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Conceptual Clustering and Relevance Feedback*

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Building the knowledge base for an expert system is connected with an immense expenditure and possible only in distinct delimitable and small areas. The necessary knowledge is distributed in many domains among diverse experts and/or exists in the form of observation data and experience materials. The automatic classification methods belong to such techniques. They are represented in the area of Artificial Intelligence by conceptual clustering. Automatic classification methods in information retrieval systems in combination with a relevance feedback process may be considered as predecessors of this method. Conceptual clustering can be completed by a relevance feedback process, which allows an (interactive) manipulation of this concept. (Author)

1. Introduction

It is assumed that the development of an *Expert system* (ES) expects a reproduction of the special knowledge of a qualified expert (in a distinctly defined and small area). This knowledge will be used for automatic or interactive solving of particular classes of complex problems. ES apply methods from the area of Artificial Intelligence (AI). These methods imply a formalization of the necessary knowledge in the application area. Therefore, an Expert system can also be called a system with *formal intelligence. Building the knowledge base* for an Expert system is connected with an immense expenditure. The necessary knowledge is distributed in many domains among diverse experts and/or exist's in the form of observation data and experience materials. Automatic knowledge acquisition from this material and its interpretation is termed automatic knowledge extraction. In the literature these methods are assigned to the area of *machine learning*. In theory and practice of Expert systems, effective instruments supporting automatic knowledge extraction are still missing.

2. Conceptual Clustering

The *methods of Conceptual Clustering* (CC) were recently developed in the area of machine learning. The CC-algorithm is founded upon a preliminary work by Michalski (198●). *CC-algorithms* return characteristic (or summary) description of object groupings. They strive to optimize object clusters according to criteria imposed at the characteristic description level (e.g. the simplicity of characteristic description of object groups) and/or the map between characteristic descriptions and the objects they describe (e.g. the degree of generality)[1].

The representants of CC distinguish between three types of *cluster analysis* methods. These methods depend on the following *similarity measures*:

- *Context-free* similarity measure S1.
- *Context-sensitive* similarity measure S2:

$$S2(A,B) = f(A^*,B^*,O^*).$$

In addition to S1 the similarity between A and B is also dependent on their relation to other objects in a set of objects O. O* is a set of symbolic descriptions of O (O* includes also A* and B*).
In addition to S2, a *conceptual* measure is the function of a priori defined conceptual entities. The set of concepts may be used to describe structures within an object set:

$$S(A,B) = f(A^*,B^*,O^*,C).$$

The symbol C represents a set of *predefined rules* (criteria) which can be used *to generate concepts*. The quality of the object clusters depends on the quality of concepts which describe the clusters.

A *concept* can be defined as a *generalization* of an object set if the value set of each variable of the concepts includes each object's value for that variable. "When we state that a concept is a generalization of an object set, we are referring to a property of the concept, and *not* to the process which generated the concept. Concept generation may employ *spezialization* operators, as well as generalization operators."[2] Similarly it may be said that an object is a *member* of a concept. A *variable* is a dimension which is used to describe an object (e.g. color, size, shape). It is the same as an attribute (i.e. feature) in cluster analysis. All concepts and objects are defined by the same variables and within the same formalism. A *CC-program* is given a set of rules or operators which can be used to generate concepts from a set of object descriptions.

Three processes will be distinguished in CC (CC-program)[3]:

1) *Aggregation process* ("learning from observation") involves determining useful subsets of an initial object set. This process corresponds to the process of cluster formation.
2) *Characterization process* involves determining a useful characteristic (*conceptual*) description for some cluster or for each of multiple object classes (clusters), which was extensionally defined in the aggregation process.
3) *Evaluation process:* the quality of each of the conceptual description will be evaluated and the best descriptions will be selected.

The *characterization* step is reduced to search for the best cluster combination. For that purpose all possible descriptions of the available cluster sets are created[4].

