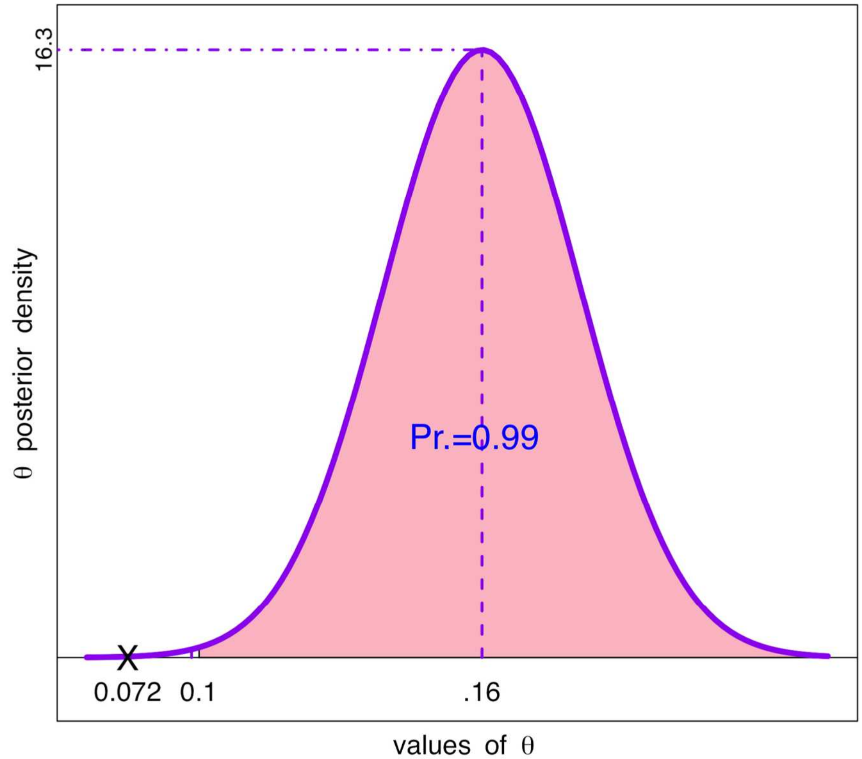
Figure. 3. Posterior distribution for $\theta = \beta_1 - \beta_2$. The highlighted area is Pr (> .1| Athletes’ data) = .99



Left: Prior distributions for β1 (red/solid line) and β2 (blue/broken line). Right: Prior distribution for θ=β1-β2.
159x164mm (300 x 300 DPI)



Prior distribution (red/broken line), likelihood function (blue/dotted line) and posterior distribution (highlighted/purple line) for θ=β1-β2.
177x177mm (300 x 300 DPI)



Posterior distribution for θ=β_1-β_2. The highlighted area is Pr (> .1| Athletes’ data) = .99
159x163mm (300 x 300 DPI)