

# Logic Regression

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## Introduction and Motivation

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$X_1, \dots, X_k$  are 0/1 (False/True) predictors.

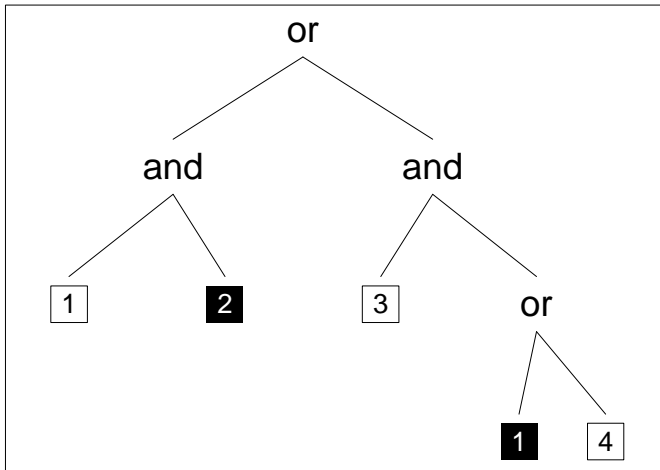
$Y$  is a response variable.

Fit a model  $g(F(Y)) = \beta_0 + \sum_{j=1}^t \beta_j \times L_j$ , where  $L_j$  is a Boolean combination of the covariates, e.g.  $L_j = (X_1 \vee X_2) \wedge X_4^c$ .

Determine the logic terms  $L_j$  and estimate the  $\beta_j$  simultaneously.

# Logic Trees

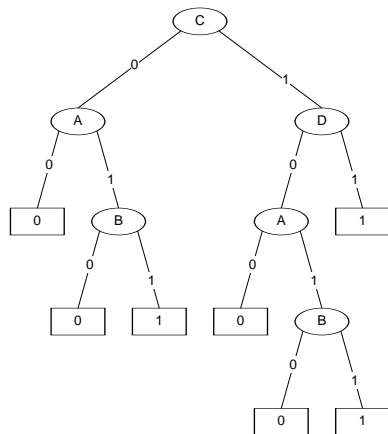
An equivalent representation of  $(X_1 \wedge X_2^c) \vee (X_3 \wedge (X_1^c \vee X_4))$  is the following:



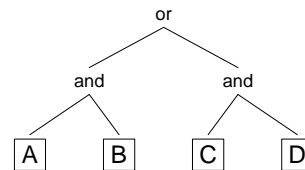
This is a Logic Tree!