The *quality* of each of these conceptual descriptions (concepts) is *evaluated* and one (or more) of the best (i.e. the simplest and most comprehensive) descriptions is returned (specialization process). E.G. the following *criteria* can be applied for measuring clustering quality[5]:

- *simplicity* of a set of concepts is the total number of variables used in each concept;

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- *disjointness* (discrimination index) between two concepts is a function of the number of variables in the two concepts whose values do not intersect. The *inter-cluster difference* (dissimilarity) of a set of concepts is the sum of the disjointness of all pairs of concepts;
- *dimensionality* tells us how many variables are used to describe clusters and thus how many variables have to be measured to classify objects into these clusters.

Therefore the *concepts* are extracted only from the object collection on the basis of the variable's value set. These concepts can not be manipulated or modified. Concepts and object representations are defined within the same formalism. This implies that all object representations are concept representations, but not vice versa. The concept problem can be reduced to the choice of an appropriate object representation and description resp. (e.g. the choice of attributes).

The methods of *concept selection* by conceptual clustering are primarily suited e.g. for cluster analysis methods similar to the *multicriteria dynamic clustering method* (MDC-method) of Diday (1976) or to the *monothetic divisive clustering technique*[6] (cf. Fisher (1984)). They are not suited for the methods which generate so-called optimal partitions. The MDC-method (the ISO-DATA-method is a variation of it) depends on many parameters. These parameters cannot be determined exactly (the structural properties of the actual object set must approximately be known[7]). Different cluster sets of objects to be classified are created by combination of different values of these parameters. In the monothetic divisive clustering process the objects will be classified each time according to only one attribute. It is evident that the classification created depends upon the order (rank) of separative variables. The CC-algorithms can often be replaced by a method for the determination of a sequence of separative attributes for this classification procedure. Several heuristic rules, which have been used in cluster analysis for a long time, can be applied for that purpose[8]. A similar effect of the evaluation step can be gained by application of an extended relevance feedback process. Additionaly the created clusters or the classification can be modified. The *pragmatic aspect* of this process can thus be accentuated.

A *correction of incorrect object descriptions* or an interactive improvement of the object descriptions (e.g. by an a posteriori (later) weighting of the attributes or the attribute value) by user feedback is not planned[9].

The examples used in the CC-literature, are relatively simple, the object sets used and the number of attributes are small. Several author used always the same or similar examples[10]. A great number of these examples can be solved more effectively by some known cluster analysis method. The agglomerative clustering methods are not used in CC-approaches. The problems with an additional reduction of the number of attributes (i.e. *reduction of dimensionality*) is not explored.

3. Similar approaches in information retrieval systems

Several approaches in theory and practice of information retrieral (IR) systems (e.g. automatic thesaurus construction[11]) can also be called conceptual in connection with their application. The *thesaurus theory (and practice)* deals with the conception of a concept and its designations (descriptors and non-descriptors), i.e. in a similar context as in the knowledge base of an Expert system. I do not know of any work in the AI-domain, taking into consideration the many years of experience in thesaurus research[12]. An analogous situation should be applied to the area of automatic classification in IR-Systems.

Sometimes the *method of Litofsky* (1969) is assigned to automatic thesaurus construction[13]. This method can be extended for any object and attribute types, so it can be applied for a construction of concept-based object classes.

The *STEINADLER-approach* (cf. Panyr (1986)) is suited primarily for a large set of attributes and/or objects. These attributes are first distributed in different distinct hierarchy levels. The objects (and attributes) are classified only in these levels and only with the proper subsets of attributes occuring in each actually existing hierarchy level. Cluster sets in different levels are created independently. They are compared with each other and the independently produced cluster sets will be adjusted (matched) one to the other. Attribute values, which are placed along the paths of the classification tree created, are then used for a description of the object classes under the nodes (in direction from the root to the leaves). The classification can be updated interactively by relevance feedback.

The *graph-theoretic classifications* are very expressive and therefore easy to interpret[14]. An examination of their applicability to knowledge extraction from texts or from object sets with any attributes has not as yet been done.

The *reduction of the variable set* (i.e. reduction of dimensionality) was already applied by Crouch (1972). The Crouch classification process has two steps[15]:

- *categorization* with reduction of a variable set; the object collection is clustered only with this reduced attribute set (core attributes);
- *classification* with a part of the remaining attributes.

