CLASSIFICATION REASONING AS A MODEL OF HUMAN COMMONSENSE REASONING

Xenia A. Naidenova

Military Medical Academy, Saint-Petersburg, Russian Federation

ksennaidd@gmail.com

Abstract. In this article, it is proposed to consider classification reasoning based on inducing and using implicative dependencies as a model of commonsense reasoning. The main concept of this reasoning is a good classification test considered as a formal concept of the FCA. The Galois lattice is used for constructing good classification tests. Special rules are determined for constructing Galois lattices over a given context. All the operations of lattice construction take their interpretation in human mental acts.

Keywords: Commonsense reasoning, Classification test, Machine Learning, Inductive-deductive reasoning, Formal Concept Analysis.

1 Introduction

The symbolic methods of machine learning work on objects with symbolic, Boolean, integer, and categorical attributes. From this point of view, these methods can be considered as the methods of mining conceptual knowledge or the methods of conceptual learning. Currently the theory of symbolic machine learning is not recognized as a model of classification reasoning, although precisely this reasoning constitutes an integral part of any mode of reasoning (1, 2). The sole exception to this is the DSM method of hypothesis generation developed by V.K. Finn (3) and based on simulating inductive reasoning rules revealed in human thinking by D. S. Mill (1). There is also a tradition to consider induction separately from deduction. Classification task of mining hypotheses distinguishing and describing classes of a given object classification is conventionally solved separately from hypothesis's application except the deductive-inductive integrated model developed by Zakrevskij (4) and based on representation of data and knowledge in Boolean space of attributes.

However the role of classification in human reasoning is enormous. Classification, as a process of thinking, performs the following global operations: 1) forming knowledge and data contexts adequate to a current situation of reasoning; 2) reducing the domain of the search for a solution of some problem; 3) generalizing or specifying object descriptions; 4) interpreting logical expressions on a set of all thinkable objects; 5) revealing essential elements of reasoning (objects, attributes, values of attributes etc); 6) revealing the links of object sets and their descriptions with external contexts interrelated with them. This list can be continued.

Reasoning requires a lot of techniques related to increasing its efficiency such as valuation, anticipation, making hypotheses, generalization and specification. One of the important techniques is decomposition of the main problem into sub-problems. It implies using the following operations: choosing sub-problems, ordering sub-problems (ordering arguments, attributes, objects, variables, etc.), optimizing sub-problem selection, and some others. The most familiar examples of sub-problem ordering are so called tree-like scanning and level-wise scanning methods. Some interesting variations of selecting sub-problems are the choice of a more flexible sub-problem, for example, one with minimal difference from a previous sub-problem and a sub-problem with minimal possible number of new solutions. Intermediate results of reasoning are used for decreasing or locally bounding the number of sub-problems.

We limit our consideration of classification reasoning to a special class of logical reasoning based on mining and using conceptual knowledge the elements of which are objects, attributes (values of attributes), classifications (partitions of objects into disjoint blocks), and links between them. If we take into account that implications express relations between concepts (the object ↔ the class, the object ↔ the property, the property ↔ the class), we can assume that schemes of mining and applying implications form the core of classification processes, which, in turn, form the basis of human commonsense reasoning.

Our approach is based on the concept of a good diagnostic test (GDT) for a given classification of objects (5). A good classification test has a dual nature: on the one hand, it is a logical expression in the form of implication or functional dependency, on the other hand, it generates the partition of a training set of objects equivalent to the given classification of this set or the partition that is nearest to the given classification with respect to the inclusion relation between partitions. Inferring good test allows in principle mining from data not only structures of formal concepts but also structures of classification ordered by the inclusion relation.

Mathematical structure for GDTs' construction is Galois's lattice. The formal model of classification as an algebraic lattice has been obtained in two independent ways. One way goes back to the work of great psychologist J. Piaget who introduced the concept of grouping (2) to explain methods of object classification developed by 7-11 years children. In this book, a conception of classification is given based on mutually coordinated operations on objects, classes of objects, and properties of objects.

The coordinated classification operations generate logical implicative assertions. The classification operations are connected with understanding the operations of quantification: "not all c are a", "all b are c", "no b are c", "some c are b", "some b are not a" and so on. The violation of the coordinated classification operations implies the violation of reasoning. Piaget J. shows that a key problem of personal understanding operational classification is the problem of understanding the inclusion relation. He adds that the lattice structure is the source of classification operations (2, pp. 195, 387-389).