## Comparison to Decision Trees

Decision Tree



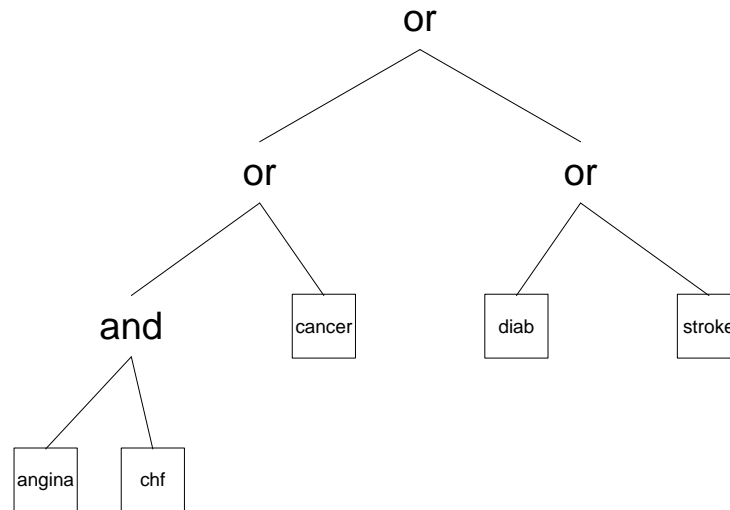
Logic Tree



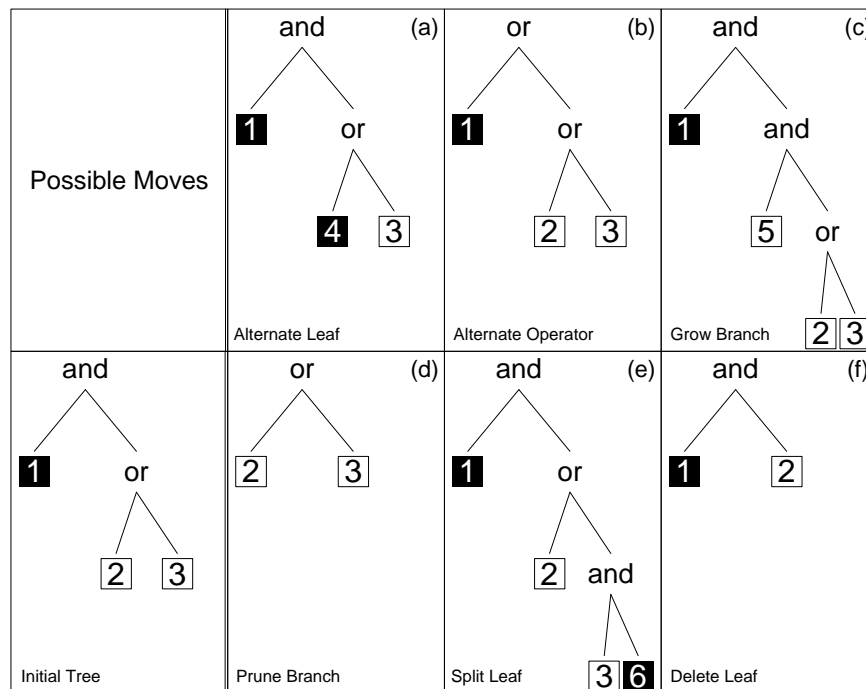
A Decision Tree (CART) is something different!

# An Example

$$\text{logit}(\text{death}) = -9.01 + 0.06 \times \text{age} + 1.07 \times L$$



# The Move Set



# Simulated Annealing for Logic Regression

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We try to fit the model  $g(F(Y)) = \beta_0 + \sum_{j=1}^t \beta_j \times L_j$ .

- Select a scoring function (RSS, log-likelihood, ...).
- Pick the maximum number of Logic Trees.
- Pick the maximum number of leafs in a tree.
- Initialize the model with  $L_j = 0$  for all  $j$ .
- Carry out Simulated Annealing Algorithm:
  - Propose a move.
  - Accept or reject the move, depending on scores and temperature scheme.

## Simulated Annealing for Logic Regression (2)

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- We use the acceptance function  $\alpha(\epsilon_{old}, \epsilon_{new}, t) = \min \{1, \exp([\epsilon_{old} - \epsilon_{new}] / t)\}$
- We run homogeneous Markov chains at constant temperatures.
- We constructed the move set to be irreducible and aperiodic, therefore each homogeneous Markov chain has a limiting distribution  $\pi_t(S)$ .
- The limit (as  $t \rightarrow 0$ ) of those distributions assigns probability 1 to the optimal scoring states.
- With limited resources, we cannot guarantee to find an optimal scoring state.

# Another Example

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## The Cardiovascular Health Study

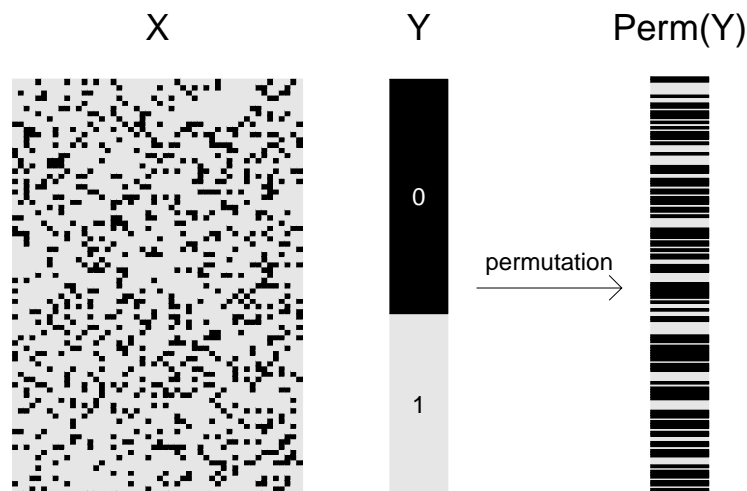
(Fried et. al. , Annals of Epidemiology, 1991).

- The Cardiovascular Health Study (CHS) is a study of coronary heart disease and stroke in elderly people.
- Between 1989 and 1993, 5888 subjects over the age of 65 were recruited in four communities in the United States.
- During 1992 and 1994, a subset of these patients underwent an MRI scan.
- For 3647 CHS participants, MRI detected strokes (infarcts bigger than 3mm that led to deficits in functioning) were recorded as entries into a 23 region atlas of the brain.
- The mini-mental state examination is a brief screening test for dementia. The response  $Y$  is a variable derived by transforming the mini-mental score.