Another criterium for a reduction of attributes can be attained on the basis of the *discrimination value model* (developed and described by Salton et al. (1975); cf. also Panyr (1987a)).

The most interesting application is the relevance feedback. We can say also "learning from example". In the next part of the paper a combination between Relevance Feedback and Conceptual Clustering will be discussed.

4. Relevance Feedback strategies and Conceptual Clustering

In the CC-process an *interactive intervention by user feedback is missing*[16]. These problems were detected as relevance feedback (RF) very early in IR-Systems research (since 1965). The RF-methods were at first applied in the SMART system (cf. Salton (1971, 1975)). They are applied in IR-Systems as interactive strategies and can be divided into *two main groups* (cf. Panyr (1987b)):

- *search query modification* (in an IR-System);
- *modification of the object spaces*, in which the objects are searched.

Both modifications are based on the user's judgement of the retrieved documents as relevant or non-relevant.

The *query modification* is based on the assumption that the user query is formulated inexactly and unclearly (e.g. in consequence of ambiguous search arguments). The *modification of the object space* (in an IR-System the objects are equal to the documents) is additionally based on the assumption, that the unsatisfied retrieval results are a consequence of an incorrect object description or of an incorrect object classification. The combination of these two approaches is termed a *hybride strategy*.

The user feedback is called a *positive feedback* only if the objects being identified as "relevant" by the user are applied to modification, otherwise, if in addition the nonrelevant objects are applied to a modification, the user feedback is termed as a *negative feedback*. The "negative" technique may be applied, if the positive feedback is not possible.

4.1 Modification of an object collection (object space)

The methods for an object space modification can be subdivided into:
- *modification of the initial objects* and of their descriptions;
- modification of the object classification (i.e. *modification of a clustered space*)

The *first group* can be applied for a general improvement of the object representation (e.g. through the installation and the modification of an attribute weighting), the methods of the *second group* can be used e.g. for the modification of the concepts obtained. The concepts will be treated as the cluster centre (i.e. centroid). The description of these methods will not be explained in detail. The basic idea of the RF-strategies will be described roughly[17].

Both, query and documents (and the centroids as well) are described by terms of a common term set. These *terms are weighted* by nonnegative numbers (usually between 0 and 1) both in the queries and in the documents. This weight demonstrates the relative importance of the considered term (also in connection to other terms) in the document or in the query. If such a weighting is not available, the weights can initially be set to 1 for the present terms and to 0 for the absent terms.

The *similarity between the query q and a document D* will be computed on the basis of a *correlation coefficient* K(D,q). The retrieved documents are ordered according to the magnitude of their correlation coefficient with the search query.

The *documents are judged* after each retrieval's iteration as relevant or as nonrelevant by the user. According to this judgement, the *weights of the document terms*, which are present in the search query, will be *adapted* in the total document collection. They will either increase (in relevant documents) or decrease (in nonrelevant documents). The modification will be finished if the user is satisfied with the retrieval results or if no new relevant document is being returned[18].

If the *document space is clustered*, then the document descriptions (i.e. the term weights) will be adapted and the document collection will be newly classified (clustered). Subsequently the cluster centres will also be transformed.

In the *reverse case*, the centroids are at first modified. Subsequently the documents will be newly assigned to the adapted cluster centres.

4.2 Relevance Feedback for Conceptual Clustering

Several *similarities* exist between the modification of the document space and a possible potential modification of conceptual clustering:

- all objects and all concepts are defined (described) by the same variables (with the same values); similarly all documents and all queries are represented by the same terms;
- each user of CC has (similar to each user of IR-System) a specific relevance concept with respect to his (user's) need.

Similar to an application in IR-Systems, the object space of CC can be designated as a *dynamic object space*.

Two strategies can be pursued:

- *classification objects* will be transformed close to a desired selected concept;
- *concepts* will be adapted on the actual "situation" in the object space, so that they describe more accurately the structural properties of the object set to be classified.

The attributes (or their values) can be assigned to a vector with nonnegative numerical weights. The components of this vector, i.e. the *weights*, correspond to the variables (or their values). These weights will be adapted through the following modification process and they are used by the classification algorithm. The weights can initially be set to 1 for the present variables and to 0 for the absent variables (or values).

