# Introduction to Linear Models

STA721 Linear Models Duke University

Merlise Clyde

August 25, 2015

# Coordinates

- Instructor: Merlise Clyde
  214 Old Chemistry
  Office Hours MWF 1:00-2:0 or right after class (or by appointment)
- Teaching Assistants: Nicole Dalzell & Kaoru Irie
- Course: Theory and Application of linear models from both a frequentist (classical) and Bayesian perspective

# Coordinates

- Instructor: Merlise Clyde
  214 Old Chemistry
  Office Hours MWF 1:00-2:0 or right after class (or by appointment)
- Teaching Assistants: Nicole Dalzell & Kaoru Irie
- Course: Theory and Application of linear models from both a frequentist (classical) and Bayesian perspective
- Prerequisites: linear algebra and a mathematical statistics course covering likelihoods and distribution theory (normal, t, F, chi-square, gamma distributions)

# Coordinates

- Instructor: Merlise Clyde
  214 Old Chemistry
  Office Hours MWF 1:00-2:0 or right after class (or by appointment)
- Teaching Assistants: Nicole Dalzell & Kaoru Irie
- Course: Theory and Application of linear models from both a frequentist (classical) and Bayesian perspective
- Prerequisites: linear algebra and a mathematical statistics course covering likelihoods and distribution theory (normal, t, F, chi-square, gamma distributions)
- Introduce R programming as needed

# Coordinates

- Instructor: Merlise Clyde
  214 Old Chemistry
  Office Hours MWF 1:00-2:0 or right after class (or by appointment)
- Teaching Assistants: Nicole Dalzell & Kaoru Irie
- Course: Theory and Application of linear models from both a frequentist (classical) and Bayesian perspective
- Prerequisites: linear algebra and a mathematical statistics course covering likelihoods and distribution theory (normal, t, F, chi-square, gamma distributions)
- Introduce R programming as needed
- Introduce Bayesian methods, but assume that you are co-registered in 601 or have taken it previously

# Coordinates

- Instructor: Merlise Clyde
  214 Old Chemistry
  Office Hours MWF 1:00-2:0 or right after class (or by appointment)
- Teaching Assistants: Nicole Dalzell & Kaoru Irie
- Course: Theory and Application of linear models from both a frequentist (classical) and Bayesian perspective
- Prerequisites: linear algebra and a mathematical statistics course covering likelihoods and distribution theory (normal, t, F, chi-square, gamma distributions)
- Introduce R programming as needed
- Introduce Bayesian methods, but assume that you are co-registered in 601 or have taken it previously
- more info on Course Website
  `http://stat.duke.edu/courses/Fall15/sta721`

# Introduction

Build “regression” models that relate a response variable to a collection of covariates

# Introduction

Build “regression” models that relate a response variable to a collection of covariates

- Goals of Analysis?

# Introduction

Build "regression" models that relate a response variable to a collection of covariates

- Goals of Analysis?
  - Predictive models
  - Causal interpretation
  - Testing of hypotheses
  - confirmatory or validation analyses
- Observational versus Experimental data?

# Introduction

Build "regression" models that relate a response variable to a collection of covariates

- Goals of Analysis?
  - Predictive models
  - Causal interpretation
  - Testing of hypotheses
  - confirmatory or validation analyses
- Observational versus Experimental data? (Confounding)

# Introduction

Build “regression” models that relate a response variable to a collection of covariates

- Goals of Analysis?
  - Predictive models
  - Causal interpretation
  - Testing of hypotheses
  - confirmatory or validation analyses
- Observational versus Experimental data? (Confounding)
- Sampling Schemes

# Introduction

Build “regression” models that relate a response variable to a collection of covariates

- Goals of Analysis?
  - Predictive models
  - Causal interpretation
  - Testing of hypotheses
  - confirmatory or validation analyses
- Observational versus Experimental data? (Confounding)
- Sampling Schemes Generalizibility

# Introduction

Build “regression” models that relate a response variable to a collection of covariates