The idea that classification is a lattice arose also from practical tasks of pattern recognition. In 1974, J. Shreider has described the classification algebra (6) as idempotent semigroup with the unit element. In 1974, N. Boldyrev advanced (7) the formalization of pattern recognition system as algebra with two binary operations of refinement and generalization defined by an axiom system including lattice axioms.

The paper is organized as follows: basic definitions are given in Section 2, Section 3 describes briefly a model of lattice construction as inductive-deductive commonsense or classification reasoning; some words of conclusion terminate this article.

2 Basic Definitions

IMPLICATIVE ASSERTIONS (logical rules of the first kind) describe regular relationships connecting together objects, properties and classes of objects. We consider the following forms of assertions: implication (a, b, $c \rightarrow$ d), forbidden rule (a, b, $c \rightarrow$ false (never), diagnostic rule (x, $d \rightarrow a$; x, $b \rightarrow$ not a; d, $b \rightarrow$ false), rule of alternatives (a or $b \rightarrow$ true (always); a, $b \rightarrow$ false), compatibility (a, b, $c \rightarrow VA$, where VA is the occurrence's frequency of the rule).

In our consideration, COMMONSENSE REASONING RULES (CRRs) are rules with the help of which implicative assertions are used, updated and inferred from instances. The deductive CRRs infer consequences from observed facts with the use of implicative assertions. An analysis of human commonsense reasoning shows that these rules are the following ones: modus ponens: "if A, then B"; A; hence B; modus ponendo tollens: "either A or B" (A, B – alternatives); A; hence not B; modus tollendo ponens: "either A or B" (A, B – alternatives); not A; hence B; modus tollens: "if A, then B"; not B; hence not A; generating hypothesis: "if A, then B"; B; A is possible.

The inductive CRRs are the canons formulated by John Stuart Mill (1): Method of Agreement, Method of Difference, Joint Method of Agreement and Difference, Method of Concomitant Changes, and Method of Residuum. These methods are not rules but they are the processes in which implicative assertions are generated and used immediately. Therefore inductive inferences are not separated from deductive ones.

Let $G = \{1, 2,\dots, N\}$ be the set of objects' indices (objects, for short) and $M = \{m_1, m_2, \dots, m_j, \dots m_m\}$ be the set of attributes' values (values, for short). Each object is described by a set of values from M. The object descriptions are represented by rows of a table the columns of which are associated with the attributes taking their values in M (see, please, Table 1).

The definition of good tests is based on correspondences of Galois on $I = G \times M$ (8) and two relations $G \rightarrow M$, $M \rightarrow G$. Let $A \subseteq G$, $B \subseteq M$. Denote by B_i, $B_i \subseteq M$, $i = 1,\dots, N$ the description of object with index i. We define the relations $G \rightarrow M$, $M \rightarrow G$ as follows: $G \rightarrow M$: $A' = \text{val}(A) = \{$intersection of all B_i: $B_i \subseteq M$, $i \in A\}$ and $M \rightarrow G$: $B' = \text{obj}(B) = \{i$: $i \in G$, $B \subseteq B_i\}$. Of course, we have obj(B) = {intersection of all obj(m): obj(m) $\subseteq G$, $m \in B$}.

Operations val(A), obj(B) are reasoning operations (derivation operators) related to discovering general features of objects and all objects possessing a given set of features.

We introduce two generalization operations: generalization_of(B) = B'' = val(obj(B)); generalization_of(A) =A'' = obj(val(A)). These operations are actually closure operators (8). A set A is closed if A = obj(val(A)). A set B is closed if B = val(obj(B)). For $g \in G$ and $m \in M$, $\{g\}'$ is denoted by g' and called **object intent**, and $\{m\}'$ is denoted by m' and called **value extent**.

The generalization (specification) operations are usual mental acts. Suppose that somebody has seen two films with the participation of Gerard Depardieu. After that he tries to know all the films with his participation. Suppose that one can know that Gerard Depardieu acts with Pierre Richard in several films. After that he can discover that these films are the films of the same producer Francis Veber.

