

Robust Regression---what we're doing

What LOESS robust regression does:

Assume y_k was originally generated using the following recipe:

With probability p :

$$y_k = \beta_0 + \beta_1 x_k + \beta_2 x_k^2 + N(0, \sigma^2)$$

But otherwise

$$y_k \sim N(\mu, \sigma_{huge}^2)$$

Computational task is to find the Maximum Likelihood $\beta_0, \beta_1, \beta_2, p, \mu$ and σ_{huge}

Mysteriously, the reweighting procedure does this computation for us.

Your first glimpse of two spectacular letters:

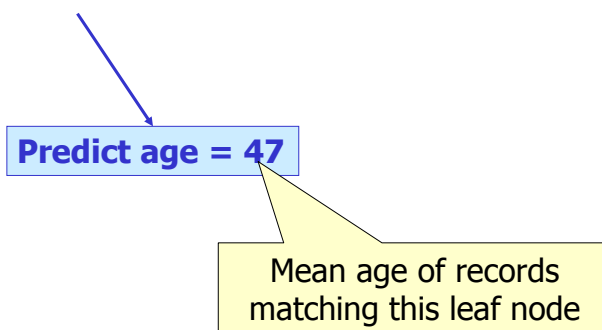
E.M.

Regression Trees

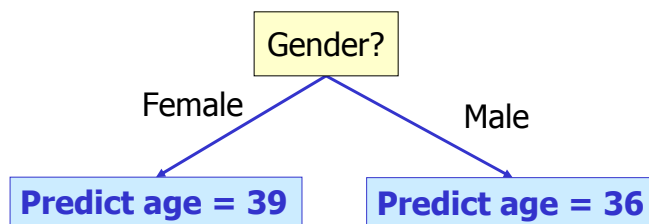
Regression Trees

- “Decision trees for regression”

A regression tree leaf



A one-split regression tree



Choosing the attribute to split on

Gender	Rich?	Num. Children	Num. Beany Babies	Age
Female	No	2	1	38
Male	No	0	0	24
Male	Yes	0	5+	72
:	:	:	:	:

- We can't use information gain.
- What should we use?

Choosing the attribute to split on

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Male	Yes	0	5+	72
:	:	:	:	:

$MSE(Y|X)$ = The expected squared error if we must predict a record's Y value given only knowledge of the record's X value

If we're told $x=j$, the smallest expected error comes from predicting the mean of the Y-values among those records in which $x=j$. Call this mean quantity $\mu_y^{x=j}$

Then...

$$MSE(Y | X) = \frac{1}{R} \sum_{j=1}^{N_X} \sum_{(k \text{ such that } x_k=j)} (y_k - \mu_y^{x=j})^2$$

Choosing the attribute to split on

Gender	Rich?	Num. Children	Num. Beany Babies	Age
Female	N			
Male	N			
Male	Y			
:	:			

Regression tree attribute selection: greedily choose the attribute that minimizes $MSE(Y|X)$
 Guess what we do about real-valued inputs?
 Guess how we prevent overfitting

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Pruning Decision

...property-owner = Yes

Gender?

Do I deserve to live?

Female

Male

Predict age = 39

Predict age = 36

property-owning females = 56712
 Mean age among POFs = 39
 Age std dev among POFs = 12

property-owning males = 55800
 Mean age among POMs = 36
 Age std dev among POMs = 11.5

Use a standard Chi-squared test of the null-hypothesis "these two populations have the same mean" and Bob's your uncle.

Linear Regression Trees

...property-owner = Yes

Gender?

Also known as "Model Trees"

Female

Male

Predict age =
 $26 + 6 * \text{NumChildren} - 2 * \text{YearsEducation}$

Predict age =
 $24 + 7 * \text{NumChildren} - 2.5 * \text{YearsEducation}$

Leaves contain linear functions (trained using linear regression on all records matching that leaf)

Split attribute chosen to minimize MSE of regressed children.

Pruning with a different Chi-squared

Linear Regression Trees

...property-owner = Yes

Gender?

Female

Predict age =

$$26 + 6 * M + 2 * Year$$

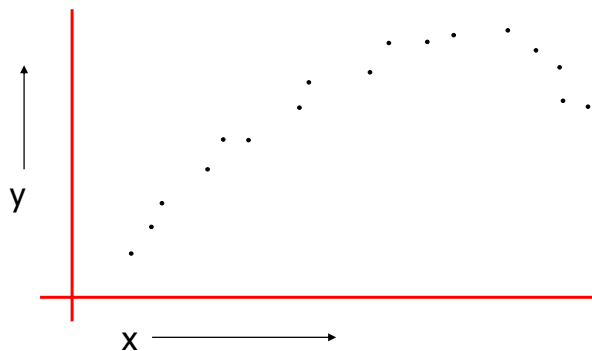
Also known as "M... Trees"

Detail: You typically ignore any categorical attribute that has been tested on higher up in the tree during the regression. But use all untested attributes, and use real-valued attributes even if they've been tested above

Leaves contain linear regression functions (trained on records matching the path to the leaf). Attributes are chosen to minimize the error of the regression. Pruning with a different Chi-squared

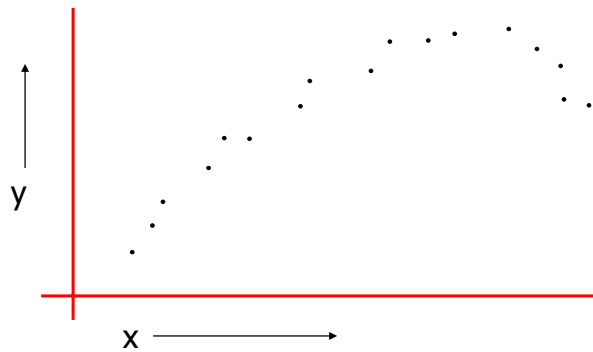
Test your understanding

Assuming **regular** regression trees, can you sketch a graph of the fitted function $y^{est}(x)$ over this diagram?



Test your understanding

Assuming **linear** regression trees, can you sketch a graph of the fitted function $y^{est}(x)$ over this diagram?



Multilinear Interpolation