Bayesian Statistics the Fun Way

Understanding Statistics and Probability with Star Wars, LEGO, and Rubber Ducks

by Will Kurt

errata updated to print 6

Page	Error	Correction	Print corrected
17	Equation replacement	$P(H_{\text{no article}}) = 20 \times (1 - P(H_{\text{no article}}))$	Print 2
29	So, using our die roll and coin toss example, the probability of rolling a number less than 6 or flipping a heads is:	So, using our die roll and coin toss example, the probability of rolling a number equal to 6 or flipping a heads is:	Print 3
40	Figure replacement	Binomial Distribution for 10 Rolls of a Six-Sided Die 0.3 0.1 0.0 2.5 5.0 7.5 10.0 k Figure 4-2: The probability of getting 6 k times when rolling a six-sided die 10 times	Print 3
51	Figure replacement	Distribution for Beta(14,27) 4 2 0 0.00 0.25 0.50 0.75 1.00 P Figure 5-3: Visualizing the beta distribution for our data collected about the black box	Print 3

51	the probability	we get in the end is a function that describes obability of each possible hypothesis for our elief in the probability of getting two heads the box What we get in the end is a function that describes the probability of each possible hypothesis for our true belief in the probability of getting two coins from the box			Print 5		
53	Here we calculate the probability that the chance of getting two coins from the box is 0.5, given the data:				late the probability that the chins from the box is less than the data:		Print 3
71	numberOfRedStuds = P (yellow red) × numberOfRedStuds = 1/5 × 20 = 4				dUnderYellow = P(yellow 1 Studs = 1/5 × 20 = 4	red) ×	Print 5
87	We just add the alphas for our prior and posterior and the betas for our prior and posterior , and we arrive at a normalized posterior. Because this is so simple, working with the beta distribution is very convenient for Bayesian statistics. To determine our posterior for Han making it through the asteroid field, we can perform this simple calculation: Beta (20002,7401) = Beta (2 + 20000, 7400 + 1)			and the betas farrive at a normal simple, working convenient for posterior for I field, we can p	the alphas for our prior and post- for our prior and likelihood at malized posterior. Because thing with the beta distribution is Bayesian statistics. To determ Han making it through the asto- erform this simple calculation (2,7441) = Beta (2 + 20000, 744)	nd we s is so s very nine our eroid :	Print 5
88	Figure replace	ment		150 100 Age 20 50	our likelihood with our prior gives us a more intriguin		Print 5
105	Observation	Difference from mean		Observation	Difference from mean		Print 5
	Group b			Group b			
	2.80	-0.16		2.80	-0.2		
105	Equation replacement			$\sum_{i=1}^5 a_i - \mu_a$	$=0 \qquad \sum_{i=1}^{5} b_i - \mu_b = 0$		Print 5
106	Equation replacement			$\frac{1}{5} \times \sum_{1}^{5} a_{i} -$	$ \mu_a = 0.04 \frac{1}{5} \times \sum_{i=1}^{5} b_i - \mu_b = 0.04$	0.416	Print 5

116	Equation replacement	$N(\mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \times e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	Print 3
127	<pre>xs <- seq(0.005,0.01,by=0.00001) xs.all <- seq(0,1,by=0.0001)</pre>	xs <- seq(0.005,0.01,by=0.00001) xs.all <- seq(0,1,by=0.0001)	Print 5
130	As Figure 3-5 illustrates, the point where this line intersects the x-axis gives us our median!	As Figure 13-5 illustrates, the point where this line intersects the x-axis gives us our median!	Print 5
163	$P(D H_1) = 0.94 \times 0.89 = 0.78$	$P(D H_1) = 0.94 \times 0.83 = 0.78$	Print 3
164	The prior odds look like this:	The probabilities look like this:	Print 5
164	Equation replacement	$O(H_1) \times \frac{P(D \mid H_1)}{P(D \mid H_2)} = \frac{11}{37,000} \times 2.23 = \frac{245}{370,000}$	Print 5
178	Equation replacement	$PO = O(H_2)' \times \frac{P(D_{15} \mid H_2)}{P(D_{15} \mid H_3)} = \frac{1}{1,000} \times \frac{\left(\frac{9}{10}\right)^{14} \times \left(1 - \frac{9}{10}\right)^1}{\left(\frac{9}{10}\right)^{14} \times \left(1 - \frac{9}{10}\right)^1} = \frac{1}{1,000}$	Print 3
224	Since you've run half a mile, using this simple formula, we can figure out:	Since you've run half an hour, using this simple formula, we can figure out:	Print 5
234	A3. This is the same as B(5; 10, 1/23). As expected, the probability of this is extremely low: about 1/32,000.	A3. This is the same as B(5; 10, 1/13). As expected, the probability of this is low: about 1/2,200.	Print 6
236	Luckily we already did all this work earlier in the chapter, so we know that $(A) = \frac{4}{1,000}$ and $P(B) = \frac{3}{100,000}$.	Luckily we already did all this work earlier in the chapter, so we know that $(A) = 8/100$ and $P(B) = 3/(100,000)$.	Print 5
237	Plugging in our numbers, we get an answer of 100,747/25,000,000 or 0.00403.	Plugging in our numbers, we get an answer of 800,276/10,000,000 or 0.0800276.	Print 5
242	temp.sd <- my.sd(temp.data)	temp.sd <- sd(temp.data)	Print 4
250	$P (D \mid H2) = 0.63 \times 0.55 \times 0.49 = 0.170$	P (D H2) = 0.94 x 0.83 x 0.49 = 0.382	Print 5
250	This means that given the Bayes factor alone, vestibular schwannoma is a roughly two times better explanation than labyrinthitis. Now we have to look at the odds ratio:	This means that given the Bayes factor alone, vestibular schwannoma is a roughly four times better explanation than labyrinthitis. Now we have to look at the prior odds ratio:	Print 5
251	The end result is that labyrinthititis is only a slightly better explanation than vestibular schwannoma.	The end result is that vestibular schwannoma is only a slightly better explanation than labyrinthititis .	Print 5

254	Equation replacement		Print 5
		$50 = \frac{9}{19} \times 950$ $BF = 950$	
254	<pre>dx <- 0.01 hypotheses <- seq(0,1,by=0.01)</pre>	<pre>dx <- 0.01 hypotheses <- seq(0,1,by=dx)</pre>	Print 5