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A Methodology for Multistrategy Knowledge Discovery

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Abstract

This paper presents a methodology for multistrategy data analysis based on the application of diverse learning and discovery programs and tools. Research in the area of integrated learning systems has led to the development of INLEN, an intelligent assistant for discovering knowledge in large databases. The architecture of INLEN is based on the interaction of a number of *knowledge generation operators* – manifestations of diverse learning tools within a uniform environment. There are difficulties in the application of traditional learning programs to database analysis that do not appear in the laboratory environment; the responses to these problems that have been built into INLEN are briefly presented. Finally, the methodology is demonstrated through examples of INLEN's application to databases consisting of world economic and demographic facts.

Keywords: Multistrategy Learning, Knowledge Discovery in Databases, Knowledge Transmutations, Economic and Demographic Databases

1. Introduction

As the amount of electronically available information grows explosively, it is becoming both critically important and increasingly difficult to analyze the data to derive desired knowledge from them. Traditional tools for data analysis employ mostly statistical concepts and methods. These methods can be particularly useful for such tasks as detecting statistical trends, correlations between attributes, data distributions, etc. They are, however, limited in the types of knowledge and regularities they can derive from data.

For example, a statistical analysis can detect a correlation between given factors, but cannot produce a conceptual explanation why such a correlation exists, nor can it formulate any specific quantitative and/or qualitative law(s) responsible for this correlation. A statistical technique can determine a central tendency and variability of some properties, or fit a curve to a set of datapoints, but it cannot explain them in terms of causal dependencies or qualitative relationships. Attributes that define a similarity and the measures of similarity involved must be given in advance. In short, these techniques require that an interpretation of the findings, i.e., a "conceptual" analysis of data, be performed by a human analyst. As the quantity of available data increases, the complexity of such an analysis can easily outstrip human capabilities.

Because of this, the machine learning community has taken an interest in the problem of knowledge extraction from databases. Machine learning approaches can overcome some of the limitations inherent in traditional data analysis methods. For instance, constructive induction and deduction methods can improve the data description space based on the

nature of the data itself, the knowledge learned by the discovery system, and/or the background knowledge provided by the domain expert. Symbolic learning methods have the advantage of representing their knowledge in such a way that it is very easy for users to understand and explain the meaning of the discovered knowledge.

Machine learning researchers have developed an assortment of domain-independent programs that can perform a narrow set of symbolic learning tasks. The weakness of these programs is the fact that they are so task-specific. No conceptual clustering program, for example, can generate equations governing quantitative data, create rules distinguishing between classes of objects, select representative examples from a larger database, or improve a ruleset based on new data. Recent research in multistrategy learning has attacked the problem of integrating diverse learning tools into composite systems whose wholes may exceed the sums of their parts.

One such approach to this problem, called INLEN, applies an integrated system to the specific problem of knowledge discovery in databases. It was designed to overcome some of the limitations of statistical data analysis by applying advanced methods of machine learning. Its architecture integrates database, knowledge base and machine learning technologies into a single package for data analysis and knowledge discovery. In doing so, it offers a data analyst a powerful tool for discovering patterns of non-statistical nature, determining logic-style data descriptions, and producing justifications or explanations of the discovered patterns (Michalski et al, 1992).

Symbolic learning programs, such as those that comprise many of INLEN's available tools, can determine rules for distinguishing between many classes of items, find conceptually useful ways to group objects, apply knowledge in order to predict missing values in a data set, select representative subsets of a large data set best suited for a particular learning task, etc. The various learning and discovery programs in INLEN are accessed in the form of *knowledge generation operators* (KGOs) that can be applied in sequence, with each KGO capable of taking advantage of its predecessor's findings. Because of the symbolic nature of these operators and their adaptability to different problems, this methodology is well-suited for many domains in which databases contain a large number of records and attributes, and in which the results of analysis must be understood by non-experts.

