

# Ch 7.2-7.4: Step Functions, Basis Functions, Start Splines

## Lecture 22 - CMSE 381

Prof. Mengsen Zhang

Michigan State University

::

Dept of Computational Mathematics, Science & Engineering

Mon, Oct 27, 2025

## **Last time:**

- 7.1 Polynomial regression
- 7.2 Step functions

## **This lecture:**

- 7.2 Step functions
- 7.3 Basis functions
- 7.4 Regression Splines (Finish next lecture)

## **Announcements:**

- HW #6 Due Sunday
- Exam 2 graded. What worked?  
[PollEv](#)

# Section 1

Last time

# Polynomial regression

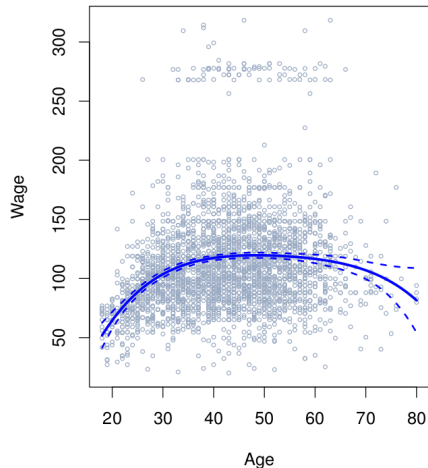
Replace linear model

$$y_i = \beta_0 + \beta_1 x_1 + \varepsilon_i$$

with

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_i^2 + \cdots + \beta_d x_i^d + \varepsilon_i$$

## Example with wage data



$$-184.1542 + 21.24552 * age + -0.56386 * age^2 + 0.00681 * age^3 + -3e - 05 * age^4$$

# Step functions

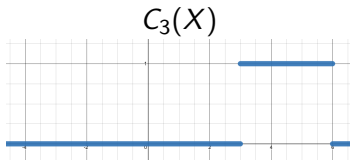
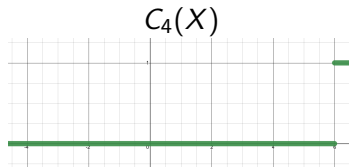
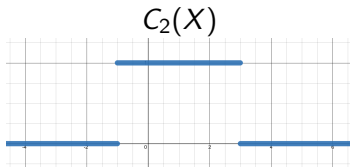
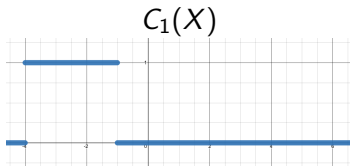
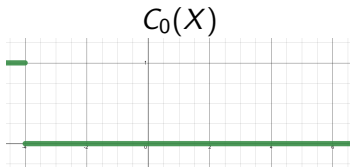
- $I(X < c)$
- $I(c_1 \leq X < c_2)$
- $I(c \leq X)$

$$\begin{aligned}C_0(X) &= I(X < c_1), \\C_1(X) &= I(c_1 \leq X < c_2), \\C_2(X) &= I(c_2 \leq X < c_3), \\&\vdots \\C_{K-1}(X) &= I(c_{K-1} \leq X < c_K), \\C_K(X) &= I(c_K \leq X),\end{aligned}$$

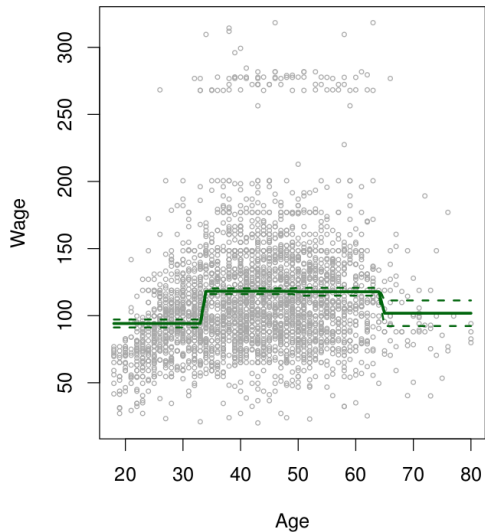
Learned model:

$$y_i = \beta_0 + \beta_1 C_1(x_i) + \beta_2 C_2(x_i) + \cdots + \beta_K C_K(x_i) + \varepsilon_i$$

Example: Cut points at -4, -1, 3, 6



# Step function example





# What will you learn today?

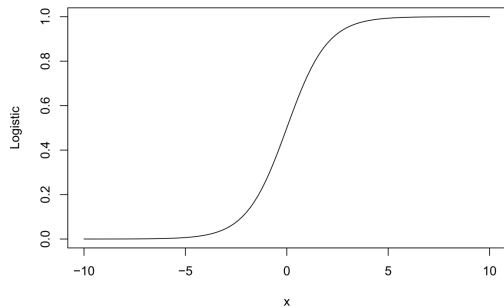
- How to fit step function models for classification problems?
  - ▶ You should also be able to implement them in Python.
- What are basis functions?
  - ▶ You should be able to articulate what the basis functions  $b_i$  are for different models that we have covered.
  - ▶ Examples include polynomial, step functions, and cubic splines.
- What is the purpose of using basis functions?
  - ▶ How do they influence model flexibility?
  - ▶ How does this purpose manifest in different models, such as regression splines?
- How to define cubic splines mathematically?
  - ▶ You should be able to write down the equations for the model between knots.
  - ▶ And the equations for constraints at the knots.
- How to calculate the cubic spline coefficients by hand by applying the above mathematical definitions?

