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PROBABILISTIC MODELS IN CLUSTER ANALYSIS

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Abstract: This paper discusses cluster analysis in a probabilistic and inferential framework as opposed to more exploratory, heuristic or algorithmic approaches. It presents a broad survey on probabilistic models for partition-type, hierarchical and tree-like clustering structures and points to the relevant literature. It is shown how suitable clustering criteria or grouping methods may be derived from these models in the case of vector-valued data, dissimilarity matrices and similarity relations. In particular, we discuss hypothesis testing for homogeneity or for a grouping structure, the asymptotic distribution of test statistics, the use of random graph theory and combinatorial methods for simulating random dendrograms. Our presentation of hierarchies includes, e.g., Markovian branching processes and phylogenetic inference based on molecular sequence data.

Keywords: Probabilistic cluster analysis; Partition-type clustering; Hierarchical clustering models; Testing for a clustering structure; Phylogenetic inference

1. Cluster analysis: Data types and classification structures

Cluster analysis is designed to detect hidden 'groups' or 'clusters' in a set of objects which are described by numerical, linguistic or structural data such that the members of each cluster behave similarly to each other (with respect to the given data) and groups are hopefully well separated. Clustering techniques are often considered as a part of exploratory statistics, in particular if the used clustering algorithms are 'model-free' or only heuristically motivated. In contrast, this paper emphasizes an inferential approach and presents a brief survey on clustering and clustering-related methods which

are based on probabilistic models. It shows how suitable clustering strategies can be derived from these models by tools from classical statistics, and analyzed in a probabilistic way. Such an approach clarifies the conditions under which a proposed clustering method can be successful, and characterizes its performance. Our presentation includes some formal test procedures for testing the existence of a 'clustering structure' as well as models for a 'purely random (homogeneous) data constellation'. Whilst this survey can point to many topics only very briefly, a more detailed account and additional references may be found in Bock (1974, 1985, 1989a, 1995), Perruchet (1983), Jain & Dubes (1988), Godehardt (1990) and Gordon (1994a, 1994b).

We consider a set $\mathcal{O} = \{1, ..., n\}$ of n objects $k = 1, ..., n$ described by data which are considered, in a probabilistic framework, as realizations of random variables. Then any inherent clustering (or non-clustering) structure for the objects is characterized by the probability distribution of these variables. We will consider the following data types:

a) n *feature vectors* $x_1, ..., x_n$, each with p metric or qualitative components, describing the observed properties of the n objects. These data are realizations of n $p-$dimensional independent random vectors $X_1, ..., X_n$;

b) a *dissimilarity matrix* $(d_{kl})_{n \times n}$ with entries d_{kl} characterizing the dissimilarity of the objects $k, l \in \mathcal{O}$ (with $0 = d_{kk} \leq d_{kl} = d_{lk}$ for all k, l; they are realizations of $n(n-1)/2$ random dissimilarities D_{kl}, $k \neq l$ (with $D_{kk} \equiv 0$ for all k);

c) a *binary similarity relation* $(s_{kl})_{n \times n}$ with $s_{kl} = 1$ resp. $= 0$ if the objects k, l are considered to be 'similar' or not (with $s_{kk} = 1$ for all k), with corresponding random Bernoulli variables S_{kl}. These data are equivalent to a *similarity graph* G with n vertices (objects) and a link (edge) between two different vertices $k, l \in \mathcal{O}$ whenever $s_{kl} = 1$.

In this paper we will consider two basic types of classification structures:

(1) *Partitions* $\mathcal{C} = \{C_1, ..., C_m\}$ of $\mathcal{O}$ with a suitable (or specified) number m of non-empty disjoint classes $C_1, C_2, ... \subseteq \mathcal{O}$;

(2) *Hierarchies* $\mathcal{H} = (A, B, ...)$ with nested classes $A, B, ... \subseteq \mathcal{O}$ (including all singletons as well as $\mathcal{O}$) such that $A \cap B \in \{A, B, \emptyset\}$ for all $A, B \in \mathcal{H}$, and *dendrograms* $(\mathcal{H}, h)$ where $h \geq 0$ is an isotone heterogeneity index defined on the classes of $\mathcal{H}$.

Thus we exclude here overlapping classifications (coverings) of $\mathcal{O}$ and fuzzy clustering concepts.

2. Partition-type models for data vectors $\mathbf{X_1}, ..., \mathbf{X_n}$

If the data are n random feature vectors $X_1, ..., X_n$ a probabilistic clustering model has been defined mainly in one of the five following ways (where we must distinguish models which incorporate explicitly an m-partition from those which describe a 'clustering tendency' only).

2.1 The fixed-classification model:

This model assumes, for a fixed number m, an unknown m-partition $\mathcal{C} = (C_1, ..., C_m)$ of $\mathcal{O}$, m unknown class-specific parameters $\vartheta_1, ..., \vartheta_m$ compiled in the vector $\theta = (\vartheta_1, ..., \vartheta_m)$ and a known parametric density family $f(\cdot; \vartheta)$ such that

$$X_k \sim f(\cdot; \vartheta_i) \qquad \text{for all} \quad k \in C_i, \ i = 1, ..., m. \tag{2.1}$$

If m is known we may estimate the two 'parameters' $\mathcal{C}$ and θ by the maximum likelihood method which leads to the following clustering criterion (using the negative log likelihood):

$$g(\mathcal{C}, \theta) \ := \ \sum_{i=1}^{m} \sum_{k \in C_i} [-log f(x_k; \vartheta_i)] \qquad \rightarrow \qquad min_{\mathcal{C},\theta}. \tag{2.2}$$

Minimizing with respect to $\mathcal{C}$ and θ in turn leads to the well-known $k-$means clustering algorithm which yields a sequence $\mathcal{C}^0$, θ^0, $\mathcal{C}^1$, θ^1,... of successively improving partitions and parameter values (iterative minimum-distance clustering, nuées dynamiques; Bock 1974, Schroeder 1976). Other optimization methods (combinatorial, exchange, dynamic programming etc.) are described in Bock (1974), Späth (1985), Hansen (1994).

Fixed classification models provide a very flexible tool for clustering since suitable specifications of the density f (normal, double exponential etc.), of the class-specific parameters ϑ_i (central points or hyperplanes, variances, interactions etc.) and the inclusion of parameter constraints can cope with special needs of practice and yield various interesting clustering methods:

- the *classical cases* which assume spherical or ellipsoidal normal distribution clusters with class-specific centers and lead, e.g., to the well-known

SSQ (trace, variance) criterion $g(\mathcal{C},\theta)=\sum_{i=1}^{m}\sum_{k\in C_i}||x_k-\vartheta_i||^2$ and the determinantal criterion (Bock 1974, Späth 1985);

- *principal component clustering* which assumes class-specific hyperplanes as in Bock (1969, 1974, 1987), possibly even with common *and* class-specific dimensions (Bock 1987);
- *regression clustering* based on class-specific regression hyperplanes planes for data (X_k, z_k) comprizing an explanatory vector z_k (Bock 1969, 1987);
- *projection pursuit clustering* where all class centers $\vartheta_i \in R^p$ are located on an unknown low-dimensional hyperplane H of R^p (Bock 1987)
- *minimum-volume clustering* where classes correspond to convex sets in R^p (Rasson et al. 1988, Hardy 1994);
- *entropy clustering* for discrete data and assuming loglinear models for the X_k with class-specific interactions (Bock 1986, 1993, Céleux & Govaert 1991);
- *binary regression clustering* (e.g. for credit scoring) yielding entropy criteria again (Bock 1986, 1993).

