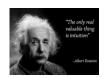
#### **Piecewise Linear Models**



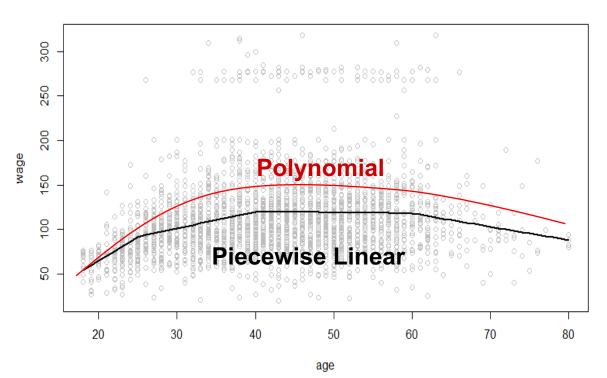






#### **Piecewise Linear: Intuition**

- Piecewise linear models are an attractive alternative to polynomials
- Rather than a curve we fit connected linear regression models
- Piecewise linear models retain the simplicity of linear models and are easier to interpret.
- But because the slope of the regression can change at any selected point, it can provide better training fit with less overfitting.





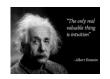
#### Piecewise Linear Example Wage{ISLR}

- Say, you want to predict wage as a function of age
- But you notice that the wage patterns change at ages 25, 40 and 60
- So, we want to fit a **piecewise linear** function that give us **4** different regression **slopes** between these particular **"knots"**
- We do this by creating interaction dummy variables as follows:

```
lm(wage \sim age + I((age-25)*(age>25)) + I((age-40)*(age>40)) + I((age-60)*(age>60)), data = Wage) \rightarrow
```

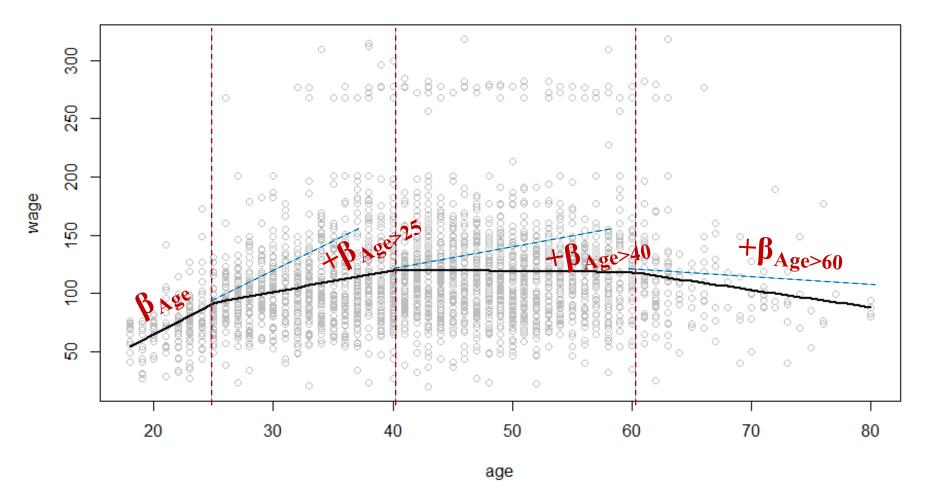
- > The coefficient for age gives the effect of age up to age 25
- ➤ The function *I((age-25)\*(age>25))* is an **interaction** variable that takes a value of **0** (when *age*<25) (i.e., does **not change** the **slope** of the variable *age*
- ➤ But if *age*>25 then it multiplies the age beyond 25 (*age*-25) by 1 (because *age*>25)
- It's coefficient provides the increment (or reduction) in slope
- ➤ Same thing for (age>40) and (age>60)







## **Graphical Illustration**

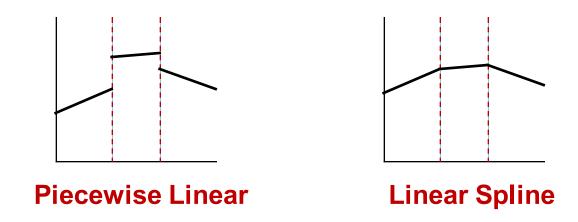


Note in this example (see R script) that  $\beta_{Age}$  is (+) but the remaining  $\beta$ 's are (-)  $\rightarrow$  the **effect of age** goes down **diminishes** at ages 25, 40 and 60.



### Piecewise Linear vs. Linear Spline

 The only difference between piecewise linear and a linear spline is that the former does not connect the regression lines at the knots (i.e., the lines shift), whereas the latter does connect at the knots



However, as you saw in the previous example, we can force a
piecewise linear model to have connected lines at the know (i.e., a
linear spline), simply by subtracting the knot value from the x values
after the knot (e.g., age-25). This is equivalent to shifting the Y axis to
towards the right to the knot.







The coefficient of x provides the slope of the regression line for x <= 25; the next coefficient (e.g., for x > 25) provides the "change" in slope after the x > 25 knot; and so on





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