For representing a classification, we use factually the way proposed by S.O. Kuznetsov in (9) for the case when the set M is the set of attribute's values. Let a context $K = (G, M, I)$ be given. In addition to values of M, a target value $\omega \notin M$ of an attribute is considered. The set G of all objects is partitioned into two subsets: the set G_+ of objects having property ω (positive objects), the set G_- of objects not having property ω (negative objects). We have $K = K_+ \cup K_-$, where $K_+ = (G_+, M, I_+)$, $K_- = (G_-, M, I_-)$, $G = G_+ \cup G_-$ $(G_- = G \setminus G_+)$. Diagnostic test is defined as follows.

Definition 1. **A diagnostic test** for G_+ is a pair (A, B) such that $B \subseteq M$ (A = obj(B) $\neq \emptyset$), $A \subseteq G_+$ and $B \not\subset$ val(g) & $B \neq$ val(g), $\forall g$, $g \in G_-$. Equivalently, obj(B) $\cap\, G_- = \emptyset$.

In general case, a set B is not closed for diagnostic test (A, B), i. e., a diagnostic test is not obligatory a concept of FCA. This condition is true only for the special class of tests called 'maximally redundant ones'.

Definition 2. A diagnostic test (A, B), $B \subseteq M$ (A = obj(B) $\neq \emptyset$) for G_+ is **maximally redundant** (GMRT) if obj($B \cup m$) $\subset$ A, for all $m \notin B$ and $m \in M$.

Definition 3. A diagnostic test (A, B), $B \subseteq M$ (A = obj(B) $\neq \emptyset$) for G_+ is **irredundant** if any narrowing $B^* = B \setminus m$, $m \in B$ implies that (obj(B^*), B^*)) is **not a test** for G_+.

Definition 4. A diagnostic test (A, B), $B \subseteq M$ (A = obj(B) $\neq \emptyset$) for G_+ is **good** if and only if any extension $A^* = A \cup i$, $i \notin A$, $i \in G_+$ implies that (A^*, val(A^*)) is **not a test** for G_+.

If a good test (A, B), $B \subseteq M$ (A = obj(B) $\neq \emptyset$) for G_+ is irredundant, then any narrowing $B^* = B \setminus m$, $m \in B$ implies that (obj(B^*), B^*)) is **not a test** for G_+. If a good test (A, B), $B \subseteq M$ (A = obj(B) $\neq \emptyset$) for G_+ is maximally redundant, then any extension $B^* = B \cup m$, $m \notin B$, $m \in M$ implies that (obj($B^* \cup m$), B^*) is **not a good test** for G_+.

Definition 5. Let t be a set of values such that (obj(t), t) is a test for a given set of objects. We say that the value $m \in M$, $m \in t$ is essential in t if (obj($t \setminus m$), ($t \setminus m$)) is not a test for a given set of object.

Definition 6. Let s be a subset of objects belonging to a given positive class of objects; assume also that (s, val(s)) is not a test. The object t_j, $j \in s$ is said to be an essential in s if ($s \setminus j$, val($s \setminus j$)) proves to be a test for a given set of positive objects.

To illustrate using essential values and generalization operations in the process of good tests' generation, we consider a partition of objects in Table 1 into positive and negative ones. Let $G(+)$ be equal to {4,5,6,7,8} and $splus(m)$ = obj(m) $\cap$ $G(+)$, $m \in T$. The value *'Red'* corresponds to a test for positive objects because obj(Red) =

splus(*Red*) $\subseteq$ *G*(+). Delete '*Red*' from consideration. The value *'Tall'* is essential one in object 7 and does not correspond to a test: obj(*Tall*) = {3,4,5,7,8} ≠ *splus*(*Tall*). The projection of the value '*Tall*' on the set of positive objects is in Table 2. Here *splus*(*Bleu*) = {5,7,8}, val(*splus*(*Bleu*)) = '*Tall Bleu*', obj(*Tall Bleu*) = *splus*(*Tall Bleu*), hence '*Tall Bleu*' corresponds to a test for Class 2. We have also that '*Tall Brown*' corresponds to a test but not a good one. We delete '*Bleu*' and *'Brown*' from the projection as shown in Table 3.