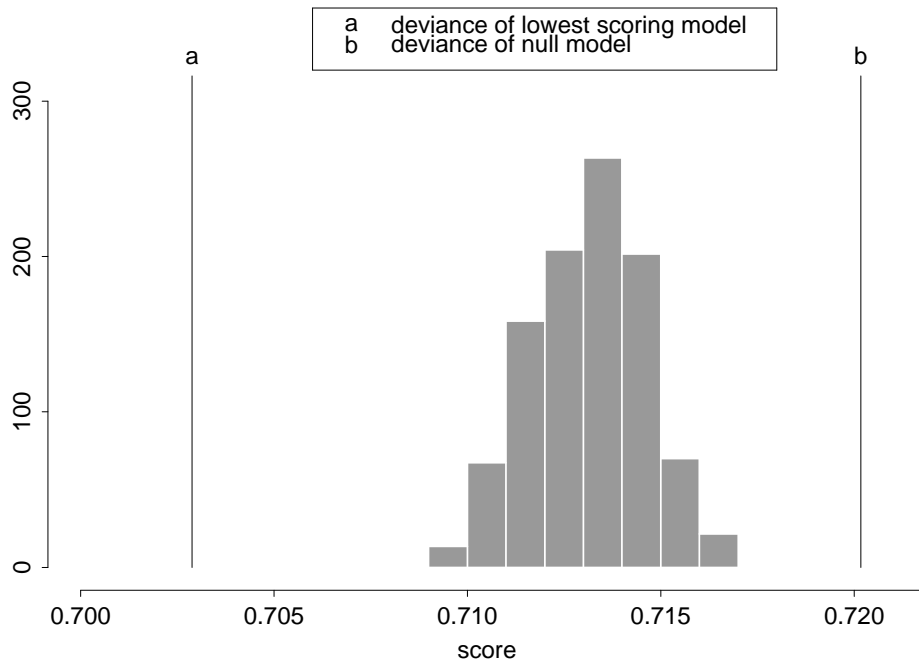
We investigated models of the form  $Y = \beta_0 + \beta_1 \times L_1 + \dots + \beta_p \times L_p + \epsilon$ .

