Nearest Neighbours: nagdmc_knnc

Purpose

 $nagdmc_knnc$ computes k-nearest neighbour classifications given a binary tree computed by $nagdmc_kdtree$ using training data.

Declaration

Parameters

1:	rec1 – long On entry: the index in the data of the first data record used in the analysis.	Input
2:	Constraint: $rec1 \ge 0$. nvar - long On entry: the number of variables in the data. Constraint: $nvar > 1$.	Input
3:	mrec – long On entry: the number of consecutive records, beginning at rec1 , used in the analysis. Constraint: mrec > 1.	Input
4:	dblk – long On entry: the total number of records in the data block. Constraint: dblk \geq rec1 + nrec .	Input
5:	data[dblk * nvar] - double On entry: the data values for the <i>j</i> th variable (for $j = 0, 1,, nvar-1$) are stored in data[<i>i</i> *nv for $i = 0, 1,, dblk - 1$.	$Input \\ \mathbf{ar}+j],$
6:	iproot – long On entry: the integer value of the root node of a binary tree as returned by nagdmc_kdtree	Input
7:	prior $[c]$ – double $On \ entry:$ if prior is set to 0, uniform priors are used; otherwise prior $[i]$ gives the prior probability for the <i>i</i> th of <i>c</i> categories on the dependent variable in the analysis, for $i = 0, 1,, c - 1$. <i>Constraints:</i> if prior is not 0, prior $[i] \ge 0$, for $i = 0, 1,, c - 1$, and the elements in prior must sum equal to one.	
8:	rho - doubleInputOn entry: the value of maximum probability of group membership that must be exceeded for classification. Each data record with a maximum probability of group membership less than or equal to rho is classified as uc.Constraint: $0 \leq rho < 1$.	
9:	uc – double On entry: the value that should be assigned to data records if the value of rho is not exceed	Input led.
10:	norm - int	Input

On entry: the norm used to compute distances. If **norm** = 1, the ℓ_1 -norm (or Manhattan distance) is used; otherwise **norm** = 2 and the ℓ_2 -norm (or Euclidean distance) is used.

Constraint: **norm** $\in \{1, 2\}$.

11: $\mathbf{k} - \text{long}$

 $On\ entry:$ the number of nearest neighbours used in the computation.

Constraint: $0 < \mathbf{k} < \mathbf{nrec}$.

12: res[nrec] - long

On exit: res[i] contains the k-nearest neighbour classification of the *i*th data record, for i = 0, 1, ..., nrec - 1.

13: nn[nrec*k] - long

On exit: if **nn** is set to 0, it is not referenced; otherwise $\mathbf{nn}[i * \mathbf{k} + j]$ contains the index in the training data for the *j*th nearest neighbour to the *i*th data record, for $j = 0, 1, ..., \mathbf{k} - 1$; for $i = 0, 1, ..., \mathbf{nrec} - 1$.

14: dist[nrec*k] - double

On exit: if dist is set to 0, it is not referenced; otherwise dist[i * k + j] contains the distance from the *i*th data record to its *j*th nearest neighbour, for j = 0, 1, ..., k - 1; for i = 0, 1, ..., nrec - 1.

15: **info** - int *

On exit: info gives information on the success of the function call:

- 0: the function successfully completed its task.
- i; i = i = 1, 2, 3, 4, 7, 8, 10, 11: the specification of the *i*th formal parameter was incorrect.
- 57: information in the binary tree has been corrupted.
- 99: the function failed to allocate enough memory.
- 100: an internal error occurred during the execution of the function.

Notation

nrec	the number of data records to classify, n .		
data	the data values, X .		
prior	the prior probabilities p_l , for $l = 1, 2, \ldots, c$.		
rho	the threshold for accepting classifications, ρ .		
uc	the dummy value representing unclassified data records, z .		
k	the number of nearest neighbours used in the calculations, k .		

res the nearest neighbour classifications \hat{y}_i , for i = 1, 2, ..., n.

Description

Let X be a set of n data records x_i , for i = 1, 2, ..., n, on p independent variables and a categorical dependent variable y. The jth value of the ith data record is denoted by x_{ij} . Each member of X is to be classified into one of c categories where the prior probability of the lth category is p_l , for l = 1, 2, ..., c.

The k-nearest neighbour approach searches a set of training data records T (i.e., data records with known categories for y) to find the k-nearest data records to x_i . Nearest neighbours are found by using a binary tree search, e.g., see Bentley (1975). The proximity of x_i to a member t of T is defined by a distance calculated over the independent variables and can defined by using one of:

(a) the ℓ_1 -norm or Manhattan distance:

$$\sum_{j=1}^{p} |x_{ij} - t_j|$$

where $|\cdot|$ denotes the modulus operator; (b) the ℓ_{2} -norm or Euclidean distance:

(b) the
$$\ell_2$$
-norm or Euclidean distance

$$\left[\sum_{j=1}^{p} (x_{ij} - t_j)^2\right]^{1/2}.$$

Input

Output

Output

Output

Output

Let S_i be a set containing the k-nearest neighbours in T to x_i , and h_{il} be the number of members of S_i belonging to the *l*th category. The posterior probability θ_{il} of x_i belonging to the *l*th category is given by,

$$\theta_{il} = \frac{p_l h_{il}}{\sum_{m=1}^c p_m h_{im}}.$$

Let q denote the index of the maximum value in θ_{il} , for $l = 1, 2, \ldots, c$. Given a user-supplied value for ρ , x_i is classified by setting the *i*th value of the dependent variable, \hat{y}_i , to category value q if $\theta_{iq} > \rho$; otherwise x_i is unclassified and \hat{y}_i is assigned a dummy value, say z.

References and Further Reading

Bentley J L (1975) Multi-dimensional binary search trees used for associative searching Communications of the ACM 18(9) 509–517.

Duda R O and Hart P E (1972) Pattern Classification and Scene Analysis Wiley New York.

Storer J A and Cohn M (1993) Algorithms for fast vector quantization *Proc. Data Compression Conference* 381–390 IEEE Computer Society Press.

See Also

nagdmc_kdtree	computes a binary tree for a nearest neighbour analysis.
nagdmc_free_kdtree	frees the memory containing a binary tree.
nagdmc_load_kdtree	loads a binary tree from a file into memory.
nagdmc_save_kdtree	writes a binary tree to file.
knnc_ex.c	the example calling program.