As an alternative to maximum likelihood methods several authors have proposed a Bayesian approach which leads (under suitable prior assumptions and loss functions) to the optimization of a posterior risk (posterior probability) for the unknown m-partition $\mathcal{C}$ (see, e.g., Bock 1972, 1974, Binder 1978 and, for segmented prediction, Bernardo 1994).

2.2 The mixture model

The usual marginal approach assumes the same mixture density $f(x)=\sum_{i=1}^{m}\pi_i f(x;\vartheta_i)$ for all vectors $X_1,...,X_n$ with the purpose to estimate the unknown parameters π_i and ϑ_i: This model involves no explicit clustering. – However, when considering, additionally, the random binary class indicator vectors $I_k \in \{0,1\}^m \sim Mult(1;\pi_1,...,\pi_m)$ which define a random (unobservable) partition $\mathcal{C}$ of $\mathcal{O}$, the n i.i.d. pairs (I_k, X_k) yield a minus log likelihood function $l(\pi,\theta;I_1,...,I_n,x_1,...,x_n)$ which can be minimized with respect to π,θ **and** the missing values $I_1,...,I_n$ (equivalently: with respect to the induced partition $\mathcal{C}$ where the number of classes is bounded by m). Substituting

the m.l. estimates $\hat{\pi}_i = |C_i|/n$ into $l(\cdot)$ leads to the partition-type clustering criterion:

$$\hat{g}(\mathcal{C},\ \theta) = \sum_{i=1}^{m} \sum_{k \in C_i} [-\log f(x_k; \vartheta_i)] - n \cdot \sum_{i=1}^{m} (|C_i|/n) \cdot \log(|C_i|/n) \rightarrow min_{\mathcal{C},\theta} \quad (2.3)$$

which adds an entropy term to the criterion (2.2) (Anderson 1985, Bock 1995). Mixtures are thoroughly investigated by Titterington, Smith & Makov (1985) and Redner & Walker (1984), the relationship to clustering and the determination of the class number m is fully discussed, e.g., in Windham (1987), McLachlan & Basford (1988), Windham & Cutler (1992, 1994), Furmann & Lindsay (1994), Roeder (1994), Bozdogan (1994) and Bock (1995).

2.3 Multimodality and high-density (density-contour) clusters

Any density $f(x)$ is characterized by its level sets $B(c) := \{x \in R^p | f(x) \geq c\}$ for all $c > 0$. 'High-density clusters' at a fixed level c are defined as the connected components $B_1(c), B_2(c), ...$ of $B(c)$ which characterize, for a multimodal density f, the domains of point aggregations when sampling from f (Bock 1974). Starting from n data points $x_1, ..., x_n$, corresponding estimates $\hat{B}_i(c)$ can be obtained from a (non-parametric or kernel-type) density estimate $\hat{f}$ of f from which suitable object clusters $\hat{C}_i(c) := \hat{B}_i(c) \cap \{x_1, ..., x_n\}$ are easily constructed. There exist many modifications, e.g., using k-nearest neighbour distances, and methods based on discretized (grey-level) density values which use morphological operations such as the dilatation and erosion of binary sets or the thinning and thickening of functions (well-known from pattern recognition and image analysis; see Postaire 1993, Sbihi & Postaire 1994).

The clustering tendency provided by f respectively the induced distribution P_f can be characterized by the *probability excess mass function* given by

$$\begin{aligned} E(c) \quad &:= \quad \int [f(x) - c]^+ \, dx = \sum_{i=1}^{m} \int_{B_i(c)} [f(x) - c] \, dx \\ &\stackrel{*}{=} \quad \sup_{(B_1,...,B_m)} \sum_{i=1}^{m} [(P_f(B_i) - c \cdot vol_p(B_i)] \ =: \ E^{(m)}(c), \quad (2.4) \end{aligned}$$

i.e. the difference between the probability masses contained in the $B_i(c)$ under P_f and a uniform distribution, respectively. The equality $\stackrel{*}{=}$ holds for

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any m-modal density f and the supremum is taken over all sets of m disjoint connected subsets B_i of R^p (Müller & Sawitzki 1991, Sawitzki 1994).

2.4 Mode clusters

A closely related model starts from the idea that the local maxima $\xi_1, \xi_2, ...$ of a (smooth) multimodal density f can be considered as the kernels of suitable cluster regions $D_1, D_2, ...$ in R^p where D_i is the set of all $x \in R^p$ which attain, after some hill-climbing relocation procedure (to be specified), the i-th mode ξ_i. Point clusters for a sample $x_1, ..., x_n$ are usually built up by a similar relocating process using a (smooth) density estimate $\hat{f}$.

2.5 Clustered point processes

Spatial statistics provides a series of models for clustered point constellations $X_1, X_2, ...$ in a (often finite) domain $G \subset R^p$. Typical examples include the non-homogeneous *Poisson process* with a (multimodal) intensity function $\lambda(x)$ and the *Neyman-Scott process* where parent points $Y_1, Y_2, ...$ are randomly located in G and a random (Poisson distributed) number N_i of daughter points $X_{i1}, X_{i2}, ..., X_{iN_i}$ is located near to Y_i (e.g., with a Gaussian distribution $N_p(Y_i, \sigma^2 I_p)$ or with a uniform distribution in the ball $K(Y_i, r)$ for some radius $r > 0$). Statistical analysis concerns primarily the estimation of the incorporated parameters (λ, σ^2, r etc.; see Ripley 1981, Cressie 1991) and insofar the clustering tendency only (instead of locating single clusters).

3. Partition-type probability models for dissimilarity data

Even if many clustering methods start from an $n \times n$ matrix (d_{kl}) of pairwise dissimilarities between objects, elaborated clustering models for this case are rarely found in the literature. The following fixed-classification approach has been proposed by Bock (1989b): We start with the idea that in a homogeneous or unstructured population all $\binom{n}{2}$ random nonnegative dissimilarities $\tilde{D}_{kl}$ are independently distributed, all with the same (standardized) distribution, e.g., an exponential distribution $exp(1)$. The clustering model states that, for a fixed unknown m-partition $\mathcal{C} = (C_1, ..., C_m)$ of the objects, the observed dissimilarities D_{kl} with $k < l$ are distributed according to:

$$D_{kl} \quad \sim \quad \vartheta_{ij} \cdot \tilde{D}_{kl} \qquad \text{for all } k \in C_i,\ l \in C_j \tag{3.1}$$

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where the positive scaling factors ϑ_{ij} describe the reduction or increase of the standard dissimilarities in and between the classes, respectively (typically with side constraints $\vartheta_{ii} \leq \vartheta_{ij}$ for all i, j). They must be estimated, together with $\mathcal{C}$, from the observed data $(d_{kl})_{n\times n}$, e.g. by maximizing the likelihood. The independence assumption must be weakened for many practical applications.

