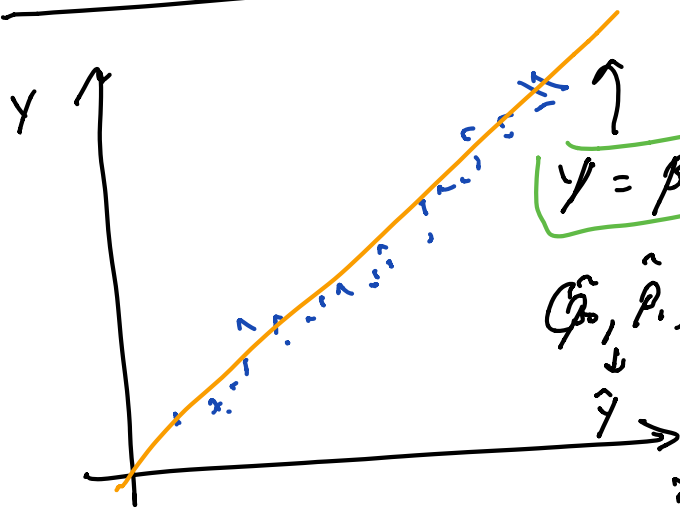


Regression Trees

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \epsilon$$



$$y = \beta_0 + \beta_1 x + \epsilon$$

fit using
OLS or
MLE

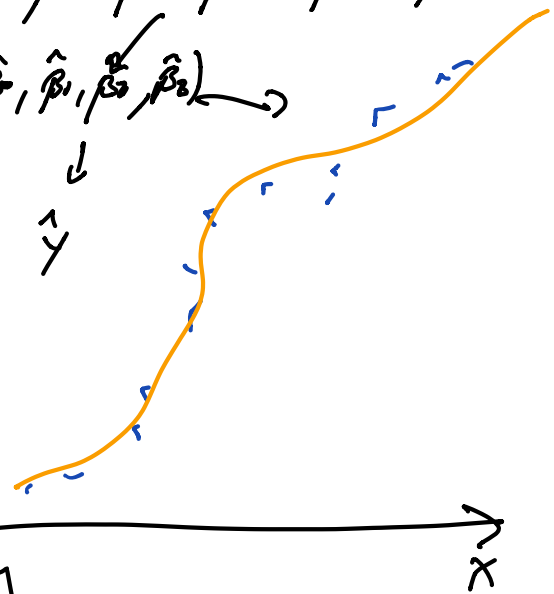
$(\hat{\beta}_0, \hat{\beta}_1)$

\hat{y}

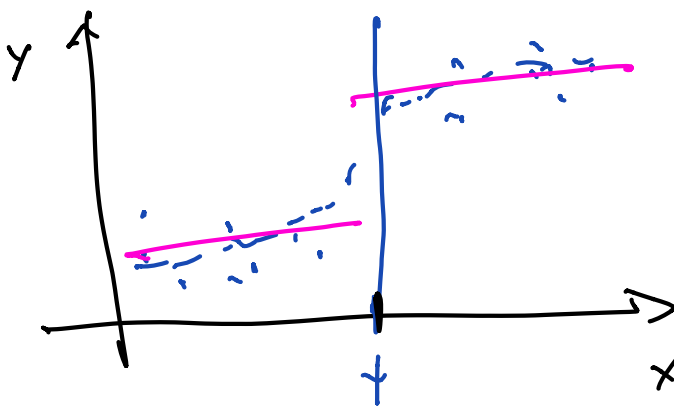
$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \epsilon$$