Table 1. Example of a data classification

Index ofexample	Height	Color of hair	Color of eyes	Class
1	Low	Blond	Bleu	1
2	Low	Brown	Bleu	1
3	Tall	Brown	Hazel	1
4	Tall	Blond	Hazel	2
5	Tall	Brown	Bleu	2
6	Low	Blond	Hazel	2
7	Tall	Red	Bleu	2
8	Tall	Blond	Bleu	2

Table 2. The projection of the value 'Tall' on objects of *G*(+)

Index of example	Height	Color of hair	Color of eyes	Class
4	Tall	Blond	Hazel	2
5	Tall	Brown	Bleu	2
7	Tall		Bleu	2
8	Tall	Blond	Bleu	2

Table 3. The reduction of the projection of the value 'Tall' on objects of *G*(+)

Index of example	Height	Color of hair	Color of eyes	Class
4	Tall	Blond	Hazel	2
5	Tall			2
7	Tall			2
8	Tall	Blond		2

Now rows 5 and 7 do not correspond to tests for Class 2 and they can be deleted. The intersection of the remaining rows of the projection is '*Tall Blond*'. We have that obj(*Tall Blond*) = {4,8} $\subseteq$ *G*(+) and (obj(*Tall Blond*), *Tall Blond*) is a test for Class 2. As we have found all the tests for Class 2 containing '*Tall*' we delete '*Tall*' from the objects of this class. Return to Table 1. We can delete rows 5, 7, and 8 because they do not correspond to tests for Class 2: value *Tall* is essential one in these rows. The intersection of the remaining objects of Class 2 gives a test (obj(*Blond Hazel*), *Blond Hazel*) because obj(*Blond Hazel*) = *splus*(*Blond Hazel*) = {4,6} $\subseteq$ *S*(+).

3 Inferring good classification tests as commonsense reasoning

We shall consider two interconnected lattices OBJ = $(2^G, \cup, \cap) = (2^G, \subseteq)$ and VAL = $(2^M, \cup, \cap) = (2^M, \subseteq)$, where 2^G, 2^M designate the set of all subsets of objects and the set of all subsets of values, respectively; $s \in 2^G$, $t \in 2^M$. Inferring the chains of lattice elements ordered by the inclusion relation lies in the foundation of generating all diagnostic tests: (1) $s_0 \subseteq \ldots \subseteq s_i \subseteq s_{i+1} \subseteq \ldots \subseteq s_m$ (val(s_0) $\supseteq$ val(s_1) $\supseteq \ldots \supseteq$ val(s_i) $\supseteq$ val(s_{i+1}) $\supseteq \ldots \supseteq$ val(s_m)) ; (2) $t_0 \subseteq \ldots \subseteq t_i \subseteq t_{i+1} \subseteq \ldots \subseteq t_m$ (obj(t_0) $\supseteq$ obj(t_1) $\supseteq \ldots \supseteq$ obj(t_i) $\supseteq$ obj(t_{i+1}) $\supseteq \ldots \supseteq$ obj(t_m)). The dual ascending and descending processes of lattice generation are determined as follows: (3) $t_0 \supseteq t_1 \supseteq \ldots \supseteq t_i \supseteq ti+1 \supseteq \ldots \supseteq t_m$ (obj(t_0) $\subseteq$ obj(t_1) $\subseteq \ldots \subseteq$ obj(t_i) $\subseteq$ obj(ti+1) $\subseteq \ldots \subseteq$ obj(t_m)) ; (4) $s_0 \supseteq s_1 \supseteq \ldots \supseteq s_i \supseteq s_{i+1} \supseteq \ldots \supseteq s_m$ (val(s_0) $\subseteq$ val(s_1) $\subseteq \ldots \subseteq$ val(s_i) $\subseteq$ val(s_{i+1}) $\subseteq \ldots \subseteq$ val(s_m)).

The following inductive transitions from one element of a chain to its nearest element in the lattice are used: (i) from s_q to s_{q+1}, (ii) from t_q to t_{q+1}, (iii) from s_q to s_{q-1}, (iv) from t_q to t_{q-1}, where q, q+1, q-1 are the cardinalities of enumerated subsets of objects and values: s_q, s_{q+1}, and s_{q-1}, $\subseteq G$; t_q, t_{q+1}, and $t_{q-1} \subseteq M$.

The transitions can be smooth and boundary. Under smooth transition, generating sets of values (objects) is performed with preserving a given property of them. These properties are, for example, "to be a test for a given class of objects", "to be an irredundant set of values", "not to be a test for a given class of objects", and some others. A transition is said to be boundary if it changes a given property of sets of values (objects) into the opposite one.