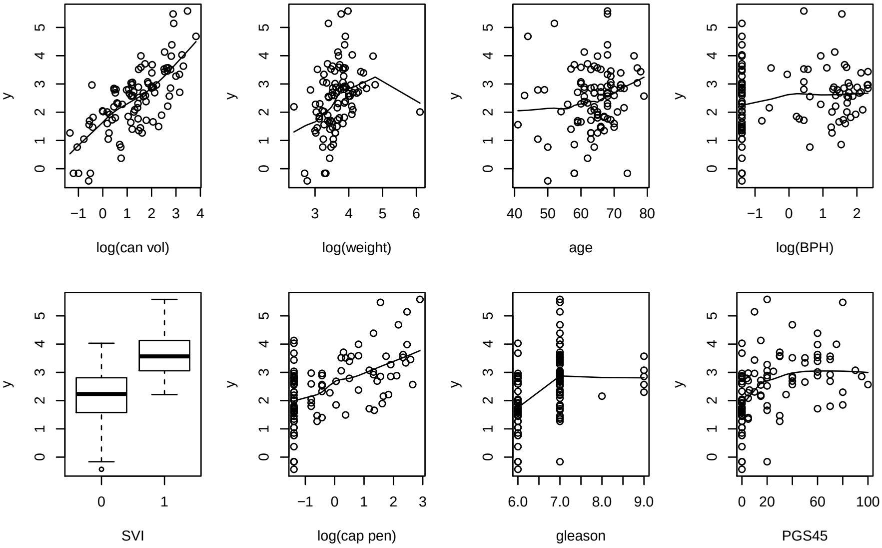
- Goals of Analysis?
  - Predictive models
  - Causal interpretation
  - Testing of hypotheses
  - confirmatory or validation analyses
- Observational versus Experimental data? (Confounding)
- Sampling Schemes Generalizibility
- Statistical Theory

# Introduction

Build "regression" models that relate a response variable to a collection of covariates

- Goals of Analysis?
  - Predictive models
  - Causal interpretation
  - Testing of hypotheses
  - confirmatory or validation analyses
- Observational versus Experimental data? (Confounding)
- Sampling Schemes Generalizibility
- Statistical Theory

# Prostate Example



# Simple Linear Regression

Simple Linear Regression:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \text{ for } i = 1, \ldots, n$$

# Simple Linear Regression

Simple Linear Regression:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vectors:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \beta_0 + \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \beta_1 + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

# Simple Linear Regression

Simple Linear Regression:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vectors:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \beta_0 + \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \beta_1 + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

# Simple Linear Regression

Simple Linear Regression:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vectors:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \beta_0 + \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \beta_1 + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

# Multiple Regression

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \beta_p x_{pi} + \epsilon_i$$

# Multiple Regression

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \beta_p x_{pi} + \epsilon_i$$

Design matrix

$$\mathbf{X} = \begin{matrix} 1 & x_{11} & \ldots & x_{p1} \\ 1 & x_{12} & \ldots & x_{p2} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{1n} & \ldots & x_{pn} \end{matrix}$$

# Multiple Regression

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \beta_p x_{pi} + \epsilon_i$$

Design matrix

$$\mathbf{X} = \begin{matrix} 1 & x_{11} & \ldots & x_{p1} \\ 1 & x_{12} & \ldots & x_{p2} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{1n} & \ldots & x_{pn} \end{matrix}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \epsilon$$

# Multiple Regression

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots \beta_p x_{pi} + \epsilon_i$$

Design matrix

$$\mathbf{X} = \begin{matrix} 1 & x_{11} & \ldots & x_{p1} \\ 1 & x_{12} & \ldots & x_{p2} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{1n} & \ldots & x_{pn} \end{matrix}$$

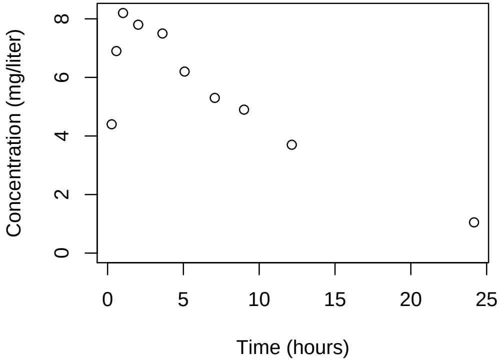
$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \epsilon$$

what should go into $\mathbf{X}$ and do we need all columns of $\mathbf{X}$ for inference about $\mathbf{Y}$?