## A Global Randomization Test of Association

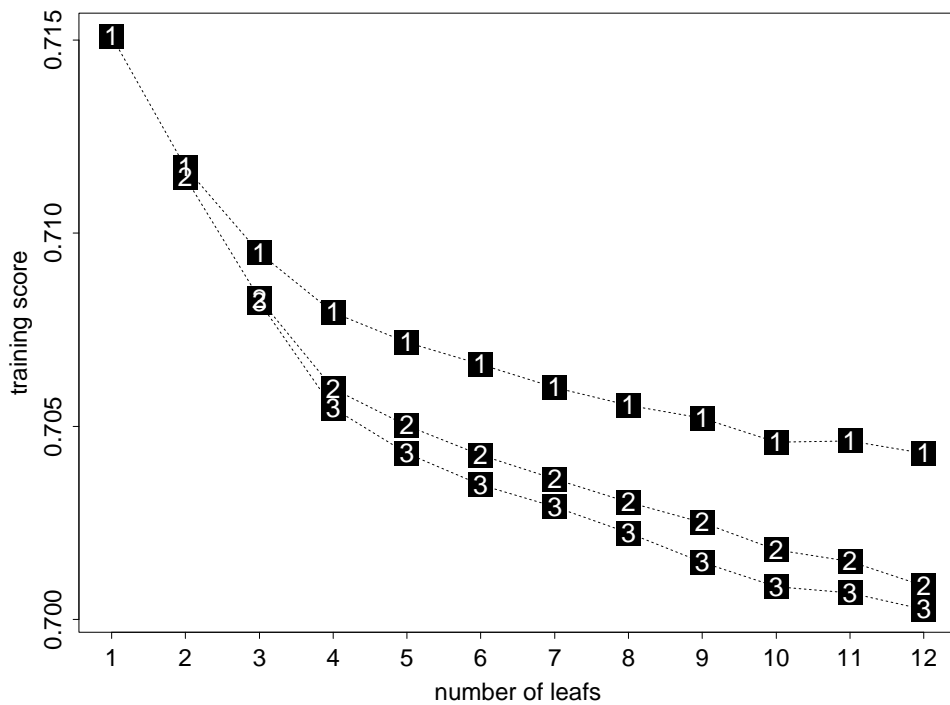
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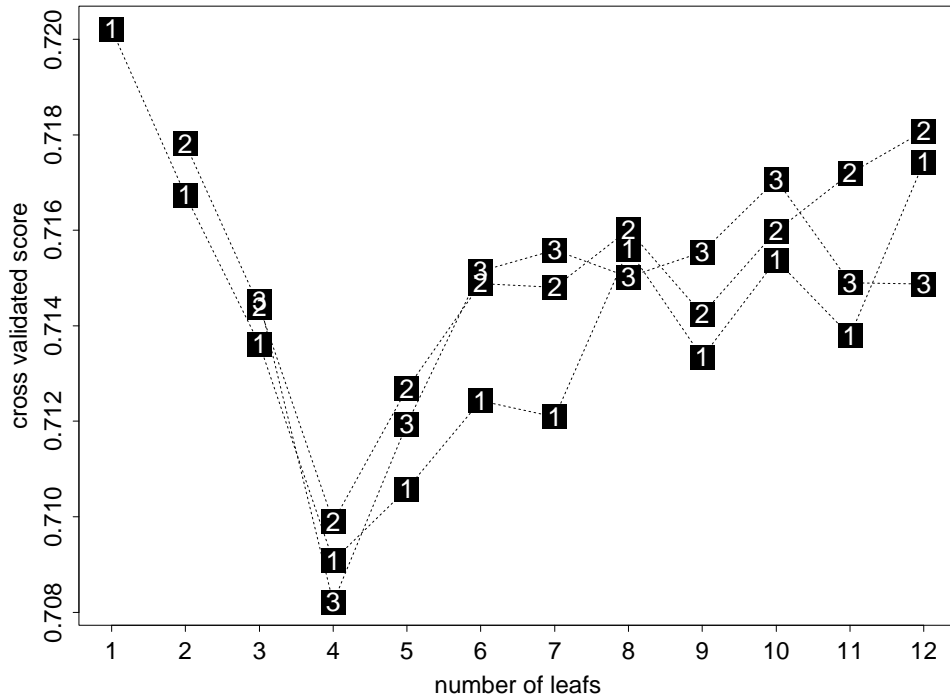
# Example Cont.



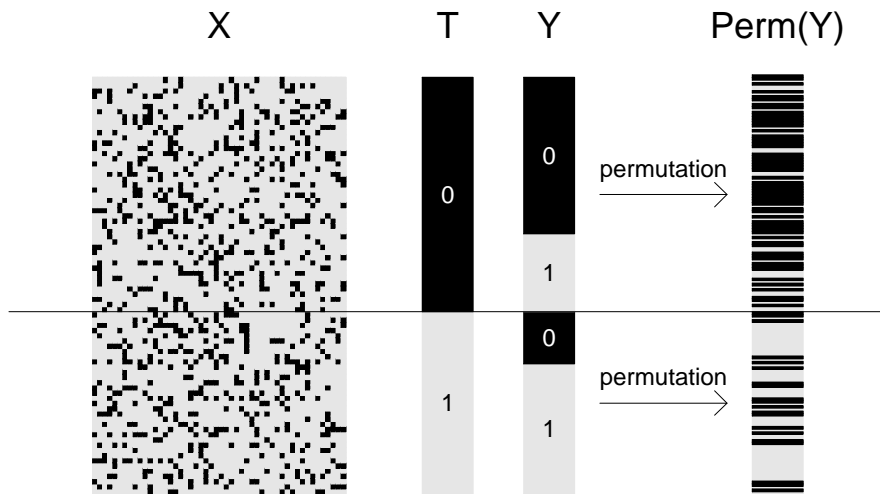
# Cross-Validation



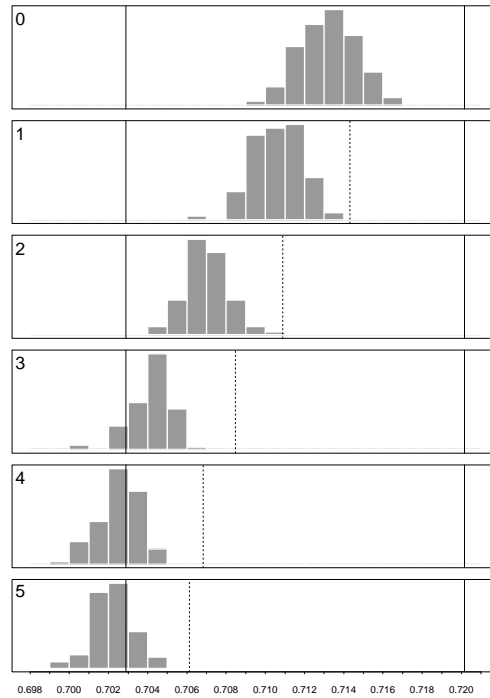
# Cross-Validation Cont.