Among the other efforts to apply multistrategy methods to data analysis are several systems incorporating symbolic learning. For instance, Alexander, Bonissone and Rau (1993) describe a system for discovering knowledge that can be used to improve marketing strategies. It combines the C4.5 decision tree learning program (Quinlan, 1990) with a statistical analysis system in order to extract information from a sales database. RECON (Simoudis et al, 1994) combines inductive and deductive reasoning into a general-purpose knowledge discovery environment. In comparison with these systems, INLEN focuses more on symbolic learning operators, and is designed for the incorporation of a large number of tools, rather than just one or two for inductive reasoning. By necessity, this leads to an increase in the complexity of the system's infrastructure and its knowledge base.

This paper presents the INLEN architecture, discusses some of the problems inherent in applying such an architecture to knowledge discovery, and presents examples of its multistrategy discovery process through its application to the analysis of several databases

consisting of world economic and demographic facts. We conclude by summarizing the development status of INLEN, the advantages and current limitations of this methodology, and outline the plans for future research.

2. The INLEN methodology

The INLEN system integrates a database, knowledge base and machine learning technologies into a unified knowledge discovery environment (Fig. 1). A relational database is used for storing data, and can be modified by the user through *data management operators.* A knowledge base stores and maintains rules, equations, decision procedures, representative examples, and concept hierarchies that are employed in the process of data analysis and knowledge discovery. The knowledge base is made up of *knowledge segments,* which store declarative, procedural, and exemplary knowledge about the application. This knowledge may include the domains of the attributes, background knowledge relevant to the problem, discovered knowledge, and any knowledge entered or modified by the user. The contents of the knowledge base can be modified by an expert through *knowledge management operators*.

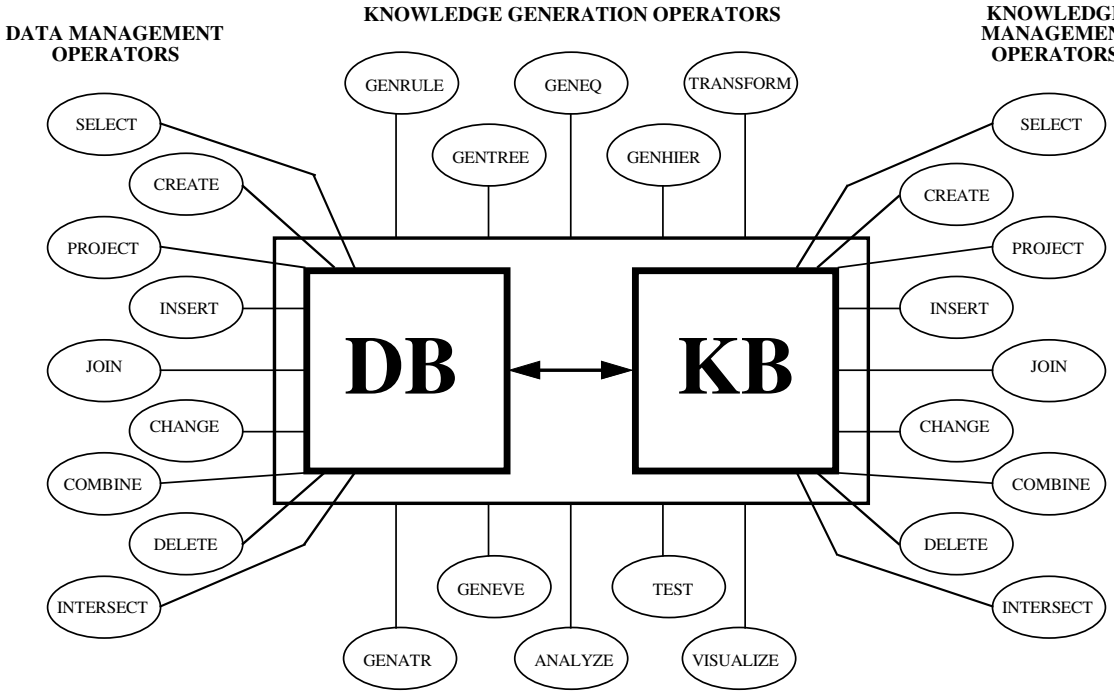

Figure 1. Functional Architecture of INLEN

The central engine of the system consists of a set of operators, called *knowledge generation operators*, that invoke learning, discovery and inference programs to perform data analysis tasks. These operators take input from the database and/or knowledge base, and produce outputs that enhance the data and/or knowledge bases. These operators are adept at diverse tasks, such as learning symbolic rules to differentiate among several classes of data items, conceptually dividing a data set into two or more groups (conceptual clustering), modifying the representation space into one more suitable for a