If single qualitative values should be weighted, they must *be binarized*. Therefore each value will be considered a binary variable[19].

The *possible RF-Strategies* for a modification of the result of a CC-algorithm can proceed as follows:

Strategy 1 with the following assumption:

The user has an idea in connection with the concept expected (or desired). Therefore, he can *search for this concept* (with a search strategy) in the clustered object set. The concepts retrieved are ranked according to a correlation value. The results of the search are:

- *concepts*, which are similar to an expected concept,
- *objects*, which were assigned to these concepts.

The initial classification will now be modified by Relevance Feedback on the basis of the plausibility of the concepts returned and of the assignment of several objects to these concepts. The process can be repeated for the modified concepts.

Strategy 2 with the following assumption:

The *user does not know any concept* and also does not know the structural properties of the object set which was classified by a CC-method. The user receives some (coincidentally) chosen concepts or all concepts and their objects one after the other. The *modification* will be performed only on the basis of an *assignment of single objects* as "correct/incorrect" to the presented concept.

The assignment of objects to selected concepts corresponds to an *inversion of the CC-process*. Here the concepts (particularly the maximally-specific discrimination concepts) have a function similar to the cluster centres (centroids) in the cluster analysis.

5. Concluding remarks

A better *cooperation* between experts from the area of *Information Science* (with IR-systems research) and experts from the *AI-area* (with ES research) is inevitably necessary for the domain of AI. At present such a cooperation (primarily in the AI-area) is an exception (cf. de Jong (1983) or Addis (1983)).

Many approaches in IR-systems research treat the concept term (frame) in connection with the cluster analysis and inductive learning resp. (cf. e.g. Wong/Ziarko/Yu (1986), Wong/Ziarko (1986), Deogum/Raghavan (1986), Croft (1986)). RF-methods are assigned by Salton (1986) to the area of knowledge extraction (i.e. machine learning). Rieger (1984) implicitly applies cluster analysis to a description of language structures (i.e. frames). The CC-methods can still be useful also for cluster analysis research. By generating concepts these methods will allow a more simple interpretation of constructed clusters.

Notes:

1 Cf. the description of CC by Michalski/Stepp (1983), Fisher (1984), Langley/Carbonell (1984), Fisher/Langley (1985) or Lebowitz (1986).
2 Cf. Fisher/Langley (1985), p. 12 (note 6). Generally it can be said that the CC-authors do not always use a unique definition for concept (cf. references in note 1).
3 Cf. Fisher/Langley (1985), p. 7 ff.
4 Cf. Michalski (1980), Michalski/Stepp (1983).
5 Cf. Michalski (1980), p. 229, Fisher/Langley (1985), pp. 19.
6 Cf. e.g. Panyr (1986), p. 84ff.
7 Cf. the comments to the ISODATA-method (wich is similar to these methods) by Panyr (1986), p. 71, and Diday/Simon (1976), p. 85, resp.
8 E.g. Gower (1967), Lance/Williams (1965); Cf. also Bock (1974), p. 417ff., or Panyr (1986), p. 84–86.
9 Cf. Langley/Carbonell (1984), p. 312f.
10 Cf. Michalski (1980), Michalski/Stepp (1983), Fisher (1984) or Fisher/Langley (1985).
11 A thesaurus is similar in its structure and function to a knowledge base.
12 Much the same should apply to USA and Canada (private comment of Dr. Bollmann – TU Berlin).
13 The Litofsky method is described by Panyr (1986), p. 99–103. Salton (1975) speaks about this method in connection with that application.
14 Cf. the work of Needham et al. in Cambridge Language Research unit – C.L.R.U. England), cf. also Panyr (1986), p. 73ff. or Uebbing/Wichmann (1978).
15 Cf. also Panyr (1986), p. 92f.
16 Cf. Langley/Carbonell (1986) or Fisher/Langley (1985).
17 Cf. the references by Panyr (1987b).
18 Cf. e.g. Friedman et al. (1971) and the method modification by Davis et al. (1968).
19 About the dependencies between variables cf. Ganter/Wille (1986).