For realizing the smooth inductive transitions, the following inductive reasoning rules are used: generalization rule, specification rule, and dual generalization and specification rules.

The generalization rule is used to get all the sets of objects $s_{q+1} = \{i_1, i_2, \ldots i_q, i_{q+1}\}$ from a set $s_q = \{i_1, i_2, \ldots i_q\}$ such that (s_q, val(s_q)) and (s_{q+1}, val(s_{q+1})) are tests for a given class of objects. The termination condition of generalization chain is: for all the extension s_{q+1} of s_q, (s_{q+1}, val(s_{q+1})) is not a test for a given class of objects.

The specification rule is used to get all the sets of values $t_{q+1} = \{m_1, m_2, \ldots, m_{q+1}\}$ from a set $t_q = \{m_1, m_2, \ldots, m_q\}$ such that t_q and t_{q+1} are irredundant sets of values and (obj(t_q), t_q) and (obj(t_{q+1}), t_{q+1}) are not tests for a given class of objects. The termination condition for specification chain is: for all the extensions t_{q+1} of t_q, t_{q+1} is either a redundant set of values or a test for a given class of objects.

The dual generalization and specification rules relate to narrowing the collection of values and objects, respectively.

These rules realize the Joint Method of Agreement and Difference.

All inductive transitions take their interpretations in human mental acts. The extending of a set of objects with checking the satisfaction of a given condition is a typical method of inductive reasoning. In pattern recognition, the process of inferring hypotheses about the unknown values of some attributes is reduced to the maximal expansion of a collection of the known values of some attributes in such a way that none of the forbidden pairs of values would belong to this expansion. The contraction of a collection of values is used, for instance, in order to delete from it redundant or non-informative values. The contraction of a collection of objects is used, for instance, in order to isolate a certain cluster in a class of objects. Thus, we distinguish lemons in the citrus fruits.

The smooth transitions require the use of searching for admissible values (objects) for extending or narrowing the set of values (objects). Consider some methods for choosing objects admissible for extending s. Let S(test) be the partially ordered set of elements $s = \{i_1, i_2, \ldots i_q\}$, $q = 1, 2, \ldots, nt - 1$ obtained as a result of generalizations and satisfying the following condition: (s, val(s)) is a test for a given class of positive objects, nt is the number of positive objects. Let *STGOOD* be the partially ordered set of elements s satisfying the condition: (s, val(s)) is a GMRT for a given class of positive objects.

Method 1. Suppose that S(test) and *STGOOD* are not empty and $s \in S$(test). Construct the set $V = \{\cup s', s \subseteq s', s' \in \{S(\text{test}) \cup STGOOD\}\}$. The set V is the union of all elements in S(test) and *STGOOD* containing s, hence, s is in the intersection of these elements. If we want an extension of s not to be included in any element of $\{S(\text{test}) \cup STGOOD\}$, we must use, for extending s, the objects not appearing simultaneously with s in V. The set of objects, candidates for extending s, is equal to CAND(s) = $nts \backslash V$, where $nts = \{\cup s, s \in S(\text{test})\}$.

An object $j^* \in$ CAND(s) is not admissible for extending s if at least for one object $i \in s$ the pair $\{i, j^*\}$ either does not correspond to a test or it corresponds to a good test (it belongs to *STGOOD*). Let Q be the set of forbidden pairs of objects for extending s: $Q = \{\{i, j\} \subseteq S(+)$: ($\{i, j\}$, val($\{i, j\}$)) is not a test for a given class of positive objects $\}$. Then the set of admissible objects is *select*(s) = $\{i, i \in$ CAND(s): $(\forall j)$ ($j \in s$), $\{i, j\} \notin \{STGOOD$ or $Q\}\}$. The set Q can be generated in the beginning of searching for all GMRTs for a given class of positive objects.

Method 2. In this method, the set CAND(s) is determined as follows. Let $s^* = \{s \cup j\}$ be an extension of s, where $j \notin s$. Then val(s^*) $\subseteq$ val(s). Hence the intersection of val(s) and val(j) must be not empty. The set CAND(s) = $\{j$: $j \in nts \backslash s$, val(j) $\cap$ val(s) $\neq \emptyset\}$.

