

## Chp. 7: Beyond Linearity Part II

## Last Time

- ▶ Polynomial Regression
- ▶ Step functions
- ▶ Regression splines
- ▶ Smoothing splines

# Generalized Additive Models

Goal: flexibly predict  $Y$  on the basis of **several** predictors.

GAMS allow non-linear functions of each predictor while maintaining *additivity* (calculate a separate  $f_j$  for each  $X_j$  and then add together all of their contributions).

# GAMs for Regression

$$y_i = \beta_0 + \sum_{j=1}^p f_j(x_{ij}) + \epsilon_i$$

$$= \beta_0 + f_1(x_{i1}) + f_2(x_{i2}) + \dots + f_p(x_{ip}) + \epsilon_i$$

## GAMs for Regression

We can 'mix & match' methods we discussed before (e.g. splines, local regression, polynomial regression) to provide different non-linear fits for each variable.

Consider the following for the Wage dataset, where 'year' and 'age' are quantitative variables and 'education' is qualitative with 5 levels (<HS, HS, <Coll, Coll, >Coll):

$$\text{wage} = \beta_0 + f_1(\text{year}) + f_2(\text{age}) + f_3(\text{education}) + \epsilon_i$$

# GAMs for Regression

Remember, with one predictor:

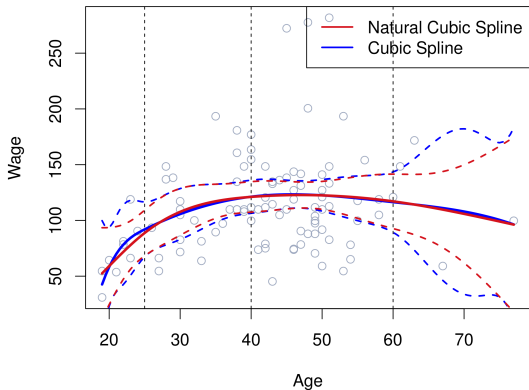


Figure 1: Fig. 7.4

# GAMs for Regression

GAM with natural splines for  $f_1$  and  $f_2$  and a step function for  $f_3$  (ISL Fig. 7.11):

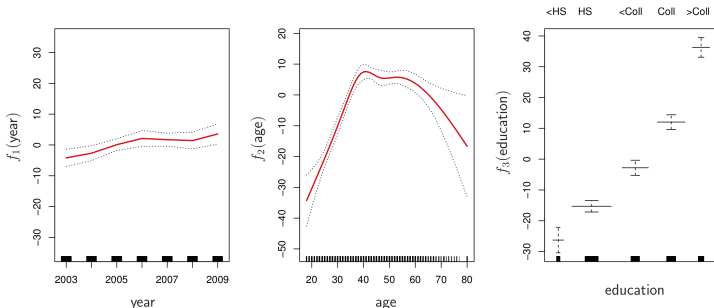


Figure 2: Fig 7.11

Because natural splines are constructed using basis functions, this model is just a big regression onto the spline basis variables and dummy variables. We can fit it with least squares.

# GAMs for Regression

GAM with smoothing splines for  $f_1$  and  $f_2$  and a step function for  $f_3$  (ISL Fig. 7.12):

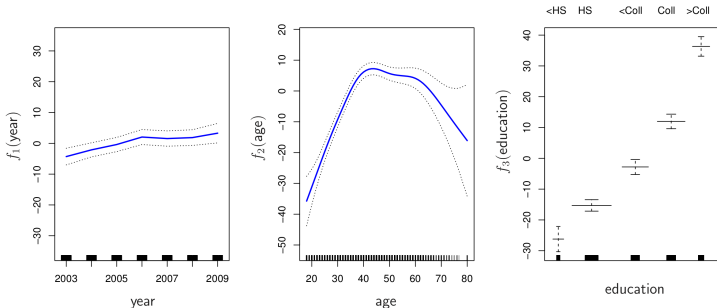


Figure 3: fig7.12

Least squares cannot be used for smoothing splines. Instead, we can use backfitting.



## GAMs for Classification

$$\log \left( \frac{p(X)}{1 - p(X)} \right) = \beta_0 + f_1(X_1) + f_2(X_2) + \dots + f_p(X_p)$$

# GAMs for Classification

Consider the Wage example:

$$\log \left( \frac{p(X)}{1 - p(X)} \right) = \beta_0 + \beta_1 \times \text{year} + f_2(\text{age}) + f_3(\text{education})$$

where  $p(X) = \Pr(\text{wage} > 250 | \text{year}, \text{age}, \text{education})$ .

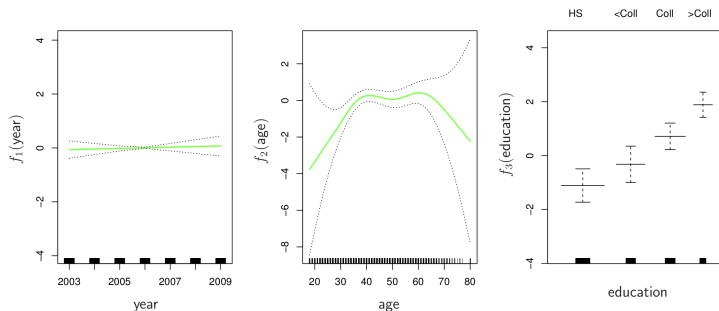


Figure 4: fig7.14

# Considerations

- ▶ Fit a different non-linear  $f_j$  to each  $X_j$  automatically
- ▶ Potential for more accurate predictions with more flexibility
- ▶ Can examine the effect of each  $X_j$  on  $Y$  individually, holding other variables fixed.
- ▶ Model is restricted to be additive (need to manually add interaction terms)