Regression Modeling — A Conceptual Introduction

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Multilevel Regression Modeling, 2009

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The Fundamental Equation of Regression Modeling

The Fundamental Equation

- At some time in the dim past, we were all exposed for the first time to simple linear regression and correlation analysis
- Because the equations surrounding these analyses were messy and very challenging, we may have missed the "big picture"
- The "big picture" is embodied in the following simple equation

$$\text{Data} = \text{Model} + \text{Error}$$

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- We do a standard linear regression, and the scatterplot looks like this

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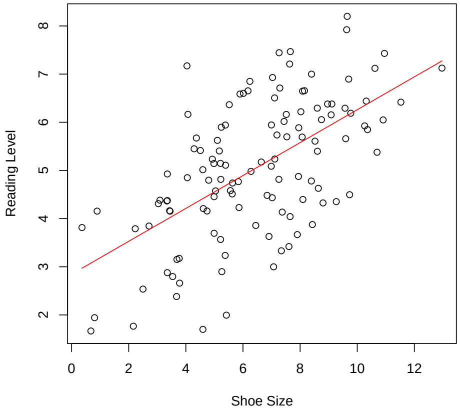

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Systematic vs. Random Error

Systematic vs. Random Error

- In the preceding slide, it appeared that, in fact, shoe size and reading level are linearly related in this sample of boys
- However, the data deviated from a straight line
- In this case, using standard linear regression, we "modeled" the error as independent and normally distributed around the regression line
- The model seems to have some validity
- Of course, that doesn't mean that the model is "conveying the truth" about the relationship between shoe size and reading ability

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- Model error can be systematic or random
- Systematic error can result from several sources:
  - The model may have ignored important predictors
  - The functional form of the model may be incorrect
  - The data may have a hierarchical structure that the model has ignored
- In general, we will find that when we eliminate systematic error, we gain in accuracy and statistical power

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Identify Missing Independent Variables

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- A model for the data generally involves selecting one or more dependent variables, then constructing a model function to explain the dependent variable data as a function of independent variables
- Often, we can improve a model by realizing that an important independent variable is missing from the model
- For example, suppose we had measured IQ scores for the 120 boys in the reading level example cited earlier
- We might wish to incorporate IQ into our model, and, in so doing, we might reduce the amount of error

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Changing the Functional Form

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- Sometimes we have the "right" independent variables, but our functional form is suboptimal
- On occasion, we can fix things by "transforming" one or more of the variables
- So, for example, if y is not a linear function of x, but is a linear function of $\log(x)$, then we can simply log-transform x and fit a linear function to the transformed data

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- For example, suppose we are interested in constructing a model to predict the probability of being admitted to law school as a function of LSAT scores
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Dangers of Overfitting

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- There is a significant danger when we modify a model repeatedly, each time rechecking the fit, to reduce error
- Almost always a more complicated variant of a model will fit better
- Adding additional independent variables, for example, almost always improves model fit
- Repeated rechecks increase the probability that you are customizing your model to conform to chance variation in the data
- We have to be careful to avoid misleading ourselves

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Incorporating Hierarchical Structure

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- Many data sets, especially in education and the social sciences, are *hierarchical* in nature
- For example, children study within classrooms, which are situated within schools, which are in turn situated within school districts, and so on
- Each level of the hierarchy may require special modeling in order to properly capture the variation between children

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- For example, suppose that, in our shoe size data, the 120 boys were taken from 4th, 5th, and 6th grades in the same school
- Our original model did not take into account this hierarchical structure
- It simply lumped all the boys together into one large group
- We should probably look inside the grade levels, fit a linear model to each grade's data separately, and see whether the relationship between shoe size and reading level persists and/or changes across levels
- It turns out that, if we do that, we get a rather different picture of the relationship between shoe size and reading level

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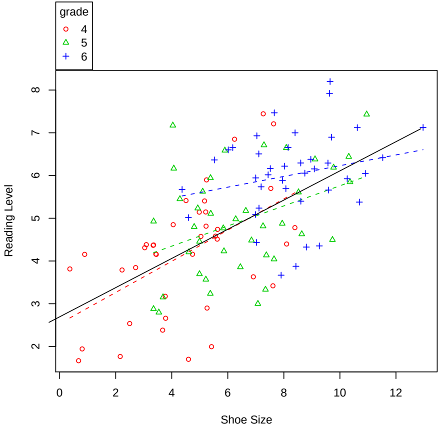
Analyzing by Grade



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- We see that the overall linear fit, shown in black, is not the same as the fit within groups
- As grade level increases, we see a change in the mean level of shoe size and reading level
- We also see a change in the slope and intercept of the lines of fit within groups
- These lines are shown in red, blue, and green

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In setting up a regression model, we need to think carefully about how to

- Select variables relevant to our theoretical goals
- Choose an appropriate linear, nonlinear, or generalized linear model for our data
- Avoid overfitting
- Reduce random error noise
- Exploit and investigate hierarchical aspects of the data structure

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In achieving these goals, and to feel comfortable reading the textbook we need to develop some skills:

- Master or recall some key aspects of linear regression modeling
- Learn a tiny bit of matrix algebra (about one day's worth)
- Learn the basic ideas behind generalized linear models
- Become familiar with R, WINBUGS, and (to a lesser extent) HLM
- Master enough technical details (things like when to center, when to standardize) to keep out of trouble

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