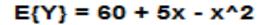
Regression Models for Quantitative/Numerical and Qualitative/Categorical Predictors

KNNL – Chapter 8

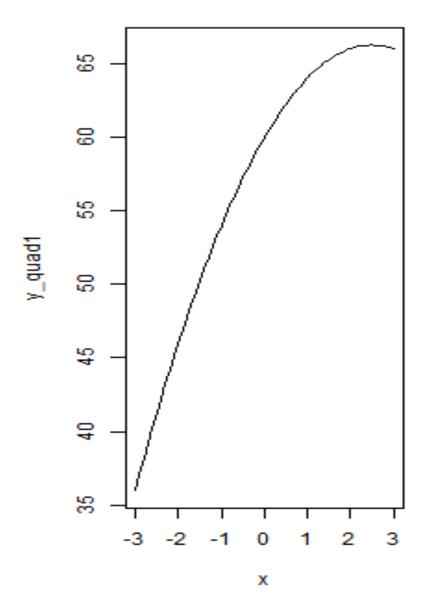
Polynomial Regression Models

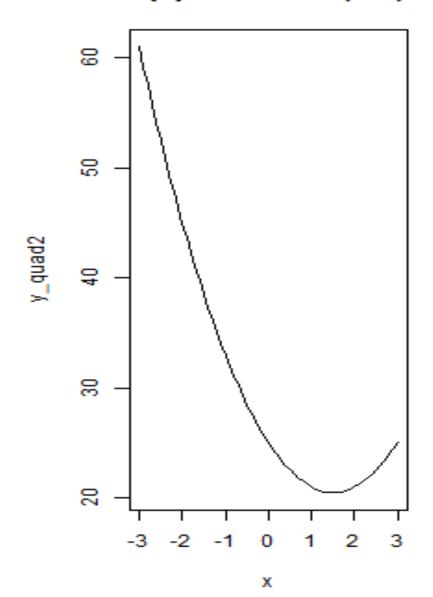
- Useful in two settings:
 - True relation between response and predictor is polynomial
 - True relation is complex nonlinear function that can be approximated by polynomial in specific range of X-levels
- Models with 1 Predictor: Including p polynomial terms in model, creates p-1 "bends"
 - -2^{nd} order Model: $E\{Y\} = \beta_0 + \beta_1 x + \beta_2 x^2$ has one bend
 - -3^{rd} order Model: $E\{Y\} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$ has two bends
- Response Surfaces with 2 (or more) predictors
 - 2nd order model with 2 Predictors:

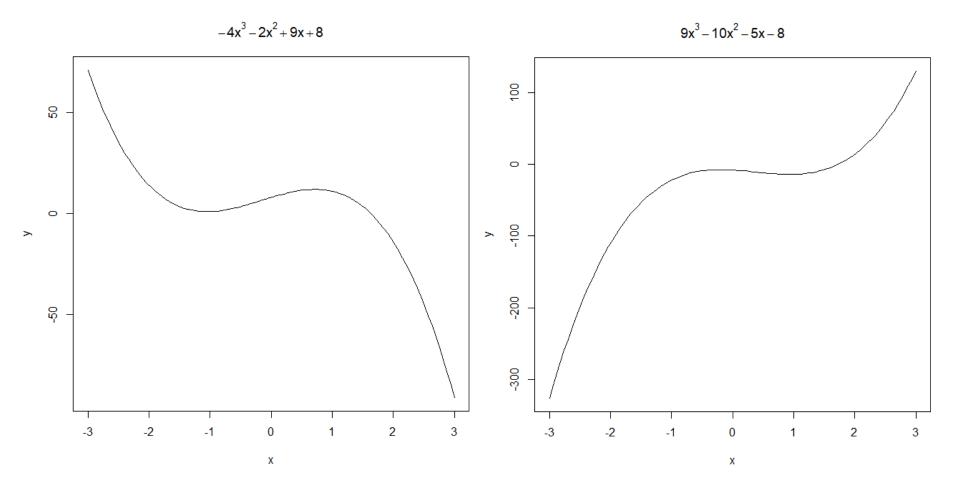
$$E\{Y\} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 \qquad x_1 = X_1 - \overline{X}_1 \quad x_2 = X_2 - \overline{X}_2$$

