

# STATISTICS 538, Lecture #12

## From lines to curves

December 1, 2010

GLM: linear predictor is linear in **parameters**, not necessarily linear in **predictors**



E.g.,  $Y$  indicates death,  $X$  indicates dose of nasty chemical. First thought

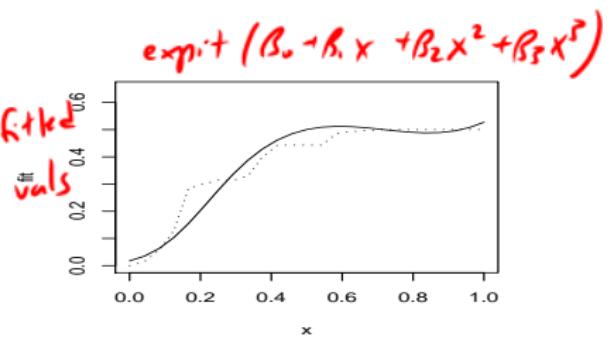
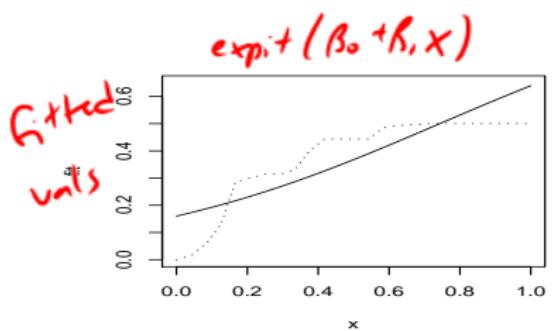
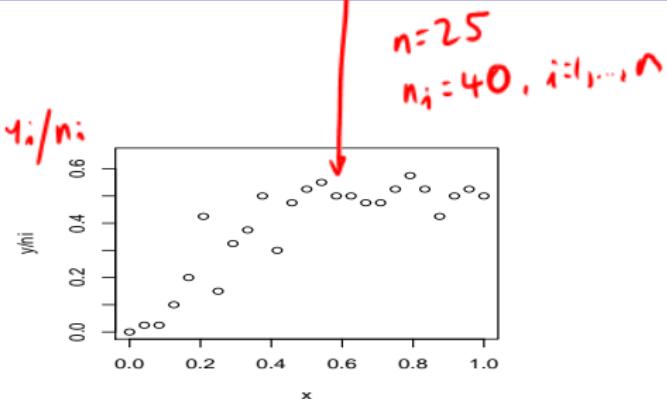
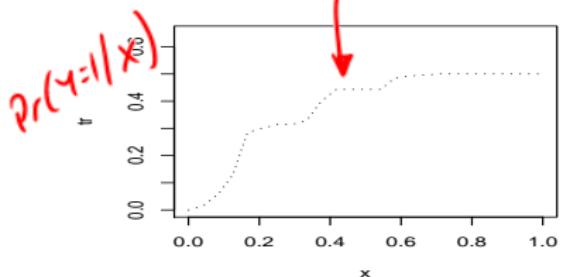
$$Pr(Y = 1|X) = \text{expit}(\beta_0 + \beta_1 X)$$

No good? Change link function? Or expand linear predictor from  $\eta = \beta_0 + \beta_1 X$  to something more complex (but still linear in parameters).

first thought

logit  $\rightarrow \text{expit}(\beta_0 + \beta_1 X)$   
probit  $\rightarrow \Phi(\beta_0 + \beta_1 X)$  .  $\eta = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 + \dots + \beta_j X^j$   
t standard normal cdf

Consider this true relationship spawning these data, and two fits



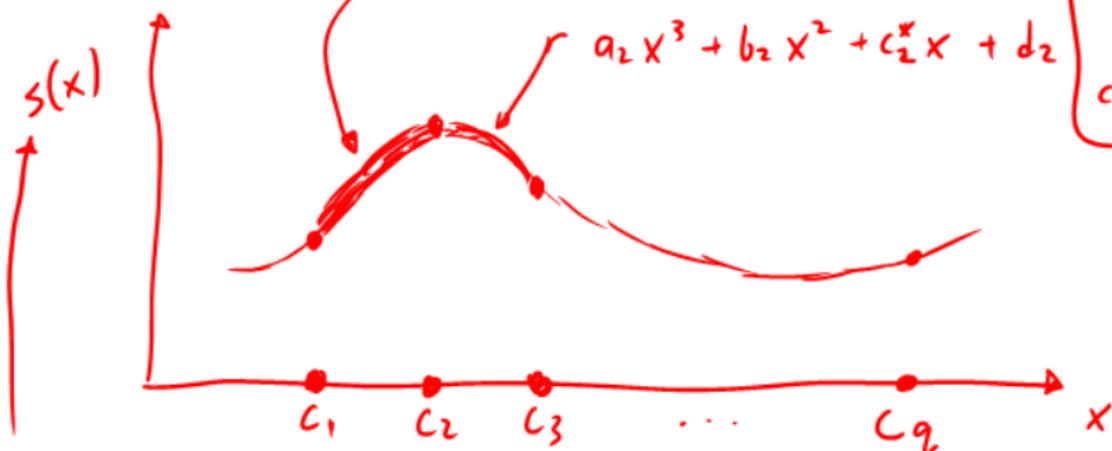
# Alternative to polynomials? Splines!