particular learning task through feature selection or constructive induction, testing a set of knowledge for consistency with respect to new data, and predicting values for missing data.

The application of these operators is controlled by the user, while the system extracts the necessary information from the data and knowledge bases to complete the input to the learning operator. Similarly, INLEN maintains more information than the operators might return in stand-alone mode; facts and links that might be useful to another operator in the future are stored in the output knowledge segments. For instance, if a rule learning operator is used to find conditions distinguishing between two sets of data records, INLEN will retain not only the discovered rules, but also the learning mode and parameters used, an estimate of the informational value of the rules and their component conditions, and links to the records that satisfy the rule. This information may be later accessed by a user or another operator, such as a prediction engine or a program for selecting representative examples from the dataset.

The idea of such a multi-operator approach to knowledge discovery was formulated by Michalski in the 1980s. The first such effort, from which INLEN derived much of its conceptual architecture, was the QUIN system (**Qu**ery and **In**ference), a combined database management and data analysis environment (Michalski, Baskin and Spackman, 1982; Michalski and Baskin, 1983; Spackman, 1983).

Figure 1 shows ten classes of knowledge generation operators. These include rule generation (from sets or sequences of examples), decision tree generation (from examples or rules), equation generation (from quantitative and qualitative data), conceptual cluster and taxonomy formation, knowledge transformation (e.g., through abstraction, generalization, or incremental learning), representation space modification (through feature selection, constructive induction, and attribute quantization), event set generation (through example selection, simulation or prediction), relational analysis (through statistical and non-statistical metrics), knowledge testing for consistency and completeness, and concept visualization. The programs that form the foundations for these operators are cited and described individually in (Michalski et al, 1992).

These operators also represent various knowledge transmutations as are catalogued in Michalski's Inferential Theory of Learning (1993). For instance, learning classification rules from examples involves an inductive generalization transmutation; conceptual clustering is an act of inductive agglomeration; representation space modification can consist of generation, selection or abstraction transmutations; and knowledge-based prediction of missing values incorporates a similization transmutation.

Another important feature of the knowledge generation operators is that many of them allow the user to define parameters and tailor their performance to a specific learning task. In this way, the user (data analyst) can specify from among the many possible outputs consistent with the data and pinpoint which type of knowledge is likely to be most useful. Two examples below illustrate the choices of parameters when using the KGOs.

One of the backbone abilities of INLEN is rule learning from examples, performed using the AQ15c learning engine (Wnek et al, 1995). The user can accept the default parameters or instruct the program to bias its rule selection toward either highly specific

characterizations, short rules for discrimination, a set of maximally simple rules, rules that tend to incorporate or avoid specific attributes if at all possible, or the user can create and specify a different set of preference criteria.

Another knowledge generation operator is based on an extension of the PROMISE program (Baim, 1982). It examines the set of attributes in the database and ranks them according to their applicability to a given classification problem. The user can then learn from the subset of the data consisting of only the attributes likely to be more relevant to the learning task. This operator can be used in two modes. In the first, each attribute's overall discrimination ability is calculated using an information gain metric similar to that used by the C4.5 (Quinlan, 1990) family of algorithms. The second mode focuses on the attributes most likely to produce concise rules; it selects attributes that contain some values that discriminate very well between classes, even if most of the other values provide little utility in classifying the examples.