# Nonlinear Models

Mean function may be an intrinsicaly nonlinear function of $t$

$$E[Y_i] = f(t_i, \boldsymbol{\theta})$$



# Quadratic Linear Regression

Taylor's Theorem:

$$f(t_i, \boldsymbol{\theta}) = f(t_0, \boldsymbol{\theta}) + (t_i - t_0) f'(t_0, \boldsymbol{\theta}) + (t_i - t_0)^2 \frac{f''(t_0, \boldsymbol{\theta})}{2} + R(t_i, \boldsymbol{\theta})$$

# Quadratic Linear Regression

Taylor's Theorem:

$$f(t_i, \boldsymbol{\theta}) = f(t_0, \boldsymbol{\theta}) + (t_i - t_0) f'(t_0, \boldsymbol{\theta}) + (t_i - t_0)^2 \frac{f''(t_0, \boldsymbol{\theta})}{2} + R(t_i, \boldsymbol{\theta})$$

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \epsilon_i \text{ for } i = 1, \ldots, n$$

# Quadratic Linear Regression

Taylor's Theorem:

$$f(t_i, \boldsymbol{\theta}) = f(t_0, \boldsymbol{\theta}) + (t_i - t_0) f'(t_0, \boldsymbol{\theta}) + (t_i - t_0)^2 \frac{f''(t_0, \boldsymbol{\theta})}{2} + R(t_i, \boldsymbol{\theta})$$

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vectors:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 \\ \vdots & \vdots & \\ 1 & x_n & x_n^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

# Quadratic Linear Regression

Taylor's Theorem:

$$f(t_i, \boldsymbol{\theta}) = f(t_0, \boldsymbol{\theta}) + (t_i - t_0) f'(t_0, \boldsymbol{\theta}) + (t_i - t_0)^2 \frac{f''(t_0, \boldsymbol{\theta})}{2} + R(t_i, \boldsymbol{\theta})$$

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vectors:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 \\ \vdots & \vdots & \\ 1 & x_n & x_n^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\beta + \boldsymbol{\epsilon}$$

# Quadratic Linear Regression

Taylor's Theorem:

$$f(t_i, \boldsymbol{\theta}) = f(t_0, \boldsymbol{\theta}) + (t_i - t_0) f'(t_0, \boldsymbol{\theta}) + (t_i - t_0)^2 \frac{f''(t_0, \boldsymbol{\theta})}{2} + R(t_i, \boldsymbol{\theta})$$

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vectors:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 \\ \vdots & \vdots & \\ 1 & x_n & x_n^2 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

Quadratic in $x$, but linear in $\beta$'s, but remainder term is in errors $\boldsymbol{\epsilon}$

# Polynomial Linear Regression

Polynomial Regression:

$$y_i = \sum_{j=0}^{q} \beta_j x_i^j + \epsilon_i \text{ for } i = 1, \ldots, n$$

# Polynomial Linear Regression

Polynomial Regression:

$$y_i = \sum_{j=0}^{q} \beta_j x_i^j + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vector notation:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \ldots & x_1^q \\ \vdots & \vdots & & & \\ 1 & x_n & x_n^2 & \ldots & x_n^q \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_q \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

# Polynomial Linear Regression

Polynomial Regression:

$$y_i = \sum_{j=0}^{q} \beta_j x_i^j + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vector notation:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \ldots & x_1^q \\ \vdots & \vdots & & & \\ 1 & x_n & x_n^2 & \ldots & x_n^q \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_q \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

# Polynomial Linear Regression

Polynomial Regression:

$$y_i = \sum_{j=0}^{q} \beta_j x_i^j + \epsilon_i \text{ for } i = 1, \dots, n$$

Rewrite in vector notation:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \dots & x_1^q \\ \vdots & \vdots & & & \\ 1 & x_n & x_n^2 & \dots & x_n^q \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_q \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

How large should $q$ be?

# Polynomial Linear Regression

Polynomial Regression:

$$y_i = \sum_{j=0}^{q} \beta_j x_i^j + \epsilon_i \text{ for } i = 1, \ldots, n$$

Rewrite in vector notation:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \ldots & x_1^q \\ \vdots & \vdots & & & \\ 1 & x_n & x_n^2 & \ldots & x_n^q \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_q \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

How large should $q$ be?