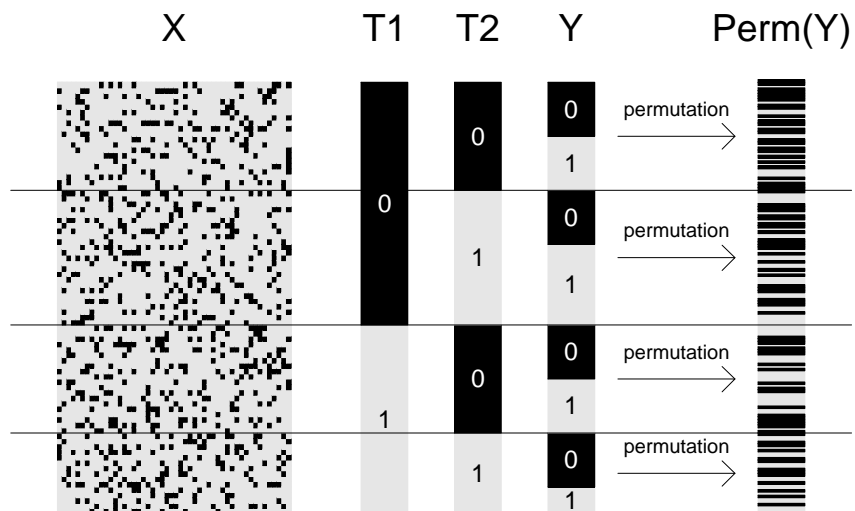
# A Sequential Randomization Test for Model Size



# Randomization Test Cont.



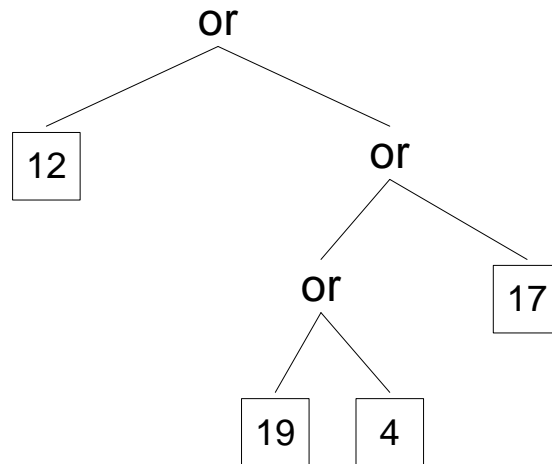
# Sequential Randomization Test for 2 Trees:



# Results

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The model we found was  $Y = 1.96 + 0.36 \times L$ , with the following Logi Tree:



## Logic vs Linear Model vs MARS

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Linear model:

	$\hat{\beta}$	$\hat{\sigma}$	t-value	p-value
Intercept	1.961	0.015	133.98	<0.001
Region 4	0.524	0.129	4.06	<0.001
Region 12	0.460	0.112	4.09	<0.001
Region 17	0.236	0.057	4.17	<0.001
Region 19	0.611	0.157	3.89	<0.001

Logic model:

$$Y = 1.96 + 0.36 \times I_{\{X_4 \vee X_{12} \vee X_{17} \vee X_{19} \text{ is true}\}}$$

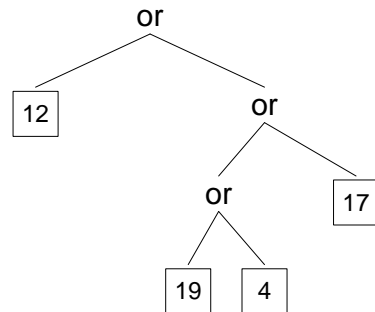
MARS:

$$Y = 1.96 + 0.53 X_4 + 0.37 X_{12} + 0.24 X_{17} + 0.61 X_{19} + 1.05 (X_{12} * X_{15})$$

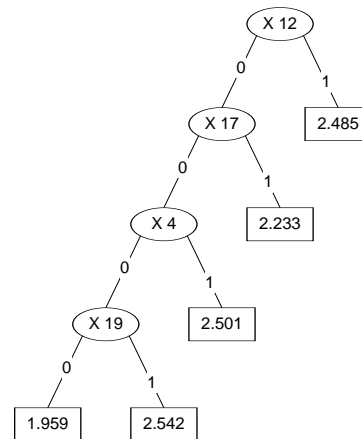
# Logic vs CART

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Logic Tree



CART Tree

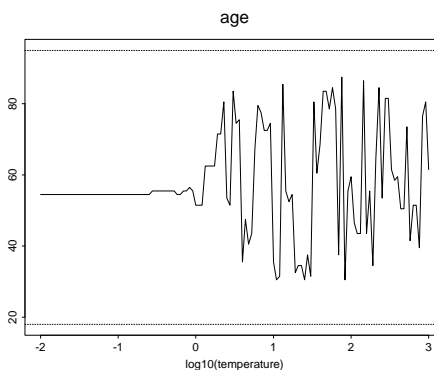


## Continuous Predictors

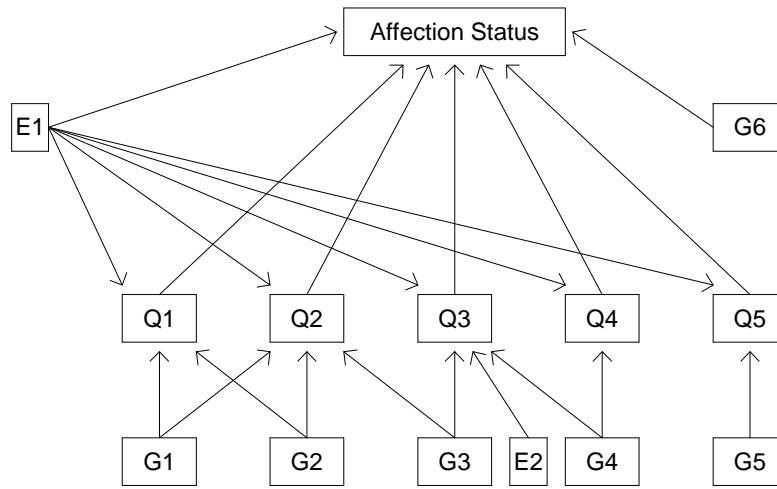
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What can we do about the continuous predictors?

- Incorporate continuous predictors in (generalized) linear model
- Dichotomize continuous predictors before starting the simulated annealing chain
- Find optimal split points during the simulated annealing run



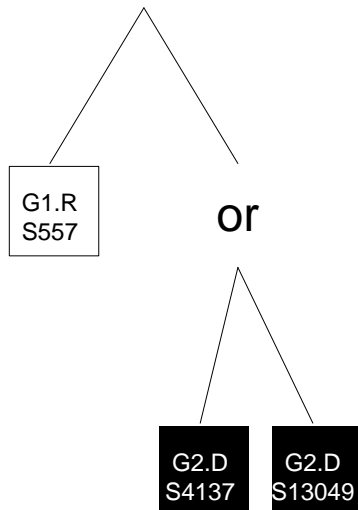
# Genetic Analysis Workshop GAW 12



## GAW12 Cont.

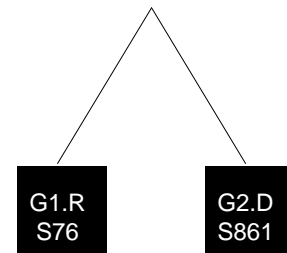
$$\text{logit}(\text{affected}) = \beta_0 + \beta_1 \times \text{ENV}_1 + \beta_2 \times \text{ENV}_2 + \beta_3 \times \text{GENDER} + \sum_{i=1}^K \beta_{i+3} \times L_i$$

$L_1 =$  and



$L_2 =$  G6.D  
S5007

$L_3 =$  or



# References

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- Breiman, L., Friedman, J. H., Olshen, R. A., and Stone, C.J. (1984), *Classification and Regression Trees*, Belmont, CA: Wadsworth.
- Friedman, J. H. (1991), *Multivariate Adaptive Regression Splines* (with discussion), *Annals of Statistics*, 19, 1-141.
- Kooperberg, C., Ruczinski, I., LeBlanc, M., and Hsu, L. (2001), *Sequence Analysis using Logic Regression*, *Genetic Epidemiology*, 21 (S1), 626-631.
- Ruczinski, I., Kooperberg, C., and LeBlanc, M. (2001), *Logic Regression* (under review), <http://biostat.jhsph.edu/~iruczins/>