3. Database Analysis based on Multistrategy Learning

The previous section discussed the architecture and major components of INLEN. Through the sequential application of KGOs, a user can link different learning and discovery programs into a stream of tasks. Many of the operators are based on machine learning programs that were not designed for the analysis of large databases, but were instead written based on the assumption that they would be operating in a supervised learning environment. As a result, they often have the following characteristics:

(1) Their inference methods are tailored to simple nominal or linear feature domains without rich domain knowledge.

(2) It is assumed that most of an example's attribute values will be provided.

(3) All of the information relevant to a problem will be available in one location.

Unfortunately, these conditions do not always hold when exploring a real-world database. The attributes in the data may be based on complex hierarchies, lattices and gradations of concepts. Many of the fields in the data may be missing due to incomplete information. And the goal knowledge may be only attainable through the extraction and combination of information from multiple sources.

These problems have been addressed by the knowledge generation operators in INLEN. INLEN supports learning with complex structured data types. Not only can a user define a data attribute to be hierarchically structured, one can also define nodes within the hierarchy as especially significant foci for learning, generalization and specialization (Kaufman and Michalski, 1996b). The justification behind the selection of such nodes is that we tend to weight the significance of nodes in a classification hierarchy unevenly. For instance, Fluffy is a beagle, which is a dog, which is a member of the order of carnivores, which is a vertebrate, which is an animal, which is a living thing. In everyday usage, we are likely to think of Fluffy as a dog or an animal, and we may think of him as a beagle, but we are unlikely to think of him as a vertebrate or a member of the carnivore order. The reason is that these levels of abstraction are typically of less use with regard to our interactions with Fluffy.

By encoding the significance of the nodes into the knowledge representation of a discovery system, the system can present discovered knowledge that focuses on these levels of abstraction when possible. We will typically prefer to see the classification rules "A living thing belongs to Class 1 if it is a dog" or "A living thing belongs to Class 1 if it is an animal" instead of "A living thing belongs to Class 1 if it is a vertebrate" or "A living thing belongs to Class 1 if it is a member of the carnivore order."

Another important feature in INLEN's structured data representation is its ability to work with multiple views of the data (Kaufman and Michalski, 1996b). Consider an application in which a user is trying to classify personal computer systems, and one of the attributes is the model of the monitor being used. Computer monitors can be classified based on their features, on their manufacturers, or on their size. We may not know prior to a learning task which classification view will provide the most useful knowledge. Also, more than one view may generate the best decision rules. A decision rule, for example, may include the condition that the system should have a 17" NEC monitor. INLEN's generalization engine automatically selects the optimal (according to user criteria) representation of the knowledge.

The knowledge generation operators have also been enhanced to cope with incomplete data sets. Experiments with sparse data exposed some of the limitations of these operators, leading to modifications in which the logical implications of unknowns are more rigorously encoded into the learning algorithm. For example, while earlier versions of the AQ operator would use a simple bit string subset check to determine if a case was covered by a rule, the algorithm is now based on the awareness that unknown values may cause unexpected answers based on that original approach.

Another aspect of this research approaches the problem of knowledge extraction from distributed sources. The INSIGHT program (Ribeiro et al, 1995) is being incorporated as an operator to perform a knowledge-driven search through multiple databases. In order to facilitate the interface with INSIGHT and other operators, INLEN maintains information on the database records described by each rule in its knowledge base. It can then measure the degree of match between a rule and a set of records in a second database matching a given set of conditions. A high degree of match suggests a linkage between the two concepts. Another use for the knowledge base's links to relevant training examples is that the listings of examples can identify significant clusters or exceptions. An example of this feature is given in Section 4.2.

The goal of all of these features is to facilitate INLEN's compatibility with real-world databases. The tools that serve as knowledge generation operators can then perform at a level close to how they perform on carefully supervised data sets, while their integration results in a system not limited to a narrow class of discovery tasks.