Use Nonlinear Regression or other Nonparametric models

# Kernel Regression

Kernel Regression:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_j e^{-\lambda (x_i - k_j)^d} + \epsilon_i \text{ for } i = 1, \ldots, n$$

where $k_j$ are kernel locations and $\lambda$ is a smoothing parameter

# Kernel Regression

Kernel Regression:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_j e^{-\lambda(x_i - k_j)^d} + \epsilon_i \text{ for } i = 1, \dots, n$$

where $k_j$ are kernel locations and $\lambda$ is a smoothing parameter

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & e^{-\lambda(x_1 - k_1)^d} & \dots & e^{-\lambda(x_1 - k_J)^d} \\ \vdots & \vdots & & \vdots \\ 1 & e^{-\lambda(x_n - k_1)^d} & \dots & e^{-\lambda(x_n - k_J)^d} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_J \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

# Kernel Regression

Kernel Regression:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_j e^{-\lambda(x_i - k_j)^d} + \epsilon_i \text{ for } i = 1, \ldots, n$$

where $k_j$ are kernel locations and $\lambda$ is a smoothing parameter

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & e^{-\lambda(x_1 - k_1)^d} & \ldots & e^{-\lambda(x_1 - k_J)^d} \\ \vdots & \vdots & & \vdots \\ 1 & e^{-\lambda(x_n - k_1)^d} & \ldots & e^{-\lambda(x_n - k_J)^d} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_J \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

Linear in $\beta$ given $\lambda$

# Kernel Regression

Kernel Regression:

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_j e^{-\lambda(x_i - k_j)^d} + \epsilon_i \text{ for } i = 1, \ldots, n$$

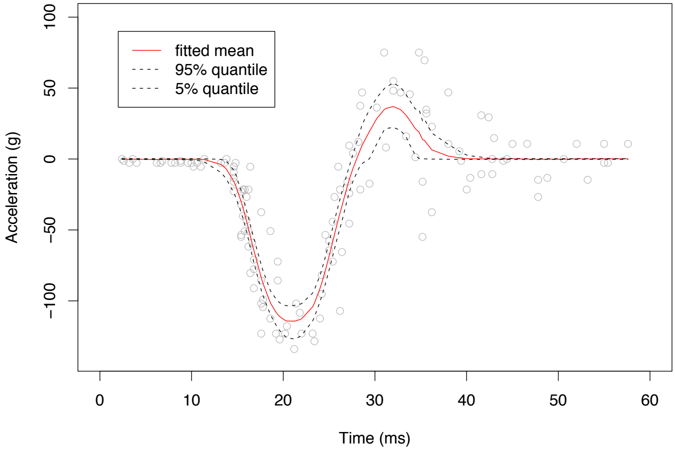
where $k_j$ are kernel locations and $\lambda$ is a smoothing parameter

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & e^{-\lambda(x_1-k_1)^d} & \ldots & e^{-\lambda(x_1-k_J)^d} \\ \vdots & \vdots & & \vdots \\ 1 & e^{-\lambda(x_n-k_1)^d} & \ldots & e^{-\lambda(x_n-k_J)^d} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_J \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

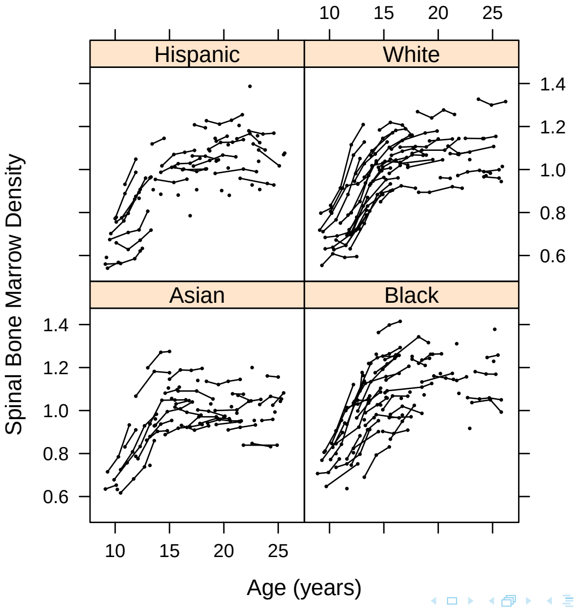
$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