## Section 2

### Classification versions

# Remember logistic regression?

$$y = \frac{e^x}{1 + e^x}$$



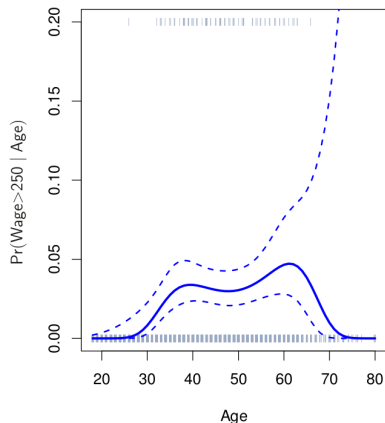
$$p(X) = \frac{e^{\beta_0 + \beta_1 X}}{1 + e^{\beta_0 + \beta_1 X}}$$

**Multiple features:**

$$p(X) = \frac{e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}$$

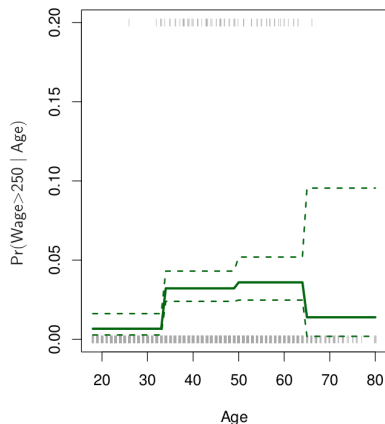
# Classification version: Polynomial regression

$$\Pr(y_i > 250 \mid x_i) = \frac{\exp(\beta_0 + \beta_1 x_i + \cdots + \beta_d x_i^d)}{1 + \exp(\beta_0 + \beta_1 x_i + \cdots + \beta_d x_i^d)}$$

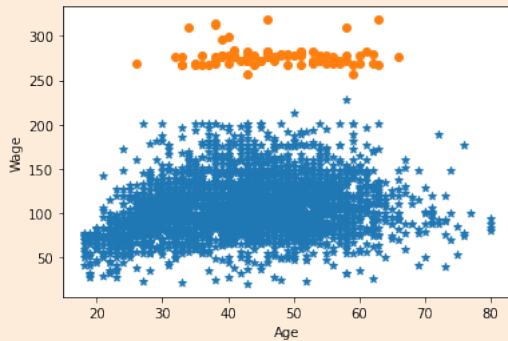


# Classification version: Step functions

$$\Pr(y_i > 250 \mid x_i) = \frac{\exp(\beta_0 + \beta_1 C_1(x_i) + \beta_2 C_2(x_i) + \cdots + \beta_K C_K(x_i))}{1 + \exp(\beta_0 + \beta_1 C_1(x_i) + \beta_2 C_2(x_i) + \cdots + \beta_K C_K(x_i))}$$



## Coding bit: classification version



## A few more comments on step functions

- Gives the chance to break up the domain, avoid forcing global structure
- Need to make decisions about the  $c_i$ .  
A bit arbitrary unless your data has natural breakpoints.
- Popular in biostats and epidemiology

## Section 3

### Basis functions



# Basis Functions Setup

Polynomial and piecewise-constant regression models are special cases of a *basis function* approach.

$$y_i = \beta_0 + \beta_1 b_1(x_i) + \beta_2 b_2(x_i) + \cdots + \beta_K b_K(x_i) + \varepsilon_i$$

## Section 4

### Regression Splines

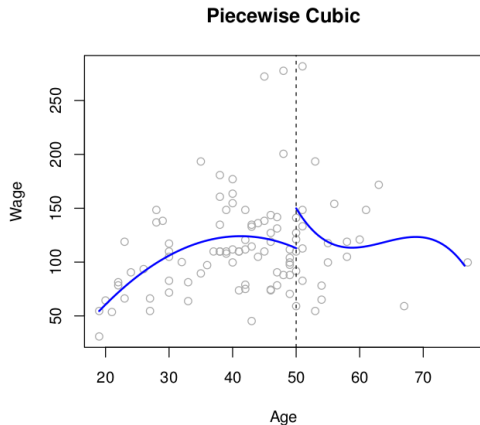
# Piecewise polynomials

- Fit a polynomial regression

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_d x_i^d + \varepsilon_i$$

- Let the  $\beta_i$ 's be different at different locations of the range.