$(\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3)$

\hat{y}

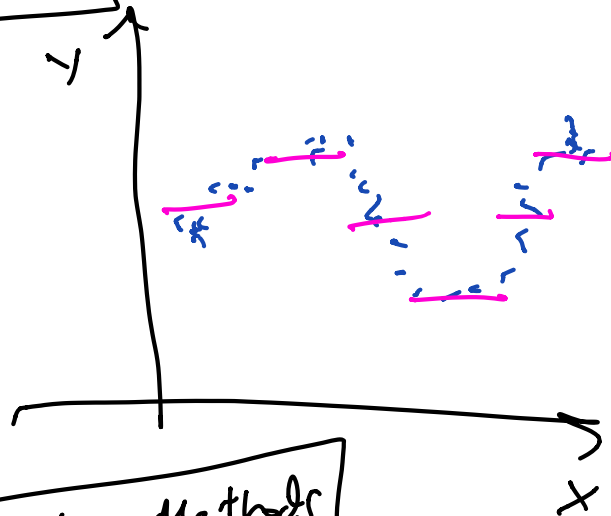


Parametric Methods



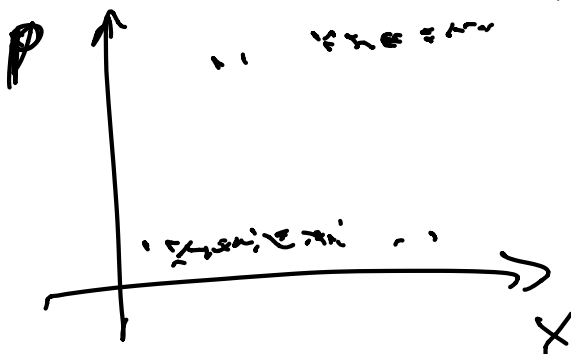
threshold

Nonparametric Methods



- We're not assuming a functional form a priori.

Logistic Reg.

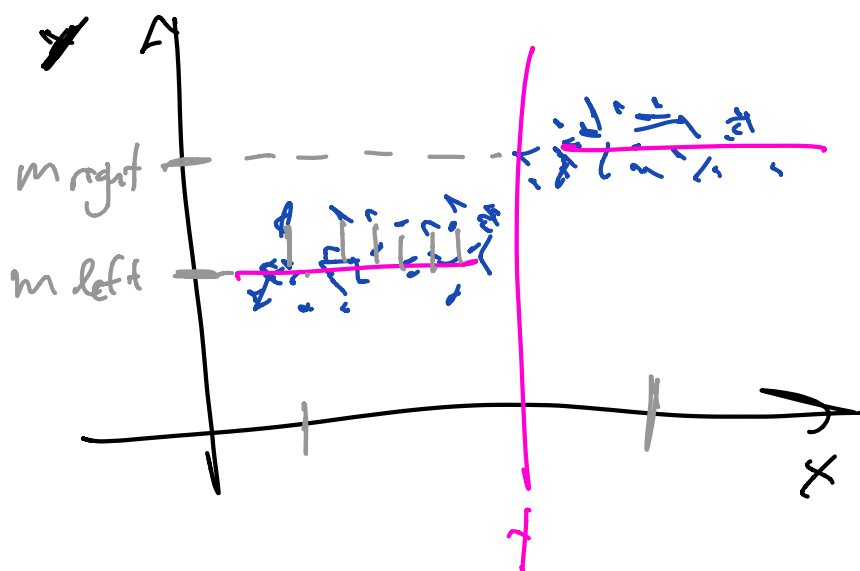


$$\lambda = \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x + \epsilon$$

$$(\hat{\beta}_0, \hat{\beta}_1)$$

$$\hat{y}$$

Goal is to find a threshold s.t.
 $\hat{y}_{left} = m_{left}$, $\hat{y}_{right} = m_{right}$ are
 as different as possible.



At a given step k of this partitioning
 algorithm

$$m_k = \frac{\sum_{i \in \text{group } k} y_i}{N_k}$$

mean of group k

Further,
$$S^2_k = \sum_{i \in \text{Group } k} (y_i - m_k)^2$$
 (Sum of Squares of group k).

Simplest
 case

$$S^2_k = S^2_{k \text{ left}} + S^2_{k \text{ right}}$$

(only holds if x doesn't explain
 any variability)



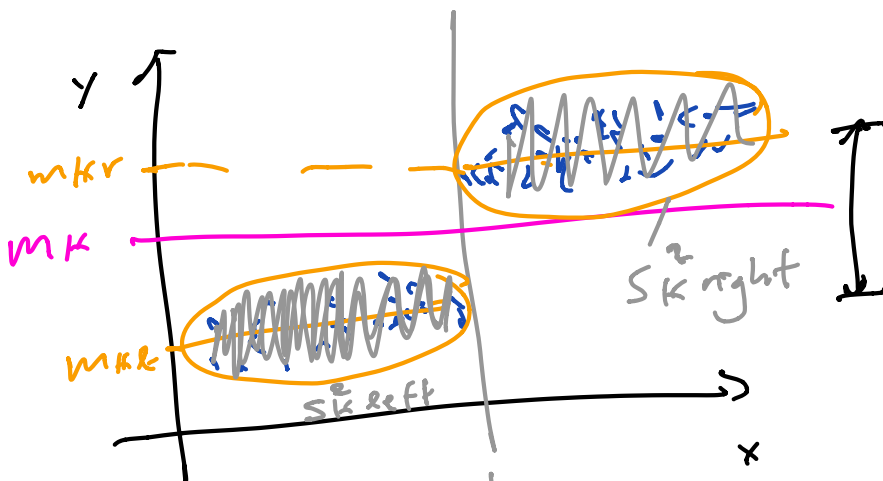
in y).