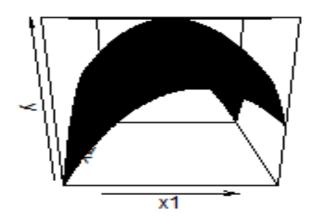


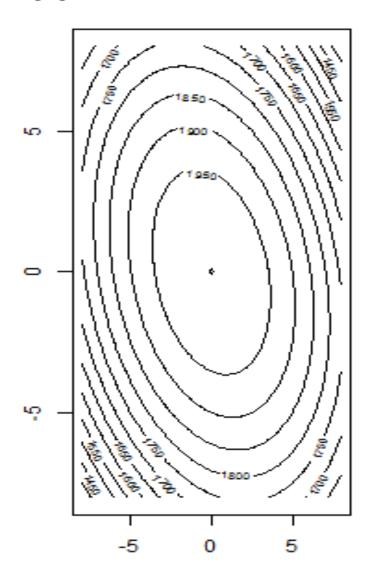
$E{Y} = 25 - 6x + 2(x^2)$











Modeling Strategies

- Use Extra Sums of Squares and General Linear Tests to compare models of increasing complexity (higher order)
- Use coding in fitting models (centered/scaled)
 predictors to reduce multicollinearity when conducting
 testing.
- Fit models in original units, or back-transform for plotting on original scale* (see below for quadratic)

Centered variables:
$$\hat{Y} = b_0 + b_1 x + b_{11} x^2 = b_0 + b_1 \left(X - \overline{X} \right) + b_{11} \left(X - \overline{X} \right)^2$$

$$= b_0 + b_1 X - b_1 \overline{X} + b_{11} X^2 - 2b_{11} X \overline{X} + b_{11} \overline{X}^2 = \left(b_0 - b_1 \overline{X} + b_{11} \overline{X}^2 \right) + \left(b_1 - 2b_{11} \overline{X} \right) X + b_{11} \overline{X}^2 = b_o' + b_1' X + b_2' X^2$$

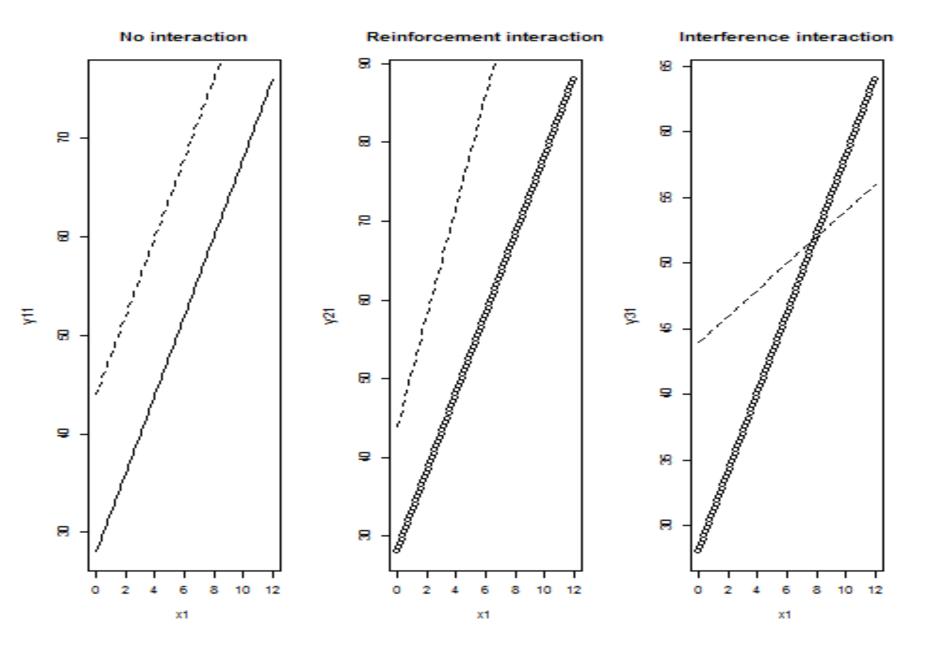
Regression Models with Interaction Term(s)

- Interaction ⇒ Effect (Slope) of one predictor variable depends on the level other predictor variable(s)
- Formulated by including cross-product term(s) among predictor variables
- 2 Variable Models: $E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2$

$$X_2 = 0 \Rightarrow E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2(0) + \beta_3(X_1(0)) = \beta_0 + \beta_1 X_1$$

$$X_{2} = 10 \Rightarrow E\{Y\} = \beta_{0} + \beta_{1}X_{1} + \beta_{2}(10) + \beta_{3}(X_{1}(10)) = \beta_{0} + \beta_{1}X_{1} + 10\beta_{2} + 10\beta_{3}X_{1} = (\beta_{0} + 10\beta_{2}) + (\beta_{1} + 10\beta_{3})X_{1}$$

Testing Hypothesis of no interaction: $H_0: \beta_3 = 0$ $H_A: \beta_3 \neq 0$



Qualitative Predictors

- Often, we wish to include categorical variables as predictors (e.g. gender, region of country, ...)
- Trick: Create dummy (indicator) variable(s) to represent effects of levels of the categorical variables on response
- Problem: If variable has c categories, and we create c dummy variables, the model is not full rank when we include intercept
- Solution: Create c-1 dummy variables, leaving one level as the control/baseline/reference category

Example - Salary vs Experience by Region

Suppose Y = salary, $X_1 = \text{experience}$, and we also want to include 3 regions as predictors. Define the following:

$$X_2 = \begin{cases} 1 & \text{if Region 1} \\ 0 & \text{otherwise} \end{cases}$$

$$X_3 = \begin{cases} 1 & \text{if Region 2} \\ 0 & \text{otherwise} \end{cases}$$

$$X_4 = \begin{cases} 1 & \text{if Region 3} \\ 0 & \text{otherwise} \end{cases}$$

If we include all three of the dummy variables X_2 , X_3 , and X_4 , the problem is that the design matrix X will not be of full rank, and X'X will not be invertible:

$$\boldsymbol{X} = \begin{bmatrix} 1 & X_{11} & 1 & 0 & 0 \\ 1 & X_{12} & 1 & 0 & 0 \\ 1 & X_{13} & 0 & 1 & 0 \\ 1 & X_{14} & 0 & 1 & 0 \\ 1 & X_{15} & 0 & 0 & 1 \\ 1 & X_{16} & 0 & 0 & 1 \end{bmatrix}$$

Example – Salary vs Experience by Region

Define the following:

$$X_2 = \begin{cases} 1 & \text{if Region 1} \\ 0 & \text{otherwise} \end{cases}$$

$$X_3 = \begin{cases} 1 & \text{if Region 2} \\ 0 & \text{otherwise} \end{cases}$$

$$X_4 = \begin{cases} 1 & \text{if Region 3} \\ 0 & \text{otherwise} \end{cases}$$

Solution:

Choose a "reference" region, say Region 3. Then use just the Region 1 dummy (X_2) and the Region 2 dummy (X_3)

(Note: it is arbitrary which region is the reference)

Then the first-order regression model will be:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \varepsilon_i$$

Example – Salary vs Experience by Region

3 regions,
$$Y$$
=salary, X_1 = experience $X_2 = \begin{cases} 1 \text{ if Region 1} \\ 0 \text{ otherwise} \end{cases}$ $X_3 = \begin{cases} 1 \text{ if Region 2} \\ 0 \text{ otherwise} \end{cases}$

$$E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$

Region 1:
$$X_2 = 1, X_3 = 0 \implies E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 (1) + \beta_3 (0) = (\beta_0 + \beta_2) + \beta_1 X_1$$

Region 2: $X_2 = 0, X_3 = 1 \implies E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 (0) + \beta_3 (1) = (\beta_0 + \beta_3) + \beta_1 X_1$
Region 3: $X_2 = 0, X_3 = 0 \implies E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 (0) + \beta_3 (0) = \beta_0 + \beta_1 X_1$

 $\beta_2 \equiv \text{Difference between Regions 1 and 3, controlling for experience}$ $\beta_3 \equiv \text{Difference between Regions 2 and 3, controlling for experience}$

 $\beta_2 - \beta_3 \equiv$ Difference between Regions 1 and 2, controlling for experience

 $\beta_2 = \beta_3 = 0$ \Rightarrow No differences among Regions 1,2,3 wrt Salary, Controlling for Experience

Interactions Between Qualitative and Quantitative Predictors

- We can allow the slope wrt to a Quantitative Predictor to differ across levels of the Categorical Predictor
- Trick: Create cross-product terms between Quantitative
 Predictor and each of the c-1 dummy variables
- Can conduct General Linear Test to determine whether slopes differ (or t-test when qualitative predictor has c=2 levels)
- These models generalize to any number of quantitative and qualitative predictors

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Salary (Y), Expediture (X<sub>1</sub>), and regions (X<sub>2</sub>, X<sub>3</sub>):

Additive Model: E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3

Interaction Model: E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1 X_2 + \beta_5 X_1 X_3

Region 1(X_2 = 1, X_3 = 0) : E\{Y\} = \beta_0 + \beta_1 X_1 + \beta_2 (1) + \beta_3 (0) + \beta_4 X_1 (1) + \beta_5 X_1 (0) = (\beta_0 + \beta_2) + (\beta_1 + \beta_4) X_1

Region 2(X_2 = 0, X_3 = 1) : E\{Y\} = (\beta_0 + \beta_3) + (\beta_1 + \beta_5) X_1

Region 3(X_2 = 0, X_3 = 0) : E\{Y\} = \beta_0 + \beta_1 X_1
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