Course: Regression Models 2 Lesson: Introduction 3 5 - Class: text 6 Output: "Introduction to Regression Models. (Slides for this and other Data Science courses may be found at github https://github.com/DataScienceSpecialization/courses if you want to use them. They must be downloaded as a zip file and viewed locally. This lesson corresponds to Regression Models/01 01 introduction.)" 7 8 - Class: text Output: This is the first lesson on Regression Models. We'll begin with the concept 9 of "regression toward the mean" and illustrate it with some pioneering work of the father of forensic science, Sir Francis Galton. 10 11 - Class: text 12 Output: Sir Francis studied the relationship between heights of parents and their children. His work showed that parents who were taller than average had children who were also tall but closer to the average height. Similarly, parents who were shorter than average had children who were also shorter than average but less so than mom and dad. That is, they were closer to the average height. From one generation to the next the heights moved closer to the average or regressed toward the mean. 13 14 - Class: text 15 Output: For this lesson we'll use Sir Francis's parent/child height data which we've taken the liberty to load for you as the variable, galton. (Data is from John Verzani's website, http://wiener.math.csi.cuny.edu/UsingR/.) So let's get started! 16 17 - Class: figure 18 Output: Here is a plot of Galton's data, a set of 928 parent/child height pairs. Moms' and dads' heights were averaged together (after moms' heights were adjusted by a factor of 1.08). In our plot we used the R function "jitter" on the children's heights to highlight heights that occurred most frequently. The dark spots in each column rise from left to right suggesting that children's heights do depend on their parents'. Tall parents have tall children and short parents have short children. 19 Figure: plot1 children vs parents.R 20 FigureType: new 21 22 - Class: figure 23 Output: Here we add a red (45 degree) line of slope 1 and intercept 0 to the plot. If children tended to be the same height as their parents, we would expect the data to vary evenly about this line. We see this isn't the case. On the left half of the plot we see a concentration of heights above the line, and on the right half we see the concentration below the line. 24 Figure: plot2 identity line.R 25 FigureType: add 26 27 - Class: figure 28 Output: Now we've added a blue regression line to the plot. This is the line which has the minimum variation of the data around it. (For theory see the slides.) Its slope is greater than zero indicating that parents' heights do affect their children's. The slope is also less than 1 as would have been the case if children tended to be the same height as their parents. 29 Figure: plot3 regression line.R 30 FigureType: add 31 32 - Class: cmd question 33 Output: Now's your chance to plot in R. Type "plot(child ~ parent, galton)" at the R prompt. 34 CorrectAnswer: plot(child ~ parent, galton) 35 AnswerTests: omnitest(correctExpr='plot(child ~ parent, galton)') 36 Hint: Type "plot(child ~ parent, galton)" at the R prompt. 37 Figure: restore 1.R 38 FigureType: new 39 40 - Class: text 41 Output: You'll notice that this plot looks a lot different than the original we displayed. Why? Many people are the same height to within measurement error, so

points fall on top of one another. You can see that some circles appear darker than

others. However, by using R's function "jitter" on the children's heights, we can spread out the data to simulate the measurement errors and make high frequency heights more visible. - Class: cmd question Output: Now it's your turn to try. Just type "plot(jitter(child,4) ~ parent,galton)" and see the magic. CorrectAnswer: plot(jitter(child, 4) ~ parent, galton) AnswerTests: omnitest(correctExpr='plot(jitter(child,4) ~ parent, galton)') Hint: You can do it! Type "plot(jitter(child,4) ~ parent,galton)" Figure: restore 2.R FigureType: new - Class: text Output: Now for the regression line. This is quite easy in R. The function lm (linear model) needs a "formula" and dataset. You can type "?formula" for more information, but, in simple terms, we just need to specify the dependent variable (children's heights) ~ the independent variable (parents' heights). - Class: cmd question Output: So generate the regression line and store it in the variable regrline. Type "regrline <- lm(child ~ parent, galton)"</pre> CorrectAnswer: regrline <- lm(child ~ parent, galton)</pre> AnswerTests: omnitest(correctExpr='regrline <- lm(child ~ parent, galton)');expr creates var('regrline') Hint: You CAN do it! Type "regrline <- lm(child ~ parent, galton)"</pre> - Class: cmd question Output: Now add the regression line to the plot with "abline". Make the line wide and red for visibility. Type "abline(regrline, lwd=3, col='red')" CorrectAnswer: abline(regrline, lwd=3, col='red') AnswerTests: omnitest(correctExpr='abline(regrline, lwd=3, col=\'red\')') Hint: Yes, you can! Type "abline(regrline, lwd=3, col='red')" Figure: restore 3.R FigureType: add - Class: cmd question Output: The regression line will have a slope and intercept which are estimated from data. Estimates are not exact. Their accuracy is gauged by theoretical techniques and expressed in terms of "standard error." You can use "summary(regrline)" to examine the Galton regression line. Do this now. CorrectAnswer: summary(regrline) AnswerTests: omnitest(correctExpr='summary(regrline)') Hint: This one's easy. Type "summary(regrline)" - Class: mult question Output: The slope of the line is the estimate of the coefficient, or multiplier, of "parent", the independent variable of our data (in this case, the parents' heights). From the output of "summary" what is the slope of the regression line? **AnswerChoices**: .64629; .04114; 23.94153 CorrectAnswer: .64629 AnswerTests: omnitest(correctVal= '.64629') Hint: Look at the line labelled "parent" and the column "Estimate" - Class: mult question Output: What is the standard error of the slope? **AnswerChoices**: .64629; .04114; 23.94153 CorrectAnswer: .04114 AnswerTests: omnitest(correctVal= '.04114') Hint: Look at the line labelled "parent" and the column "Std. Error." - Class: text Output: A coefficient will be within 2 standard errors of its estimate about 95% of

the time. This means the slope of our regression is significantly different than

Output: We're now adding two blue lines to indicate the means of the children's

either 0 or 1 since (.64629) +/- (2*.04114) is near neither 0 nor 1.

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- Class: figure

heights (horizontal) and the parents' (vertical). Note that these lines and the regression line all intersect in a point. Pretty cool, huh? We'll talk more about this in a later lesson. (Something you can look forward to.) Figure: plot4 mean heights.R FigureType: add - Class: figure Output: The slope of a line shows how much of a change in the vertical direction is produced by a change in the horizontal direction. So, parents "1 inch" above the mean in height tend to have children who are only .65 inches above the mean. The green triangle illustrates this point. From the mean, moving a "1 inch distance" horizontally to the right (increasing the parents' height) produces a ".65 inch" increase in the vertical direction (children's height). Figure: plot5 triangle1.R FigureType: add - Class: figure Output: Similarly, parents who are 1 inch below average in height have children who are only .65 inches below average height. The purple triangle illustrates this. From the mean, moving a "1 inch distance" horizontally to the left (decreasing the parents' height) produces a ".65 inch" decrease in the vertical direction (children's height). Figure: plot5 triangle2.R FigureType: add - Class: text Output: This concludes our lesson on regression toward the mean. We hope you found it above average!

110 - Class: mult question

Output: "Would you like to receive credit for completing this course on

112 Coursera.org?" 113 CorrectAnswer: NULL 114 AnswerChoices: Yes; No

115 AnswerTests: coursera on demand()

Hint: "" 116

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