**Cubic splines:** Choose **knots**  $c_1, \dots, c_q$ . Consider piecewise cubic functions (between knots) with smooth joins (at knots)

$$a_1 x^3 + b_1 x^2 + c_1 x + d_1$$

$$a_2 x^3 + b_2 x^2 + c_2 x + d_2$$

$s(), s'$   
and  
 $s''()$   
continuous



( $q+1$ ) cubic polynomials  $\rightarrow (q+1) \times 4$  parameters  
BUT -  $3q$  constraints  $\rightarrow q+4$  parameters

Splines have 'basis function' representations, i.e., linear in parameters

For instance

$$s(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \sum_{j=1}^q \beta_{j+3} \{ (x - c_j)_+ \}^3$$

Note that  $s(x)$  is indeed

a piecewise cubic function  
with smooth joins,  
described by  $q+4$   
parameters

$$\{ (x - c_j)_+ \}^3 = \begin{cases} (x - c_j)^3 & \text{if } x > c_j \\ 0 & \text{if } x \leq c_j \end{cases}$$

Knots are user-chosen -  
possible default values?

$\left( \frac{1}{q+1}, \frac{2}{q+1}, \dots, \frac{q}{q+1} \right)$  quantiles of the  
 $x$  values



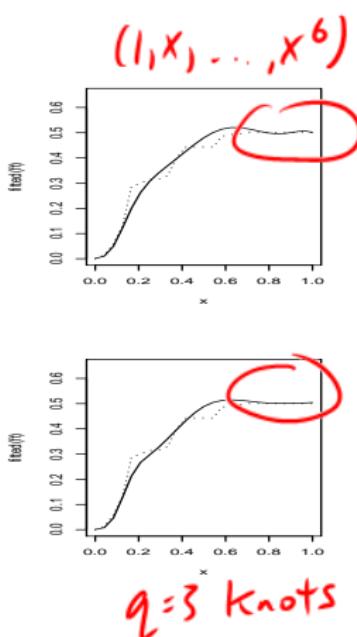
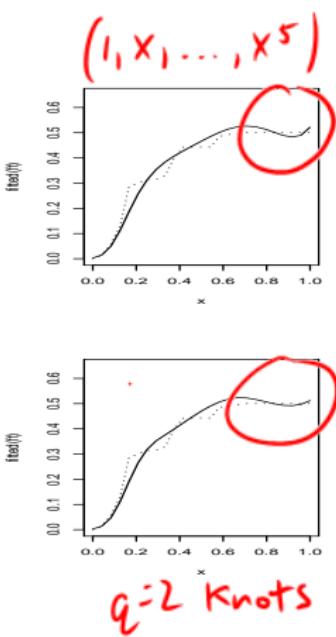
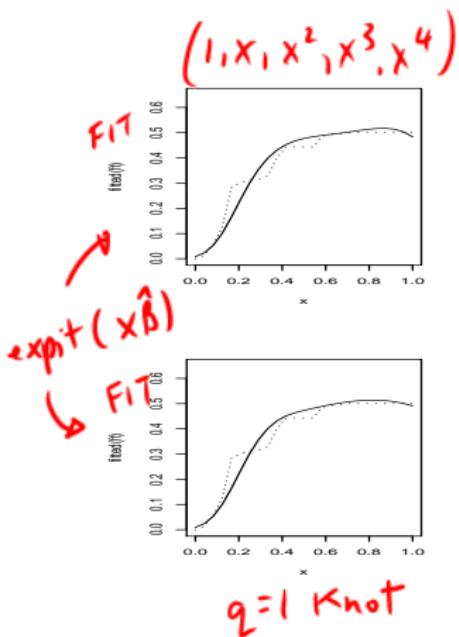
So 'cheap homemade' spline fitting...

```
xmat <- cbind(x,x^2,x^3)
for (j in 1:q) {
  xmat <- cbind(xmat, pmax(x - quantile(x,j/(q+1)),0)^3)
}
ft <- glm(cbind(y,ni-y) ~ xmat, family=binomial)
plot(x, fitted(ft)) ...
```

$$\begin{pmatrix} s(x_1) \\ \vdots \\ s(x_n) \end{pmatrix} = \underbrace{\begin{pmatrix} 1, X_{\text{mat}} \end{pmatrix}}_{n \times (q+4)} \underbrace{\beta}_{(q+4) \times 1}$$

choice of  $c_j$

Add one, two, three parameters beyond the cubic model:  
polynomials (top) versus splines (bottom)



## Further issues

Model selection: how many knots?

Usual tools available. E.g. in our example

Deviance GOF :  $(1, x)$  flunks,  $(1, x, x^2)$  borderline

$(1, x, x^2, x^3)$  or splines with  $q=1, \dots, 5$  pass

AIC : splines with  $q=2$  wins

More refined splines: natural cubic splines

take cubic spline - add additional constraints

$s(x)$  linear to the left of  $c_1$  and to the right of  $c_q$

4 more constraints

$$s''(c_1) = s'''(c_1) = s''(c_q) = s'''(c_q) = 0$$

now  $q$  knots  $\Rightarrow q$  parameters

## Further issues, continued

Lots of curve-fitting packages - don't need to do-it-yourself

```
> library(splines)  
> ft <- glm(cbind(y,ni-y) ~ ns(x,df=4), family=binomial)
```

$$s(x) = \beta_0 + \sum_{j=1}^4 \beta_j s_j(x)$$

↑  
basis functions

natural cubic spline

↑  
nbs with knots at  $\left(\frac{0}{4}, \frac{1}{4}, \frac{2}{4}, \frac{3}{4}, \frac{4}{4}\right)$  quantiles of x values