# Example of piecewise polynomial

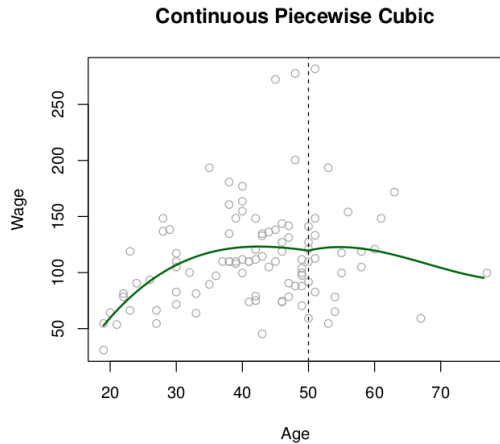


Example:

$$y_i = \begin{cases} \beta_{01} + \beta_{11}x_i + \beta_{21}x_i^2 + \beta_{31}x_i^3 + \epsilon_i & \text{if } x_i < c \\ \beta_{02} + \beta_{12}x_i + \beta_{22}x_i^2 + \beta_{32}x_i^3 + \epsilon_i & \text{if } x_i \geq c. \end{cases}$$

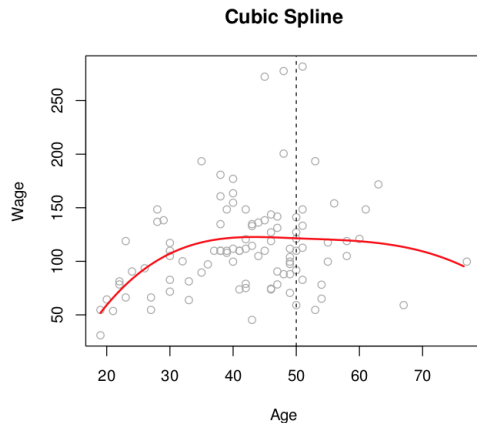
# The fix

- Fit piecewise polynomial
- Require continuity at knots



# The better fix: Cubic splines

- Fit piecewise polynomial
- Require continuity at knots
- Require the first and second derivatives to be continuous at knots



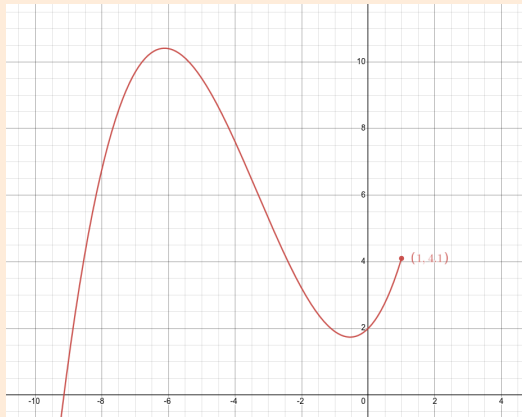
Test your understanding: [PollEv](#)

# Example

We have the following piecewise cubic polynomial:

$$f(x) = \begin{cases} 2 + x + x^2 + 0.1x^3 & x \leq 1 \\ b_0 + b_1x + b_2x^2 - x^3 & x > 1 \end{cases}$$

What are  $b_0$ ,  $b_1$ , and  $b_2$  to make this a cubic spline?



Check your answers: [www.desmos.com/calculator/kbm0zivqco](https://www.desmos.com/calculator/kbm0zivqco)

## More space for work

$$f(x) = \begin{cases} 2 + x + x^2 + 0.1x^3 & x \leq 1 \\ b_0 + b_1x + b_2x^2 - x^3 & x > 1 \end{cases}$$



# Next time

21	F	10/24	Polynomial & Step Functions	7.1-7.2	HW #5 Due Sun 10/26
22	M	10/27	Step Functions; Basis functions; Start Splines	7.2-7.4	
23	W	10/29	Regression Splines	7.4	
24	F	10/31	Decision Trees	8.1	HW #6 Due Sun 11/2
25	M	11/3	Random Forests	8.2.1, 8.2.2	
26	W	11/5	Maximal Margin Classifier	9.1	
27	F	11/7	SVC	9.2	HW #7 Due Sun 11/9
28	M	11/10	SVM	9.3, 9.4	
29	W	11/12	Single Layer NN	10.1	
30	F	11/13	Multi Layer NN	10.2	HW #8 Due Sun 11/16
31	M	11/17	CNN	10.3	
32	W	11/19	Unsupervised learning / clustering	12.1, 12.4	
33	F	11/21	<b>Review</b>		HW #9 Due Sun 11/23
	M	11/24	<b>Midterm #3</b>		
	W	11/26	Virtual: Project Office Hours		
	F	11/28	Thanksgiving		
	M	12/1	Virtual: Project Office Hours		
	W	12/3	Virtual: Project Office Hours		
	F	12/5			<b>Project Due</b>
	M	12/8			
	W	12/10			
	F	12/12	<b>No final exam</b>		<b>Honors Project Due</b>