4. Exemplary application: economic and demographic domains

INLEN and its operators have been applied to learning and discovery problems in such domains as engineering design, disease diagnosis, intelligence gathering and economic analysis (e.g., Arciszewski et al, 1992; Michalski et al, 1992). The following example illustrates the role an intelligent agent can play in the discovery of knowledge from data:

The United States government maintains records of the import and export of goods from various countries of the world. The different products and raw materials are divided and subdivided into different categories. In the early 1980s the data showed a sharp decline in the import of trucks from Japan, while there was a corresponding increase in imports from Japan in the auto parts category. It took several years before analysts noticed that fact and concluded that Japan was shipping the chassis and truck beds separately to the US, where they would be subsequently assembled, thereby avoiding a high US tariff on imported trucks that was directed primarily at Europe and had been on the books since World War II. When United States analysts inferred this, the US and Japan commenced trade negotiations pertaining to the import of trucks.

How much sooner would that trend have been noticed had a discovery program been applied to the data and pointed out to an analyst the opposite changes in two related categories? How much revenue did the undiscovered truth cost the US before they could finally work out a new agreement with Japan? Noticing economic trends and patterns is a difficult task, as humans can easily get overwhelmed by the amount of raw data.

Based on such motivations, the analysis of economic and demographic data has become one of the focus domains for INLEN development and testing. These experiments have involved two similar data sets – one provided by the World Bank consisting of information on 95 attributes in 171 countries for the period of 1965 to 1990, and one extracted from the 1993 World Factbook (CIA, 1993) containing several databases of information on 190 countries. Examples of such experiments and results follow.

4.1 Distinguishing Between Two Regions' Development Patterns

An experiment that serves as an example of the linkage of different learning and discovery methods focused on distinguishing between development patterns in Eastern Europe and East Asia (Kaufman, 1994). This experiment demonstrates a sequence of operators consisting of attribute selection, conceptual clustering, rule generation based on set characterization, and rule optimization. After the feature set was pared down to those likely to differentiate the two regions, a conceptual clustering operator determined that one way of distinguishing between the typical Eastern European country and the typical Far Eastern country was through examining the country's change in the percentage of its population in the labor force between 1980 and 1990. Most of the European countries had a labor force change below a threshold determined for the region by the learning program, while most of the Asian countries had changes above their region's threshold.

Based on this, the rule learning operator (based on the AQ15c inductive learning program) was then called upon first in characteristic mode to categorize the differences between the Asian-like countries (those above their regional thresholds) and the European-like countries (those below their regional thresholds), and then in discriminant rule-optimizing mode to condense the lengthy characterizations from the previous set (4-8 conditions per rule) into the following simple decision rules:

Country is Asian-Like if:

A.1 Change in Labor Force Participation ≥ slight_gain, *(9 countries)*

or

B.1 Working Age Population ≤ 64%,

2 Life Expectancy is in 60s. *(2 countries)*

Country is European-Like if:

A.1 Life Expectancy is not in 60s,
2 Change in Labor Force Participation is near 0 or decreasing, *(7 countries)*
or

B.1 Percentage of Labor Force in Industry ≥ 40. *(1 country)*

The rules show that the features aside from change in labor force participation instrumental in distinguishing between the European-style and Asian-style development patterns include life expectancy, working age population and degree of industrialization. In both the Asian- and European-Like cases, the first rule accounted for most of the countries fitting the class, while the second one described the remainder.

4.2. Identification of an unusual example

Because INLEN's knowledge base maintains records of the data described by each rule, this information can be used to group the records within a particular class. For example, when the AQ15 rule generation operator was called upon to characterize the 13 countries of South America, it came up with two distinct characterizations – one describing the majority of the countries, and the second describing the other four: Ecuador, French Guyana, Peru and Venezuela. By suggesting that these two subgroups of countries may have significant commononalities among themselves, the program has proposed a classification scheme for further investigation.

Another experiment clearly indicates how INLEN can detect interesting facts within the subgroups it creates. While the subgroups in a demographic domain may indicate that member countries or regions have something in common, notable exceptions may be exposed when one of the members of these constructed subsets shows a marked dissimilarity to the rest of the group. These exceptions in turn may prove be a springboard for additional discovery.