Linear in $\beta$ given $\lambda$
Learn $\lambda$ and $J$

# Kernel Regression Example



# Hierarchical Models - Spinal Bone Density



# Generic Linear Model

Generic Model in Matrix Notation is

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

# Generic Linear Model

Generic Model in Matrix Notation is

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- $\mathbf{Y}$ $(n \times 1)$ vector of response (observe)
- $X$ $(n \times p)$ design matrix (observe)
- $\boldsymbol{\beta}$ $(p \times 1)$ vector of coefficients (unknown)
- $\boldsymbol{\epsilon}$ $(n \times 1)$ vector of "errors" (unobservable)

# Generic Linear Model

Generic Model in Matrix Notation is

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- $\mathbf{Y}$ $(n \times 1)$ vector of response (observe)
- $X$ $(n \times p)$ design matrix (observe)
- $\boldsymbol{\beta}$ $(p \times 1)$ vector of coefficients (unknown)
- $\boldsymbol{\epsilon}$ $(n \times 1)$ vector of "errors" (unobservable)

Goals:

# Generic Linear Model

Generic Model in Matrix Notation is

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- $\mathbf{Y}$ $(n \times 1)$ vector of response (observe)
- $X$ $(n \times p)$ design matrix (observe)
- $\boldsymbol{\beta}$ $(p \times 1)$ vector of coefficients (unknown)
- $\boldsymbol{\epsilon}$ $(n \times 1)$ vector of "errors" (unobservable)

Goals:

- What goes into $\mathbf{X}$? (model building and model selection)

# Generic Linear Model

Generic Model in Matrix Notation is

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- $\mathbf{Y}$ $(n \times 1)$ vector of response (observe)
- $X$ $(n \times p)$ design matrix (observe)
- $\boldsymbol{\beta}$ $(p \times 1)$ vector of coefficients (unknown)
- $\boldsymbol{\epsilon}$ $(n \times 1)$ vector of "errors" (unobservable)

Goals:

- What goes into $\mathbf{X}$? (model building and model selection)
- What if several models are equally good? (model averaging)

# Generic Linear Model

Generic Model in Matrix Notation is

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- $\mathbf{Y}$ $(n \times 1)$ vector of response (observe)
- $X$ $(n \times p)$ design matrix (observe)
- $\boldsymbol{\beta}$ $(p \times 1)$ vector of coefficients (unknown)
- $\boldsymbol{\epsilon}$ $(n \times 1)$ vector of "errors" (unobservable)

Goals:

- What goes into $\mathbf{X}$? (model building and model selection)
- What if several models are equally good? (model averaging)
- What about the future? (Prediction)

# Generic Linear Model

Generic Model in Matrix Notation is

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- $\mathbf{Y}$ $(n \times 1)$ vector of response (observe)
- $X$ $(n \times p)$ design matrix (observe)
- $\boldsymbol{\beta}$ $(p \times 1)$ vector of coefficients (unknown)
- $\boldsymbol{\epsilon}$ $(n \times 1)$ vector of "errors" (unobservable)

Goals:

- What goes into $\mathbf{X}$? (model building and model selection)
- What if several models are equally good? (model averaging)
- What about the future? (Prediction)
- uncertainty quantification - assumptions about $\boldsymbol{\epsilon}$

# Generic Linear Model

Generic Model in Matrix Notation is

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

- $\mathbf{Y}$ $(n \times 1)$ vector of response (observe)
- $X$ $(n \times p)$ design matrix (observe)
- $\boldsymbol{\beta}$ $(p \times 1)$ vector of coefficients (unknown)
- $\boldsymbol{\epsilon}$ $(n \times 1)$ vector of "errors" (unobservable)

Goals:

- What goes into $\mathbf{X}$? (model building and model selection)
- What if several models are equally good? (model averaging)
- What about the future? (Prediction)
- uncertainty quantification - assumptions about $\boldsymbol{\epsilon}$

*All models are wrong, but some may be useful* (George Box)

# Ordinary Least Squares

Goal: Find the best fitting "line" or "hyper-plane" that minimizes

$$\sum_i (Y_i - \mathbf{x}_i^T \beta)^2 = (\mathbf{Y} - \mathbf{X}\beta)^T (\mathbf{Y} - \mathbf{X}\beta) = \|\mathbf{Y} - \mathbf{X}\beta\|^2$$