Another model (Mountford 1970) considers similarities S_{kl} instead of dissimilarities and proposes a normal distribution variance component model of the type $S_{kl} = \mu_{ij} + V_i + V_j + U_{kl}$ for all $k \in C_i,\ j \in C_j$ where μ_{ij} is the 'typical' dissimilarity between the classes C_i, C_j, $V_1, ..., V_m \sim N(0, \sigma^2)$ are class-specific deviations, and $U_{kl} \sim N(0, \tau^2)$ denote random errors (all variables being independent). However, since Mountford considered the partition $\mathcal{C}$ to be known, he had no real clustering situation.

4. Partition-type clustering models for random similarity relations and random graphs

A random similarity relation $S = (S_{kl})$ on $\mathcal{O}$ (with $P(S_{kk} = 1) = 1$) tells us if two objects $k, l \in \mathcal{O}$ are considered to be 'similar' ($S_{kl} = 1$, a hit) or not ($S_{kl} = 0$, a failure). S is equivalent to a random graph G with n vertices and a random number $N = \sum\sum_{k<l} S_{kl}$ of links $\overline{kl}$ with $S_{kl} = 1$ along the lines described in section 1.c. Therefore we may consider, occasionally, random graphs as well. – We mention three clustering models here:

4.1 The fixed-classification model

This model postulates the existence of an unknown m-partition $\mathcal{C} = (C_1, ..., C_m)$ of $\mathcal{O}$ and of a symmetric matrix $p = (p_{ij})_{m\times m}$ of unknown class-specific linking probabilities p_{ij} (typically with $p_{ii} \geq p_{ij}$ for all $i,\ j$) such that all $\binom{n}{2}$ Bernoulli link indicators S_{kl} with $k < l$ are independently distributed with:

$$P(S_{kl} = 1) \ = \ p_{ij} \qquad \text{for all} \ \ k \in C_i,\ l \in C_j. \tag{4.1}$$

Applying the maximum likelihood method for estimating the unknown $\mathcal{C}$ and (p_{ij}) amounts to minimizing the clustering criterion:

$$g(\mathcal{C}, p) := -\sum_{1\leq i\leq j\leq m} [N_{ij} \log p_{ij} + (n_{ij} - N_{ij}) \log(1 - p_{ij})] \ \to \min_{\mathcal{C},p} \tag{4.2}$$

where N_{ij} is the number of pairs $k \in C_i, l \in C_j$ $k < l$ with a link $S_{kl} = 1$, and $n_{ij} = |C_i| \cdot |C_j|$ resp. $n_{ii} = \binom{|C_i|}{2}$ denotes the number of different pairs $\{k, l\}$ with $k \in C_i, l \in C_j$, $k < l$. Obviously $\hat{p}_{ij} := N_{ij}/n_{ij}$ is the m.l. estimate for p_{ij} if the side constraints are fulfilled or neglected.

4.2 An error perturbation model

This model describes the unknown partition $\mathcal{C}$ by an equivalence relation $\rho = (\rho_{kl})_{n\times n}$ with $\rho_{kl} = 1$ if and only if the objects $k, l \in \mathcal{O}$ belong to the same class of $\mathcal{C}$. The model assumes that the indicators ρ_{kl} with $k < l$ are randomly perturbed in the way that $\rho_{kl} = 1$ is replaced by 0 with probability α, and $\rho_{kl} = 0$ is replaced by 1 with probability β, all perturbations being independent and symmetry maintained. This yields an observable random symmetric reflexive relation $S = (S_{kl})_{n\times n}$ with $\binom{n}{2}$ independent entries and $P(S_{kl} = 1) = \rho_{kl}(1 - \alpha) + (1 - \rho_{kl})\beta$ for $k < l$. Suitable clustering methods have to estimate the unknown parameters α, β as well as the unknown partition $\mathcal{C}$ (including m) from the observed matrix S (Frank 1978). Note that this is a special case of the previous model 4.2 with $p_{ii} = 1 - \alpha$ and $p_{ij} = \beta$ for $i \neq j$.

4.3 Markov graphs for similarity relations:

Frank & Strauss (1986) have proposed a model for a random graph G, i.e. a joint distribution for the $\binom{n}{2}$ link indicators S_{kl}, which allows for some dependence between neighbouring links S_{kl}, S_{lt} sharing a common object l. More specifically, it is assumed that for each pair of object pairs $\{k, l\}, \{r, t\}$ the link indicators S_{kl}, S_{rt} are *conditionally* independent given all other indicators S_{uv}, provided that $\{k, l, r, t\}$ comprises 4 different objects (this excludes overlapping pairs $\{k, l\}$ and $\{l, t\}$ where conditional dependence may exist). It can be shown that the resulting marginal distribution of S is equivalent to a Markov field on a related graph Γ (whose vertices are the $\binom{n}{2}$ pairs of objects), and a classical theorem of Hammersley and Clifford states that the joint distribution of the S_{kl} has, under some homogeneity and symmetry

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conditions, the form:

$$P(S = s) = const. \cdot \exp\{\alpha \cdot N_3(G) + \sum_{t=1}^{n-1} \beta_t \cdot M_t(G)\}. \qquad (4.3)$$

where G is the graph corresponding to the given realization $s = (s_{kl})$ of S, $N_3(G)$ is the number of triads (complete subsets of size 3) in G, and $M_t(G)$ the number of $t-$stars (a $k \in \mathcal{O}$ linked with exactly t other objects) in G; $\alpha > 0$ and $\beta_t \in R$ are unknown model parameters for transitivity and clustering, respectively. The estimation of these parameters requires extensive analytical and computational efforts.

Similar models have been proposed in network analysis, e.g., by Holland & Leinhardt (1981), Bollobás (1985), Fienberg, Meyer & Wasserman (1985) and Wasserman & Anderson (1987). Banks & Carley (1994) give a survey and propose a probability model of the type $P(S = s) = c(\sigma) \cdot \exp\{\sigma \cdot d(s, s^*)\}$ for all s where s^* describes a 'central' similarity graph (e.g., implied by a partition $\mathcal{C}$), $d(s, \tilde{s})$ is a mesure of the deviation between two similarity relations $s, \tilde{s}$, and the dispersion parameter σ influences the normalizing constant $c(\sigma)$.