INLEN discovered several rules from the World Factbook PEOPLE database characterizing the countries with low (less than 1% per year) population growth (Kaufman and Michalski, 1996a). One of the rules had three conditions that together were sufficient to distinguish 19 low growth countries from all of the countries with higher population growth rates. The rule is shown here with three weights attached to each condition: *Pos* represents the number of positive examples (countries with population growth rates below 1%) satisfying the condition, *Neg* represents the number of negative examples (countries with population growth rates above 1%) satisfying the condition, and *Supp*, defined as Pos / (Pos + Neg) in percent, represents an approximate measure of the degree of confidence that the condition alone provides toward the conclusion that a country will have a population growth rate below 1%.

Conditions characterizing Countries with Population Growth Rates below 1%:

		Pos	Neg	Supp
1	Birth Rate = 10 to 20 or Birth Rate ≥ 50	46	20	69
2	Predominant Religion is not defined as Muslim or Mixed or Buddhist or	40	68	37

	Christian or Tibetan			
3	Net Migration Rate ≤ +20	32	104	23

The first and strongest condition states that the country must have a low (under 20 per 1000 population) or very high (over 50) birth rate. The presence of a very high birth rate is extremely counterintuitive; using the links in the knowledge base, one may examine the 19 countries involved. Such an inspection points out that 18 have birth rates below 20, while only one, Malawi, has the high birth rate. INLEN had thereby identified an exception to normal patterns. When further learning was focused on Malawi, a massive outward net migration rate was discovered, by far the most extreme migration rate in the world. Further application of the knowledge discovery operators could explore the conditions unique to Malawi and hypothesize where else they might take place in the future.

5. Conclusion

The examples shown above use just a few of the knowledge generation operators implemented in INLEN. INLEN itself is growing steadily as operators are enhanced and added to its environment; while still in prototype form, it already has many functional operators.

The INLEN methodology is based on the application of a large arsenal of machine learning and inference programs for the purpose of discovering knowledge from databases and providing concise conceptual explanations of their findings. These diverse machine learning and inference tools can work in conjunction with traditional statistical tools. Among the major advantages of this methodology is its emphasis on providing conceptually understandable results of data analysis due to the logic-style descriptions it generates. Another advantage is its modularity that makes it easy to add new knowledge generation operators.

This report describes a work in progress in which new capabilities have been added over the course of its development. Among the limitations of the current implementation are the facts that it still awaits integration with statistical data analysis methods and that there is still too much reliance on the data analyst for guidance in the selection of operators and the setting of parameters. Another limitation is portability; while future versions of INLEN will run on other platforms, it is currently limited to PC-based systems.

As described above, topics of ongoing research include the development of methods for automated data abstraction and analysis of distributed databases. Among the areas intended for future research and development are the addition of tools for creating new attributes for improved performance (constructive induction) based on the AQ17-MCI methodology (Bloedorn et al, 1993). This methodology combines data-driven construction of attributes based on the detection of relationships between attributes, hypothesis-driven construction of attributes based on patterns detected in preliminary rulesets, and statistically-based operators for quantization of continuous numerical attributes and summarization of notable groups of examples (e.g., a region's average per capita income).

Another enhancement will be the development and incorporation of a high-level language for knowledge discovery. With such a tool, a user will be able to program in sequences

of operators, along with instructions detailing what conditions shall cause them to be invoked. The system will be able to follow such instructions as "If a new month's data shows less than a 95% consistency with the knowledge base, update the knowledge to incorporate the new data and then use characterization operators to seek out possible explanations why the behavior has changed in the new month" or "If a high-urgency network fault is detected, access the knowledge base to predict the location of the problem and the nature of a likely solution and report it immediately."

In the presented study, INLEN's knowledge generation operators were applied to databases in various domains. The system's searches unearthed some surprising facts. The experiments described here illustrate some of the potential capabilities of the application of integrated learning strategies to large databases and clearly indicate that such an application has the potential for determining important but heretofore unknown findings within the data.

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