# Ordinary Least Squares

Goal: Find the best fitting "line" or "hyper-plane" that minimizes

$$\sum_i (Y_i - \mathbf{x}_i^T \beta)^2 = (\mathbf{Y} - \mathbf{X}\beta)^T (\mathbf{Y} - \mathbf{X}\beta) = \|\mathbf{Y} - \mathbf{X}\beta\|^2$$

- Optimization problem

# Ordinary Least Squares

Goal: Find the best fitting "line" or "hyper-plane" that minimizes

$$\sum_i (Y_i - \mathbf{x}_i^T \beta)^2 = (\mathbf{Y} - \mathbf{X}\beta)^T (\mathbf{Y} - \mathbf{X}\beta) = \|\mathbf{Y} - \mathbf{X}\beta\|^2$$

- Optimization problem
- May over-fit $\Rightarrow$ add other criteria that provide a penalty "Penalized Least Squares"

# Ordinary Least Squares

Goal: Find the best fitting "line" or "hyper-plane" that minimizes

$$\sum_i (Y_i - \mathbf{x}_i^T \beta)^2 = (\mathbf{Y} - \mathbf{X}\beta)^T (\mathbf{Y} - \mathbf{X}\beta) = \|\mathbf{Y} - \mathbf{X}\beta\|^2$$

- Optimization problem
- May over-fit $\Rightarrow$ add other criteria that provide a penalty "Penalized Least Squares"
- Robustness to extreme points $\Rightarrow$ replace quadratic loss with other functions

# Ordinary Least Squares

Goal: Find the best fitting "line" or "hyper-plane" that minimizes

$$\sum_i (Y_i - \mathbf{x}_i^T \beta)^2 = (\mathbf{Y} - \mathbf{X}\beta)^T(\mathbf{Y} - \mathbf{X}\beta) = \|\mathbf{Y} - \mathbf{X}\beta\|^2$$

- Optimization problem
- May over-fit $\Rightarrow$ add other criteria that provide a penalty "Penalized Least Squares"
- Robustness to extreme points $\Rightarrow$ replace quadratic loss with other functions
- no notion of uncertainty of estimates

# Ordinary Least Squares

Goal: Find the best fitting "line" or "hyper-plane" that minimizes

$$\sum_i (Y_i - \mathbf{x}_i^T \beta)^2 = (\mathbf{Y} - \mathbf{X}\beta)^T (\mathbf{Y} - \mathbf{X}\beta) = \|\mathbf{Y} - \mathbf{X}\beta\|^2$$

- Optimization problem
- May over-fit $\Rightarrow$ add other criteria that provide a penalty "Penalized Least Squares"
- Robustness to extreme points $\Rightarrow$ replace quadratic loss with other functions
- no notion of uncertainty of estimates
- no structure of problem (repeated measures on individual, randomization restrictions, etc)

Need Distribution Assumptions of $Y$ (or $\epsilon$) for testing and uncertainty measures

# Ordinary Least Squares

Goal: Find the best fitting "line" or "hyper-plane" that minimizes

$$\sum_i (Y_i - \mathbf{x}_i^T \beta)^2 = (\mathbf{Y} - \mathbf{X}\beta)^T(\mathbf{Y} - \mathbf{X}\beta) = \|\mathbf{Y} - \mathbf{X}\beta\|^2$$

- Optimization problem
- May over-fit $\Rightarrow$ add other criteria that provide a penalty "Penalized Least Squares"
- Robustness to extreme points $\Rightarrow$ replace quadratic loss with other functions
- no notion of uncertainty of estimates
- no structure of problem (repeated measures on individual, randomization restrictions, etc)

Need Distribution Assumptions of $Y$ (or $\epsilon$) for testing and uncertainty measures $\Rightarrow$ Likelihood and Bayesian inference

# Philosophy

- for many problems frequentist and Bayesian methods will give similar answers (more a matter of taste in interpretation)
- For small problems, Bayesian methods allow us to incorporate prior information which provides better calibrated answers
- for problems with complex designs and/or missing data Bayesian methods are often easier to implement (do not need to rely on asymptotics)
- For problems involving hypothesis testing or model selection frequentists and Bayesian methods can be strikingly different.
- Frequentist methods often faster (particularly with "big data") so great for exploratory analysis and for building a "data-sense"
- Bayesian methods sit on top of Frequentist Likelihood

Important to understand advantages and problems of each perspective!