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Classification and Related Methods of Data Analysis

IFCS-87, the First Conference of the International Federation of Classification Societies on the topic as given in the headline took place from June 29 - July 1, 1987 at the Technical University of Aachen, FRG. It was the first conference dedicated exclusively to the field of mathematical, numerical, and statistical methods of classification, clustering, and data analysis as well as to the numerous applications of these methods in various domains in the Federal Republic of Germany.

This might be the reason for the large response by researchers and practitioners from the world over: In all, 294 participants attended this conference, and its international character is best illustrated by the list of the countries represented:

West Europe	Eastern Europe	America
128 Germany (FRG)	10 Poland	22 USA
30 France	5 Hungary	12 Canada
24 Benelux	2 Germany (GDR)	
16 Italy	2 Yugoslavia	Asia
11 United Kingdom	1 CSSR	2 Israel
8 Switzerland	1 Bulgaria	2 Japan
5 Austria		
4 Spain/Portugal	1 **South Africa**	6 **Australia**
2 Sweden/Norway		

42 outstanding persons had been invited to give a lecture on some specified research topic.

Altogether, the scientific program lists 194 lectures, i.e. 18 plenary, resp. extended lectures, and 176 papers presented in the Special Sessions. As a rule, the program provided a plenary lecture or 2-3 extended lectures each morning and afternoon; subsequently the program split into 3-6 parallel Sessions, each with 3-4 papers.

It would go too far to comment in detail on this wealth of presentations. However, the list of Session headings given below conveys some ideas on the scope of the program and might support the following remarks:

1. As to be expected, Sessions on Numerical Classification and Clustering Methods (in the narrow sense) have been predominant in the program. The topics investigated were diversified in many respects showing the future developments in this field: Non-classical input data (e.g., missing values, relations, shapers), probabilistic approaches (simultaneous test procedures, tests for clustering structure), modified clustering problems (multicriteria clustering, fuzzy clustering), robustness and stability problems, computational aspects, etc.

2. It was very useful to combine the clustering methodology with papers from statistical *pattern recognition*: Not only because these fields are intimately related to each other, but because the input data in pattern recognition are from a much more general type than in classical cluster analysis - a challenge for interdisciplinary research projects.

3. A quite large number of papers was devoted to *consensus* methods, i.e. to the aggregation of structures in order to find a consensus structure. It was evident that this topic is strongly related to the analysis of phylogenetic trees, of *biological taxonomy,* and of *chemical classification* as well. There is a lot of unsolved mathematical and computational problems in these fields.

4. *Data analysis methods* proved to fit the program very well since their usual mathematical formulations (e.g., as an optimization model) resemble very much some clustering problems. Moreover, the ordering properties of classification structures (systems) are expanded by data analysis methods, so the specialized models of the latter ones lend themselves to applications in the clustering framework.

5. It was very helpful to bring together *theorists and practitioners* at this Conference: Both parts were very interested and satisfied from their mutual contacts.

The following list of sessions emphasizes once more that from the spectrum of problems, from the mathematical and statistical aspects, and from the applications involved, this Conference was very successful and has put standards for further meetings, e.g., for the Second IFCS Conference to be held at Charlottesville, VA, USA in 1989.

Number of Sessions	Topic	Number of papers
12	Clustering and numerical classification	48
6	Data analysis (linear, algebraic and graph theoretical methods, aggregation)	33
4	Pattern recognition and discrimination	16
3	Similarity and distance	11
3	Classification, data bases, retrieval and expert systems	12
5	Consensus theory, Comparative sequence analysis, and Phylogenetic inference	19
3	Multidimensional scaling and seriation	11
4	Applications in medicine, sociology, marketing, voting results, etc.	16
3	Software problems	10

The conference was organized by the Institut für Statistik und Wirtschaftsmathematik (Prof. Dr. H.H. Bock) at the Technical University Aachen (FRG) under the auspices of the Gesellschaft für Klassifikation eV and its Section "Data Analysis and Numerical Classification". The scientific program was supplemented by large software presentation facilities, a series of business meetings of the involved institutions and Societies, and several social program events supported by the University and the City of Aachen.

Hans Hermann Bock