The knowledge acquired during the process of generalization (the sets Q, CAND(s), S(test), *STGOOD*) is used for pruning the search in the domain space.

The boundary inductive transitions are used to get: (1) all the sets t_q from a set t_{q-1} such that (obj(t_{q-1}), t_{q-1}) is not a test but (obj(t_q), t_q) is a test, for a given set of objects; (2) all the sets t_{q-1} from a set t_q such that (obj(t_q), t_q) is a test, but (obj(t_{q-1}), t_{q-1}) is not a test for a given set of objects; (3) all the sets s_{q-1} from a set s_q such that (s_q, val(s_q)) is not a test, but (s_{q-1}, val(s_{q-1})) is a test for a given set of objects; (4) all the sets of s_q from a set s_{q-1} such that (s_{q-1}, val(s_{q-1})) is a test, but (s_q,val(s_q)) is not a test for a given set of objects. The boundary inductive transitions realize the Method of Difference or Method of Concomitant Changes. For their implementation, we use the inductive diagnostic rule (IDR) and dual inductive diagnostic rule (DIDR). These rules require searching for essential values (IDRs) and essential objects (DIDRs).

All the boundary transitions are also interpreted as human reasoning operations. Transition 1 is used for distinguishing two diseases with similar symptoms. Transition 2 can be interpreted as including a certain class of objects into a more general one. For instance, squares can be named parallelograms, all whose sides are equal. In some intellectual psychological texts, a task is given to remove the “superfluous” (inappropriate) object from a certain group of objects (rose, butterfly, phlox, and dahlia) (transition 3). Transition 4 can be interpreted as the search for a refuting example.

Inductive reasoning rules generate implicative assertions or logical rules of the first kind, as shown in Table 4.

Table 4. Rules of the first kind obtained with the use of inductive reasoning rules

Inductive rules	Action	Inferring rules of the first kind
Generalization rule	Extending s (narrowing t)	Implications
Specification rule	Extending t (narrowing s)	Implications
Inductive diagnostic rule	Searching for essential values	Diagnostic rules, forbidden rules
Dual inductive diagnostic rule	Searching for essential objects	Compatibility rules (approximate implications)

During the lattice construction, the implicative assertions based on tests, are generated and used immediately. The knowledge acquired during the process of generalization (specialization) is used for pruning the search space (current context) with the use of deductive reasoning rules.

4 Conclusion

This work is an attempt to consider a large class of machine-learning tasks as a model of commonsense reasoning process based on using well-known deduction and induction logical rules. For this goal, we have chosen the task of inferring good classification tests for a given partitioning on a given set of objects because a lot of well-known machine-learning problems such as inferring functional, implicative, and associative dependencies from a dataset are reduced to this task.

5 References

1. Mill, J. S.: The system of logic. Russian Publishing Company “Book Affair”, Moscow (1900) (in Russian).
2. Piaget, J.: Genesis of the elementary logical structures. Classification and serializations. “EKSMO-Press“, Moscow (2002) (in Russian).
3. Finn, V.K.: Synthesis of cognitive procedures and induction problem. VINITI, NTI, Ser. 2(1, 2) (1999) (in Russian).
4. Zakrevskij, A.D.: A common logical approach to data mining and pattern recognition. In: Triantaphyllou, E. and Felici, G. (eds.). Data mining and knowledge discovery approaches based on rule induction techniques (pp. 1-43). Springer (2004).
5. Naidenova, X.: Reducing machine learning tasks to the approximation of a given classification on a given set of examples. In Proceedings of the 5-th National Conference at Artificial Intelligence (Vol. 1, pp. 275-279), Kazan, Tatarstan (1996) (in Russian).
6. Shreider, J.: Algebra of classification. VINITI, NTI, Series 2 (9), pp. 3-6 (1974) (in Russian).
7. Boldyrev, N. G.: Minimization of Boolean partial functions with a large number of “Don’t Care” conditions and the problem of feature extraction. Proceedings of International Symposium “Discrete Systems” (pp.101-109). Riga, Latvia (1974).
8. Ore, O.: Galois Connections. Transactions of the American Mathematical Society, 55(1), 493-513 (1944).
9. Kuznetsov, S. O.: Machine learning on the basis of Formal Concept Analysis. Automation and Remote Control, 62(10), pp. 1543-1564 (2001).