5. Testing for homogeneity and for a clustering structure

Most clustering algorithms, including those which minimize a clustering criterion, provide the user always with a classification of objects – whether or not the data exhibit, in reality, a clear clustering structure and even if the calculated classes show weak homogeneity or class separation properties. In order to prevent classificationists from pitfalls and wrong conclusions, it is therefore strongly recommended:

(a) to provide, before applying a clustering algorithm, some evidence that the data exhibit a

clustering structure at all and are not, in the contrary, just a sample from a homogeneous

universe;

(b) to assess, after having performed a cluster algorithm, the significance of the calculated

classification or clusters such that finally only those classifications (clusters) are retained

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which are more marked than those resulting from 'random' data sets.

Problems of this type, together with the determination of a suitable number m of classes, concern a major part of recent theoretical and computational investigations in cluster analysis. Passing over a wealth of exploratory or interactive graphical tools, we will survey here a range of probability-based inferential methods (see also Bock 1985, 1989a, 1995, Gordon 1994a, 1994b).

5.1 Nearest-neighbour methods for testing for homogeneity

Problems of type (a) are usually addressed by preliminary tests for homogeneity. The situation of 'homogenity' has been formalized either

– in the sense of a *uniform distribution* H_G of the data vectors $X_1, ..., X_n$ in a finite domain

G of the space R^p, or

– in the sense of H_{unimod}, i.e. assuming an arbitrary *unimodal density* f for the X_k.

Test statistics for H_G are provided, e.g., by nearest neighbour distances $D_k := min_{l \neq k}||X_l - X_k||$ between the n data points, the largest nearest-neigbour distance $T := \max_k\{D_k\}$ (possibly considering the boundary of G as well by using $T^* := \max_k\{\min\{D_k, ||X_k - \delta G||\}\}$), the radius R of the largest ball inside G without any data point in its interior, and modifications using the $t-$largest or $s-$smallest values. It appears that, for $n \to \infty$, the asymptotic distributions of T, T^* and R are all a rescaled Gumbel's extreme value distribution with distribution function $H(t) = \exp(e^{-t})$ such that percentage points can be easily approximated (at least for a known volume $|G|$). An asymptotic Smirnov type distribution results for the cited (and several weighted) modifications (see Henze 1982, Dette & Henze 1988, Janson 1987).

5.2 Testing for multimodality

A test for H_{unimod} versus bimodality H_2 or, more generally, for multimodality $H_{\leq m}$ with at most m modes versus $H_{>m}$ has been formulated by Silverman (1981; for $p = 1$) in terms of a kernel density estimator $\hat{f}$: H_{unimod} (respectively $H_{\leq m}$ is rejected if the smallest critical window width h_{crit} for which $\hat{f}$ has 1 mode (respectively m modes) is too large. Percentage points are are obtained by bootstrap methods. Müller & Sawitzki (1991) and Sawitzki (1994) use an empirical version $E_n^{(m)}(c)$ of their excess mass statistics $E^{(m)}(c)$ (see (2.4)) and reject the hypothesis of m-modality $H_{\leq m}$ if, e.g., the maximum

(w.r. to $c > 0$) difference $D_{n,m}(c) := E_n^{(m+1)}(c) - E_n^{(m)}(c)$ is too large. In the unidimensional case $p = 1$ the asymptotic distribution of $\max_c D_{n,m}(c)$ is described by a Brownian bridge, and for $m = 1$ the resulting test is basically equivalent to the DIP test proposed by Hartigan & Hartigan (1985).

Multivariate extensions of this latter test have been developed by Hartigan (1988; SPAN test), Hartigan & Mohanty (1992; RUNT test) and Rozál & Hartigan (1994; MAP test). They are all based on the edge lengths in the *minimum spanning tree* (MST) obtained for the Euclidean distances of the n data points $x_1, ..., x_n$ and insofar closely related to single linkage clustering. In particular, the largest edge length M_n (i.e. the level of the highest split in the single linkage dendrogram) has been investigated by Steele (1988), Steele & Tierney (1988) and Tabakis (1994). The latter paper derives asymptotic probability bounds for M_n which behaves as $[(\log n)/n]^{1/p}$ under a smooth, possibly multimodal density f (note that $M_n \geq T = \max_k\{D_k\}$). The empirical distribution of the $n-1$ edge lengths in the MST has been considered by Pociecha & Sokolowski (1989) under multivariate normal and uniform distributions for the X_k.

5.3 The max-F test and its generalizations

Another range of tests concentrates on the previously mentioned problem (b) and checks the appropriateness of a calculated optimum m-partition $\mathcal{C}^*$ by comparing the maximally (or minimally) attained clustering criterion value $k(\mathcal{C}^*) = \max_{\mathcal{C}} k(\mathcal{C})$ with a suitable percentage point $c = c(\alpha)$. For instance, the *max-F test* uses the ratio of the sum of squares between and in the classes of $\mathcal{C}$, i.e. the maximum value k^*_{mn} of:

$$k_{mn}(\mathcal{C}) \quad = \quad (\sum_{i=1}^{m} |C_i| \cdot ||\bar{x}_{C_i} - \bar{x}||^2)/(\sum_{i=1}^{m} \sum_{k \in C_i} ||x_k - \bar{x}_{C_i}||^2) \qquad (5.1)$$

such that $\mathcal{C}^*$ will be the m-partition that minimizes the SSQ or variance criterion in the denominator. The asymptotic behaviour and distribution of k^*_{mn} and of the optimum class centers $\overline{x}_{C_i^*}$ for $n \to \infty$ has been theoretically investigated, e.g., by Bryant & Williamson (1978), Hartigan (1978; $p = 1$), Pollard (1982) and Bock (1985; $p \geq 1$); these asymptotics invoke an optimum m-partition $\mathcal{B}^* = (B_1^*, ..., B_m^*)$ of the Euclidean space R^p using a continuous version of the SSQ criterion. Whilst these theoretical results have been extended to generalized criteria as well (e.g., using generalized metrics instead

of the Euclidean one), finite-sample distributions for k^*_{mn} and related test statistics (including the determinantal and Wilks type criteria; Lee 1979) under 'homogeneity' must be computed by simulations. A similar remark applies to the investigation of the power properties of these (and most) clustering tests under interesting clustering alternatives, a field which remains largely unexplored as yet.

5.4 Average similarities and U-statistics

It can be expected from an intuitive point of view that the average of all $\binom{n}{2}$ similarities s_{kl} (dissimilarities d_{kl}) is larger (smaller) for a homogeneous population of the type H_{unimod} than for a clustered one. Therefore, average similarity or dissimilarity statistics have been occasionally proposed when testing for a clustering tendency. The investigation of such test statistics proceeds leads typically to the consideration of U-statistics (Bock 1977, 1985, Silverman & Brown 1978, Bhattacharya & Ghosh 1992). Related proposals concerning a single cluster $C \in \mathcal{O}$ can be found in Gordon (1994a, 1994b) who uses, for pairs $\{k,l\},\{s,t\}$ of object pairs, binary distance comparison indicators $U_{kl,st} = 0, 1/2, 1$ for $d_{kl} <, =, > d_{st}$ in order to define *local* and *global* validation indices for a given cluster C by $U_L := \sum_{k\in C}\sum_{l\in C-\{k\}}\sum_{t\in\overline{C}} U_{kl,kt}$ and $U_G := \sum_{k\in C, l\in C}\sum_{s\in C, l\in\overline{C}} U_{kl,st}$, respectively. These indices are used as test statistics for validating a constructed cluster C of objects (with significance points obtained by simulations).

5.5 Random graphs and multigraphs

In the case of a dissimilarity matrix (d_{kl}) a test for 'randomness' is often based on graph-theoretical concepts by considering, for a fixed, but arbitrary threshold $d \geq 0$, the threshold graph $G(d)$ with n vertices and a link $\overline{kl}$ for all pairs $k, l \in \mathcal{O},\ k \neq l$, for which $d_{kl} \leq d$. $G(d)$ has exactly N edges if $d = d_{(N)}$, the N-smallest distance d_{kl} (if ties are neglected). Two (asymptotically equivalent) 'random graph' models are available for describing the 'pure randomness' of a graph:

(1) the *Bernoulli graph model* G_p which assumes $\binom{n}{2}$ independent link indicators $S_{kl} \sim Bin(1,p)$

all with the same linking probability $0 < p < 1$ (such that the number N of links in G_p

has a $Bin(n,p)$ distribution), and

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(2) the *combinatorial model* $\Gamma_{n,N}$ where a fixed number N of edges is randomly sampled over

all $\binom{\binom{n}{2}}{N}$ possible selections.

For these models random graph theory provides a range of distributional results on the exact or asymptotic (for $n \to \infty$) distribution of clustering-related test statistics (Bollobàs 1985, Palmer 1985). In the case of the threshold graph $G(d)$ with $d = d_{(N)}$, i.e. with N edges, we may consider, e.g.:

– the number N_{isol} of isolated vertices (one-element connected components $\{k\}$) of $G(d)$;
– the number N_{proper} of objects in proper (i.e. non-singleton) components of $G(d)$

such that $N_{proper} + N_{isol} = n$ holds trivially;
– the total number N_{comp} of connected components (single linkage clusters) at the level N, i.e.

after N fusions;
– the size Z_{clique} of the largest clique in $G(d)$;
– the smallest integer $N = N_{conn}$ for which the threshold graph $G_{d(N)}$ is connected etc.

The hypothesis of 'randomness' will be rejected in favour of a clustering structure (at the significance level α) if, e.g., N_{proper} or N_{comp} are smaller than their α-quantile. The exact distribution of N_{proper} in $\Gamma_{n,N}$ is derived in Ling (1973, 1975) and Ling & Killough (1976). Many asymptotic results are surveyed by Bollobás (1985), Nowicki 1988, Godehardt (1990, chap. 5, 1992) and Godehardt & Horsch (1994).

For instance, assuming $N = N(n) = \lfloor 0.5n(\log n + c + o(1)) \rfloor$ for $n \to \infty$ with some constant $c > 0$, the graph $\Gamma_{n,N}$ consists asymptotically of one large component and several isolated objects, i.e. $P(N_{proper} = 1) \to 1$. Moreover, the random variables N_{isol} and $N_{comp} - 1$ are both asymptotically Poisson distributed $Po(\lambda)$ with expectation $\lambda = e^{-c}$, implying that $P(\Gamma_{n,N}$ is connected$) = P(N_{comp} = 1) \to exp(e^{-c})$. Similar results relate to the number of vertices with a given degree m and to the number of isolated trees of size m in $\Gamma_{n,N}$ or G_{np}, but possibly for other choices of $N(n)$. Godehardt (1990, 1991) extends these results to the case of multigraphs $\Gamma_{n,N,t}$ which are the superposition of t layers of the type $\Gamma_{n,N}$, describing t different aspects of similarity for the same n objects. Matula

(1970, 1972, 1976) shows that in the graph G_{np} the clique number Z_{clique} is asymptotically within $\lfloor z(n,p) - \epsilon, z(n,p) + \epsilon \rfloor$ for any $\epsilon > 0$ where $z(n,p) := 2\log_{(1/p)} n - 2\log_{(1/p)} \log_{(1/p)} n + 2\log_{(1/p)}(e/2) + 1$ and derives various finite-sample distributional properties.

The application of these graph models in cluster analysis is somewhat hindered by the fact that the assumption of (almost) independent links is unrealistic in many cases since natural similarity relations tend to be transitive (triangle inequality). Dissimilarity-based models with dependent links have been mentioned in section 4 (see also Frank (1987) and the Euclidean incidence graphs in Godehardt & Horsch (1994)), but have not been fully developed in the 'homogeneous' or 'unimodal' case.

6. Probabilistic models for hierarchical and tree-like classifications

Hierarchical classifications are broadly used in applications in order to get a stratified structure of classes at various heterogeneity levels and to visualize the mutual similarities between classes in a two-dimensional display. A hierarchical classification is usually constructed in the form of a dendrogram $(\mathcal{H}, h)$ where $\mathcal{H}$ is a hierarchy of sets and h a numerical index on $\mathcal{H}$ such that $h(A)$ measures the heterogeneity of a class $A \in \mathcal{H}$ of objects in terms of the data. It is well known that a dendrogram can be equivalently described by the ultrametric dissimilarity matrix $\delta = (\delta_{kl})_{n \times n}$ where $\delta_{kl} = \min\{h(A) | a \in \mathcal{H},\ k, l \in A\}$ is the heterogeneity $h(A)$ of the smallest class $A \in \mathcal{H}$ that contains both objects k and l. This dissimilarity measure fulfills the ultrametric inequality $\delta_{kl} \leq \max\{\delta_{kj}, \delta_{jl}\}$ for all $j, k, l \in \mathcal{O}$ (which implies the triangle inequality), and the classes of $\mathcal{H}$ are just the δ-balls $A = B(k,d) := \{l \in \mathcal{O} | \delta_{kl} \leq d\}$ (for $d \geq 0$ and $k \in \mathcal{O}$) while $h(A)$ is the δ-diameter of A.

Even if hierachical clustering algorithms are often applied to data points $x_1, ..., x_n$ in the Euclidean space, it seems to be difficult to design a general, intuitive and spatial idea of a 'natural' *hierarchical* classification in R^p. In fact, hierarchical classifications suggest more an underlying evolutionary or branching process in time or space and the related probabilistic models are therefore often defined in terms of stochastic processes. In the following sections we will review models based on dendrograms, additive trees, Markov

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processes and combinatorial considerations.

6.1 The additive error model for dissimilarity data

The *additive error model* proposed by Degens (1983) assumes that the observed dissimilarity matrix (d_{kl}) reflects an underlying unknown dendrogram structure $(\mathcal{H}, h)$ up to some random error. More specifically, if $\delta = (\delta_{kl})$ is the ultrametric which characterizes $(\mathcal{H}, h)$, the random (observed) dissimilarities

$$D_{kl} \quad = \quad \delta_{kl} + U_{kl} \qquad \text{for } k, l \in \mathcal{O}, k \neq l \tag{6.1}$$

are obtained from δ_{kl} by independent additive error terms U_{kl} all with the same distribution density $\psi(\cdot)$ on R (e.g., a normal density). An estimate for δ resp. for $(\mathcal{H}, h)$ is then obtained by maximizing the likelihood $L := \sum \sum_{k<l} \psi(d_{kl} - \delta_{kl})$ over all ultrametrics δ and all unknown parameters in ψ (e.g., by combinatorial or heuristic algorithms).

In particular, when we assume a normal distribution $N(0, \sigma^2)$ for ψ, the maximization of L amounts to minimizing the SSQ error criterion $\sum \sum_{k<l} (d_{kl} - \delta_{kl})^2$ over δ (for combinatorial and penalty function minimization methods see, e.g., De Soete, Carroll & DeSarbo 1987, De Soete 1988, Sriram & Lewis 1993) and it turns out that the level $h(A)$ of any class A of the resulting optimum dendrogram $(\mathcal{H}, h)$ is necessarily the average of the observed distances of its direct predecessors $B, C \in \mathcal{H}$ with $B + C = A$ (inducing a generalized average linkage algorithm). Analogous results have been obtained for other situations as well, e.g., for ψ a two-sided exponential distribution (generalized median procedure), for $U_{kl} \geq 0$ with a decreasing ψ (single linkage method), or $U_{kl} \leq 0$ with an increasing ψ (modified complete linkage method). These results were obtained by Degens (1983, 1985, 1988) together with several generalizations which refer, e.g., to the analysis of genetic distance data (d_{kl}) obtained from DNA-DNA hybridization experiments. Since these experiments can be repeated several times for each pair of species (objects) $k, l \in \mathcal{O}$ it is possible to design a similar Gaussian additive error model with *pair-specific variances* $\sigma_{kl}^2 = Var(D_{kl}) = Var(U_{kl})$ which can be estimated from the replicated measurements of D_{kl}. This approach leads to hierarchical weighted average linkage algorithms and yields theoretical consistency results.

6.2 Variance component models for genetic distance data

Replicated genetic distance data d_{kl} have been typically used for reconstruct-

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ing the evolutionary tree of n given species in the form of a dendrogram. Since the evolution of these species proceeds partially in parallel (or identical) streams in the past, the independence assumption from the previous section will be unrealistic here. Therefore Lausen & Degens (1986) and Degens, Lausen & Vach (1988) have proposed and investigated several *variance component models* which take into account various causes of variability of the measurements and from the evolutionary process which leads to a non-trivial dependence structure for the dissimilarities D_{kl}. A typical example is given by:

$$D_{kl\nu} = \delta_{kl} + E_{kl} + \sum_{j \in P(k,l)} L_j + U_{kl\nu} \qquad \text{for } k,l \in \mathcal{O},\ k \neq l,\ \nu = 1,...,n_{kl} \quad (6.2)$$

where $E_{kl} \sim N(0, \sigma_e^2)$ describes a pair-specific variation, $P(k,l)$ is the set of edges j in the path joining the object k with the object l (in the dendrogram belonging to (δ_{kl})), L_j the random evolutionary fluctuation existing along these edges, and $U_{kl\nu} \sim N(0, \sigma_U^2)$ is the measurement error for the replications $\nu = 1,...,n_{kl}$ of D_{kl}. The accuracy and stability of the resulting phylogeny and the induced hierarchy can been checked by using weighted three- or four-objects estimators for the variances (Wolf & Degens 1991).

6.3 Phylogenies and evolutionary Markov models for molecular sequences

Whilst phylogenetic trees and dendrograms have been constructed from morphological data of species and from genetic distance matrices since a long time, the advent of fast and precise sequencing methods in molecular biology has revolutionized this field: Phylogenetic inference of n species $k = 1,...,n$ is nowadays primarily based on the analysis of the corresponding nucleic acid sequences $x_k = (x_{k1},...,x_{kp})$ with p sites $j = 1,...,p$ and components x_{kj} taken from an alphabet $\mathcal{A} = \{A, G, C, T\}$ with $s = 4$ 'letters' which represent the four nucleotides, bases or 'states' adenine, guanine, cytosine, and thymidine (for DNA strains); thus there are 4^p different sequences. Similar data are available, e.g., for RNA ($s = 4$) or proteins ($s = 20$). Assuming that the underlying phylogeny has evolved in time t by random mutations (substitutions) of the bases in single sites, probability models for the resulting branching process have been formulated in terms of a (homogeneous) continuous-time Markov process for each site, and the phylogenetic tree is estimated by maximum likelihood, as well as its branch lengths and other

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model parameters (substitution rates).

A simple model (Felsenstein 1981, Bishop & Friday 1985) assumes that the mutation times for any single site j form a Poisson process with rate λ and that, if a mutation takes place from a state ν, it flips to the state μ with a probability π_μ (e.g., $\pi_\mu = 1/4$ for all $\mu \in \mathcal{A}$). This yields the transition probability $P_{\nu\mu}(t) = \pi_\mu(1 - e^{-\lambda t}) + \delta^*_{\nu\mu} e^{-\lambda t}$ from ν to μ in a time period t (where δ^*_{kl} denotes Kronecker's delta). More general cases are based on a matrix $R = (r_{\nu\mu})$ of substitution rates $r_{\nu\mu}$ (with zero row sums) such that the matrix of transition probabilities is given by $P(t) = (P_{\nu\mu}(t)) = e^{Rt}$, and the probabilities π_μ correspond to the stationary distribution of the induced homogeneous Markov process.

The relationship between the n species is described by an (unrooted unweighted) tree T with n leaves $k = 1, ..., n$ characterizing the n given species and a number m of interior vertices $k = n + 1, ..., n + m$ representing m unobservable intermediate species in the past, together with branch lengths $t_1, ..., t_M$ which represent the time difference between two change points (for binary trees: $m = n - 2$ and $M = n - 3$). In order to write down the likelihood function (6.4) below, it will be appropriate to specify one arbitrary interior node k^* of T as a root ($k^* = m + n$, say, a hypothetical ancestor) such that T becomes a directed graph T^* and its M branches can be written in the form $e_l = (a_l, b_l)$ where the node a_l is the direct ancestor of the node b_l in T^* and the numeration is such that $e_1, ..., e_n$ end in the observed leaves of the tree whilst each of the remaining edges $e_{n+1}, ..., e_M$ connects two interior points of T^*.

Our data consist of n sequences $x_k = (x_{k1}, ..., x_{kp}) \in \mathcal{A}^p$ observed for p neighbouring sites of n molecular strains (note that we pass over all problems of optimum alignment here). Additionally we have to consider the (unobservable) base sequences $y_k = (y_{k1}, ..., y_{kp}) \in \mathcal{A}^p$ characterizing the putative intermediate species (interior nodes) $k = n + 1, ..., n + m$ in the mutation process. For ease of notation we consider a 'homology' model where all sites $j = 1, ..., p$ evolve independently and identically in time and the mutation rates λ_l are identical for all branches e_l of the tree. Under these assumptions, the likelihood of our sample $x_1, ..., x_n$ is given by:

$$L(T, \vartheta; x_1, ..., x_n) = \prod_{j=1}^{p} L_j(T, \vartheta; x_{1j}, ..., x_{nj}) \tag{6.3}$$

with factors given by:

$$L_j(T,\vartheta;x_{1j},...,x_{nj}) = \sum_{y_{n+1,j},...,y_{n+m,j}} \pi_{y_{m+n,j}} \cdot \prod_{l=1}^{n} P_{y_{a_l,j}x_{b_l,j}}(t_l;\vartheta) \cdot \prod_{l=n+1}^{M} P_{y_{a_l,j}y_{b_l,j}}(t_l;\vartheta) \tag{6.4}$$

and transition functions $P_{\nu\mu}(t;\vartheta)$ as specified before. Here ϑ contains all unknown parameter values of the Markov process, i.e. $\lambda_1,...,\lambda_M$, $t_1,...,t_M$ (in fact, only the products $\lambda_l t_l$ occur here), $p_{\nu\mu}$ and $r_{\nu\mu}$.

The usual procedure for estimating the phylogenetic tree T and the unknown parameter ϑ is provided by the maximum likelihood method which includes, in particular, the maximization of L over all tree topologies T. Excellent reviews of these methods were given by Felsenstein (1983a, 1988) and Goldman (1990), and many more or less general models have been proposed by Kimura (1980), Felsenstein (1981; all λ_g alike), Hasegawa et al. (1985), Cavender & Felsenstein (1987), Barry & Hartigan (1987; 12 parameters per branch), Lausen (1989, 1991), Navidi, Churchill & Haeseler (1993) and Schöniger et al. (1994). Various maximization or tree construction algorithms were described by Hendy & Penny (1982), Felsenstein (1981, 1990), Guénoche (1993a, 1993b), Barry & Hartigan (1987) and Navidi et al. (1993). A uniqueness theorem for the likelihood solution was proved by Fukami & Tateno (1989). A Bayesian approach has been followed by Felsenstein (1984) and Kishino & Hasegawa (1989).

Another likelihood approach is related to classical *parsimony methods* where the tree T and the unobservable ancestor sequences $y_1,...,y_M$ are chosen such that, e.g., the total number N_{tot} of mutations along all branches is minimized (Wagner trees). This approach considers $y_1,...,y_M$ as incidental parameters and maximizes the corresponding likelihood $L(T,\vartheta,y_1,...,y_M;x_1,...,x_n)$ with respect to these sequences as well. For example, in the case $\mathcal{A}=\{0,1\}$ with $s=2$ states, let us denote by $\vartheta = 1-\pi \in [0,1]$ the probability of a change $0\to 1$ or $1\to 0$ along a branch of T (in the previous model this corresponds to constant average times $\lambda_l t_l = c$, say, and equal transition probabilities $1-\pi = P_{01}(c) = P_{10}(c)$). Then the likelihood has the form:

$$L(T,\pi,y_1,...,y_M;x_1,...,x_n) \quad = \quad \pi^{\sum_j (N_{00}^j + N_{11}^j)} \cdot (1-\pi)^{\sum_j (N_{01}^j + N_{10}^j)} \tag{6.5}$$

where $N_{\nu\mu}^j$ denotes the number of branches e_l in T with character values (ν,μ) their end nodes (in site j). Since both sums add to the constant

$Mp = (2n-3)p$ for binary trees, the maximization of L with respect to T and $y_1, ..., y_m$ amounts to minimizing $N_{tot} = \sum_j (N_{01}^j + N_{10}^j)$, the minimum length or parsimony criterion, provided that $\pi > 1/2$. Various other parsimony models are derived or discussed in Camin & Sokal (1965; Camin-Sokal parsimony), Farris (1973), Le Quesne (1974; Dollo parsimony), Felsenstein (1983b, 1988), Sober (1985), Felsenstein & Sober (1986) and Goldman (1990). Practical optimization algorithms can be found in Fitch (1971), Hartigan (1973; Fitch's algorithm), Sankoff (1975), Day et al. (1986).

A combinatorial and probabilistic analysis of parsimony trees for randomized or uniformly distributed sequence data in the discrete space $\mathcal{A}^p$ is provided by Carter et al. (1990), Steel (1992) and Steel, Hendy & Penny (1992) which use the duality between labeled trees (with node labels from $\mathcal{A}^p$) and graph colouring problems (with $|\mathcal{A}|^p$ colours).

Sneath (1989) considers the random sampling of characters and shows that the probability of detecting the correct tree can be small if there are only few characters. Quite generally, the maximum likelihood and parsimony methods were questioned by Nei (1987) and Saitou (1988) under the aspect that the likelihood values are incomparable for different topologies T. There exist simple models where the results of a parsimony method will converge to a wrong phylogenetic tree for $n \to \infty$, even for equal mutation rates λ_l (Felsenstein 1978, Saitou 1988, Hendy & Penny 1989). This has motivated the development of improved estimation methods for T based on 'invariant functions' of the distances which involve, e.g., the 'four-point inequality' which characterizes an additive tree (Lake 1987, Cavender 1991, Day 1991, Navidi et al. 1993). In order to evaluate the confidence in estimated phylogenies Li (1989) proposes tests for the significance of the estimated internodal lengths of T, Kishino & Hasegawa (1989) consider the variance of the log likelihood ratio, and Hasegawa et al. (1988) and Felsenstein (1985) use bootstrap resampling for this purpose.

6.4 Purely random hierarchies and trees

While the previous subsections focussed on models for hierarchies originating from a 'natural' clustering process there is also some need for the specification of models for 'purely random' hierarchies (or dendrograms): In fact, such concepts are indispensable if we want, e.g.,

(a) to decide if a calculated dendrogram points really to an underlying hier-

archical structure

of the data (as opposed to a situation where it bears no more structure than a 'purely

random' dendrogram; e.g., Murtagh 1983, Frank & Svensson 1981), or

(b) to compare two dendrograms $(\mathcal{H}_1, h_1)$, $(\mathcal{H}_2, h_2)$ resp. $\delta_1,\ \delta_2$, two hierarchies $\mathcal{H}_1, \mathcal{H}_2$ or

two phylogenetic trees and to check if they are more different from each other than to

be expected under 'pure randomness' (eventually assuming the same clustering strategy;

Lapointe & Legendre 1992a, 1992b), or, as a special case,

(c) investigate if a new dendrogram $(\mathcal{H}_1, h_1)$ obtained from the data is significantly different

from a known (e.g., traditionally established) classification $(\mathcal{H}_2, h_2)$ of the objects (Nemec

& Brinkhurst 1988).

Similar questions relate to phylogenetic or additive trees as well as to 'non-weighted' modifications considering the tree topology only.

In situations like (b) or (c), the usual approach proceeds by defining, in a first step, a suitable consensus index or a distance measure $D(T_1, T_2)$ between two hierarchical structures $T_1,\ T_2$; typical examples are the *partition (or symmetric difference) metric*, *quartet metrics*, the *nearest-neighbour interchange (NNI) metric* and the *cophenetic (correlation) coefficient* (for details see, e.g., Boorman & Oliver 1973, Waterman & Smith 1978, Day 1983, Fowlkes & Mallows 1983, Brown & Day 1984, Lapointe & Legendre 1990, 1992b, Steel & Penny 1993). Then, in a second step, we have to check if the value $D(T_1, T_2)$ for the calculated classifications T_1, T_2 is significantly larger than to be expected under a hypothesis H_0 of 'pure randomness' of T_1 and/or T_2 or of the data $x_1, ..., x_n$ or (d_{kl}) (see Shao & Rohlf 1983, Shao & Sokal 1986, Lapointe & Legendre 1990). Such an approach requires the calculation of suitable percentage points or, at least, of the expectation and variance of the criterion D which proves to be quite difficult in the general case since the relation:

$$\textit{calculated-classification} \ = \ \textit{clustering-algorithm}(\text{data})$$

is usually too complex as to allow to obtain any exact null distribution for D. In most cases, randomization, permutation and Monte Carlo tests will be in order (Rohlf 1965, Hubert 1985, Archie 1989) and percentage points

of D are approximated by bootstrapping (Felsenstein 1985, Sanderson 1989, Krajewski & Dickerman 1990) and simulation under H_0.

In this latter framework, there is a lot of essentially combinatorial approaches for defining 'purely random' hierarchies, dendrograms and trees by an equidistribution on a finite set $\mathcal{S}$ of 'distinguishable' hierarchical structures (hierarchies, dendrograms, trees, eventually including size and shape constraints). The investigation and simulation of these null models requires combinatorial enumeration techniques as well as computationally simple generation algorithms. This topic is discussed and surveyed, e.g., by Simberloff (1987), Furnas (1984), Quiroz (1989), Page (1991), Lapointe & Legendre (1991) and Steel & Penny (1993) who present many algorithms. In the following we will briefly sketch some typical cases.

We start with the remark that a dendrogram $(\mathcal{H}, h)$ for n objects can be considered as a rooted labeled and weighted tree T_n with n leaves and (at most) $n-1$ interior points (corresponding to $n-1$ cluster fusions). It induces (and is induced by) an additive (or path length) tree where each leaf has the same path distance from the root. Eliminating edge lengths and the root we obtain the combinatorial structure of an undirected tree-like graph. Obviously, two dendrograms or (additive) trees may differ in various aspects such as topology T, labeling L, fusion ranks R and fusion levels (or edge weights) W and therefore the definition of a null distribution H_0 of 'pure randomness' requires a careful specification of the set $\mathcal{S}$ in order to include (only) the practically relevant aspects. In particular, we have to distinguish, between rooted and unrooted trees, unlabeled, fully and terminally labeled trees, binary and t-ary trees, ranked and weighted dendrograms (with rank-ordered resp. real-valued fusion levels) etc. which all define different levels of analysis. Exact enumerations and probabilities can be obtained in a few (unweigthed) cases, in particular for the size of $\mathcal{S}$:

(a) There are $a_n = n^{n-2}$ fully labeled unrooted trees with n vertices (Cayley 1889);

(b) The number of rooted binary and terminally labeled (unweighted) trees (T, L) with n leaves

and $n-1$ interior edges (characterizing the nesting structure in a bifurcating hierarchy $\mathcal{H}$)

is given by $b_n = (2n-3)!/[2^{n-2}(n-2)!] = 1 \cdot 3 \cdot 5 \cdots (2n-3)$ (Harding 1971);

(c) The number of unrooted binary and terminally labeled (unweighted) trees (unweighted phy-

logenetic trees) with n leaves is given by $c_n = b_n/(2n-3) = (2n-5) \cdot (2n-7) \cdots 5 \cdot 3 \cdot 1$

(Schröder 1870);

(d) There are $d_n = n!(n-1)!/2^{n-1}$ topologically distinguishable binary ranked dendrograms

(T, L, R) with n labeled leaves and $n-1$ distinct fusion ranks (Frank & Svensson 1981).

For this latter random dendrogram case (d), Dale & Moon (1988) obtain the exact distribution of the size of the smaller subtree attached to the root, the number S of terminal single objects (i.e., the last S joins in the dendrogram join all a single object to non-singleton classes), and the number M_k of subtrees with $k+1$ leaves. Harding (1971) derives probabilities relating to the shape of rooted (unlabeled and labeled) binary trees, Day (1986) and Steel & Penny (1993) obtain the expectation, variance and (simulated or asymptotically Poisson) distributions for several tree comparison metrics under various specifications for H_0.

Since the number of trees or hierarchies is extensively large even for a small number n of objects, a full enumeration is not possible and therefore effective methods for the generation and simulation of random structures become very important: Furnas (1984) describes, e.g., a two-step procedure for generating random additive trees by first obtaining a random rooted binary and terminally labeled tree (T, L) (using an enumeration technique for the classical Prüfer code of a tree), and then assigning random lengths to its branches. Similarly, De Soete (1984) constructs a random binary dendrogram (T, L, W) by assigning random fusion level values to the vertices of (T, L) whilst Rohlf (1983) and Murtagh (1983) consider random binary *ranked* dendrograms (T, L, R) assuming $n-1$ different fusion ranks. Murtagh (1984) investigates a packed representation of the 'shape' (T, R) of labeled dendrogams (T, L, R). The method of Lapointe & Legendre (1991) starts with $n-1$ random uniformly distributed fusion level values $W_1, ..., W_{n-1} \in [0, 1]$, arranges them in an ultrametric distance matrix $(\delta_{kl})_{n \times n}$ and assigns random labels to its n rows (and columns) in order to construct a random dendrogram (with extensions for the case of other level distributions by using a double permutation method). The triple permutation algorithm in Lapointe & Legendre (1992a) constructs a random additive tree by means of the fact that any additive tree metric (a_{kl}) has a composition $(a_{kl}) = (\delta_{kl}) + (\tau_{kl})$ with an ultrametric δ and a star metric τ. Finally, Quiroz (1989) describes the construction of random rooted fully or terminally labeled t-ary trees with several generaliza-

tions, and Van Cutsem (1993) proposes, in analogy to Harding (1971), an iterative Markovian bifurcating process for obtaining a random rooted and terminally labeled binary tree (which is implemented recursively by means of a suitable declarative computer language).

Lapointe & Legendre (1992a, 1992b) have used these generation methods to derive simulated percentage points for various distance indices $D(T_1, T_2)$ (e.g., cophenetic correlation) and random dendrograms and/or additive trees T_1, T_2.

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