In general some x 's can explain some variability in y . In this case we'll prove it in the problem session).

$$\sigma_K^2 = \underbrace{\sigma_{K\text{left}}^2 + \sigma_{K\text{right}}^2}_{\text{unexplained}} + \underbrace{\frac{N_{K\text{left}} \cdot N_{K\text{right}}}{N_K} (m_{K\text{left}} - m_{K\text{right}})^2}_{\text{Explained}}$$

→ Our model for the data is pretty much just $m_{K\text{left}}$ and $m_{K\text{right}}$ + threshold which defines $N_{K\text{left}}$ $N_{K\text{right}}$.
Computed wrt m_K .

Thus, your threshold value doesn't matter.



$$\sigma_{K\text{left}}^2 = \frac{\sum_{i \in \text{left}} (y_i - m_{K\text{left}})^2}{N_{K\text{left}}}$$

$$\sigma_{K\text{right}}^2 = \frac{\sum_{i \in \text{right}} (y_i - m_{K\text{right}})^2}{N_{K\text{right}}}$$

$$N_{K\text{left}} + N_{K\text{right}} = N_K$$

$$\sigma_K^2 = \sigma_{K\text{left}}^2 + \sigma_{K\text{right}}^2 + \frac{N_{K\text{left}} N_{K\text{right}}}{N_K} (m_{K\text{left}} - m_{K\text{right}})^2$$

Want to maximize $\frac{N_{Kl} \cdot N_{Kr}}{N_K} (m_{Kl} - m_{Kr})^2$
 (Maximizing Information Gain).

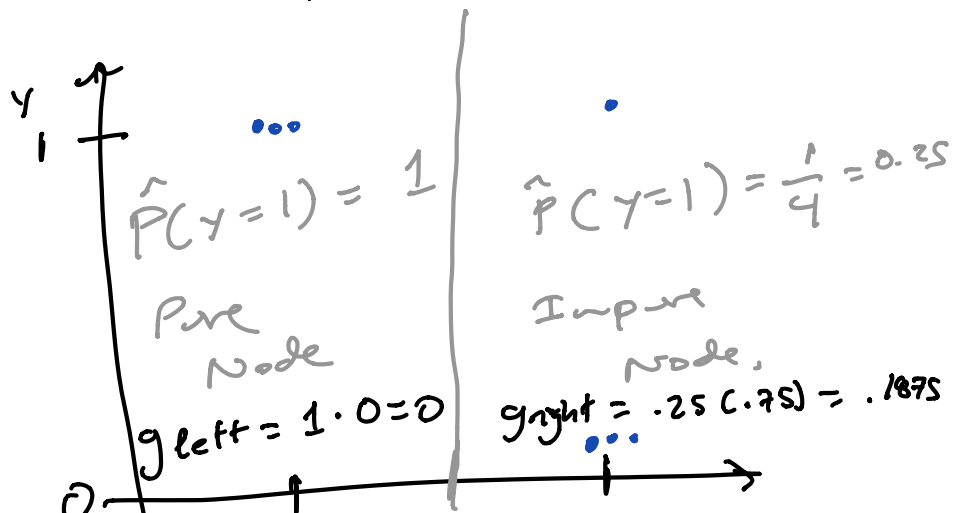
How do we run this regression practically?

- ① Pick a variable
- ② Find a threshold that maximizes

Finally, let's define impurity of a node
 as a measure - A deviation from the
 predicted behavior of the node.
 In our regression case: s_{Kl}^2
 or s_{Kr}^2

• In the classification context, impurity is
 the probability that our prediction is incorrect.

	y	x_1
✓	1	1
✓	0	2
✓	1	1
✓	0	2
✓	1	2
✓	1	1



we usually measure impurity by the Gini Index

$$g = \sum_{i \in K} P(y=i) \cdot (1 - P(y=i))$$

Example:

