LOCOMOTION. See ROBOTS, LEGGED; ROBOTS, MOBILE.

LOGIC

THE NATURE OF LOGIC

A central concern of logic is to take a situation described by a particular set of statements that are assumed, supposed, or otherwise accepted as true and then to determine what other statements must also be true in that situation. These other true statements are implicit in that situation and are, thus, said to be implied by the original ones. Thus, logic can be used to make implicitly true statements explicit. The original statements are called premises, the "new" statements are called conclusions, and the process of making conclusions explicit is called inference.

One natural criterion for such inference is to be truth preserving. Deductive logic employs inferential methods that achieve this goal: A deductive argument—a set of premises and a conclusion inferred from them—is said to be valid iff any situation in which the premises are (assumed to be) true is thereby also a situation in which the conclusion is (assumed to be) true.

The rules for determining when a statement is true in a situation are among the concerns of semantics. A valid argument whose premises are in fact true is said to be sound. However, the determination of the actual truth value of a given statement is beyond the scope of both logic and semantics; it is either subject-matter specific or else depends on observation (empirical investigation). It should be noted that "actual truth," or correspondence to "facts" in the actual world, is not required. Statements can merely be assumed to be true, or taken as if true, and deduction proceed from there.

The rules for inferring a statement from other statements can be arbitrary relations among statements serving as premises and conclusions. The study of such rules is among the concerns of syntax. It is a not always reachable ideal of logic that syntactic and semantic methods should "overlap":

1. that all statements syntactically inferrable from others (ie, those conclusions that follow from premises according to rules of inference) also be validly inferrable from them, that is, that the conclusions be true if the premises are;
2. that all statements semantically inferrable from others (including those that are tautologies—true in all situations) be syntactically inferrable from them (or be theorems).

A perfect overlap, in which both 1 and 2 hold, is referred to as completeness (qv) of the logic in question.

SYSTEMS OF LOGIC

Traditionally, systems of logic have been classified as either inductive or deductive. Inductive logics employ inferential methods that can fall short of truth preservation. They are used for reasoning in situations where there is incomplete information, such that only statistical or provisional conclusions can be drawn. For example, inductive inference (qv) might only guarantee that a conclusion is highly likely to follow from given premises. Nonmonotonic logics can be considered to fall under this category.

Besides the standard propositional and predicate logics, there are several varieties of deductive logics: Modal logics deal with the concepts of necessity and possibility; epistemic and doxastic logics deal with the concepts of knowledge and belief, respectively; deontic logics deal with moral notions such as obligation and permission; erotetic logics are the logics of questions; and there are also several logics of commands. Relevance logics and logics of counterfactual conditionals deal with more subtle analyses of the if–then connective. (Relevance logic is historically related to the development of modal logic.) Deductive logics need not be limited to the two truth values of truth and falsity: There are many-valued logics and logics with truth value "gaps" (for dealing with statements whose truth values are not determinable). Nor need deductive logics be limited to what actually exists or whether anything exists: There are logics of nonexistent objects (including fictional objects), logics for dealing with inconsistent situations (Rescher and Brandom, 1979), and free logics (logics that are free of existence presuppositions).

Discussions of many of these logics and references to the literature may be found in the articles on logic in this encyclopedia. An especially good survey is Gabbay and Guenthner (1983), and issues of the *Journal of Philosophical Logic* frequently contain articles of relevance to AI.

LOGIC AND ARTIFICIAL INTELLIGENCE

The relevance of logic to AI should be clear. First, logic is at the heart of reasoning, and reasoning is at the heart of intelligence. Since so much is known about the nature of logical reasoning, and since its algorithmic nature has been well-studied, it was one of the earliest and most successful targets of AI researchers [eg, the Logic Theorist (Newell and co-workers, 1963) and the method of resolution (qv) (Robinson, 1979)]. Second, the wide variety of systems of logic offers an equally wide variety of formats for representing information (together with built-in inference mechanisms). Thus, the expressive power of various logics has become one of the central aspects of the field of knowledge representation (qv).

Because actual human reasoning is often not logical (Kahneman, Slovic, and Tversky, 1982) and because some researchers have perceived or misperceived standard logic to be overly formal or limiting, several AI researchers have disdained the use of logic. This has given rise to what has been called the "neat–scruffy debate." In a survey article, Kolata (1982) characterized these two positions as follows: The so-called neat approach to AI "is to design computer programs to reason according to well worked out languages of mathematical logic, whether or not that is actually the way people think"; John McCarthy and Patrick Hayes are among the leading proponents of this approach. The so-called scruffy "approach is to try to get computers to imitate the way the human mind works which . . . is almost certainly not with mathematical logic;" Marvin Minsky and Roger Schank are among the leading proponents of this approach. Thus, neatness is associated with formality, mathematics, and logic, and scruffiness is associated with psychological validity. Scruffy methods are attacked as being not well-defined, whereas neat methods are attacked as being overly defined, hence not flexible enough. Neat methods are seen as artificial and unable to handle certain phenomena, such as default reasoning or nonmonotonicity; yet surely any realm that is amenable to algorithmic treatment is thereby formalizable. On the scruffy side, automatic theorem provers (see THEOREM PROVING) and general problem solvers (see PROBLEM SOLVING) are objected to on the grounds that they are not intelligent or that they are too general; as one neat-sympathizer paraphrases the scruffy position, "classical theorem-provers know very little about what to do, and are incapable of being told it" (Hayes, 1977). On the neat side, logic, because of its semantics, is considered to be "the most successful precise language ever developed to express human thought and inference" (Hayes, 1977). Logic *"justifies* inferences," whereas a processor *"performs* inferences" (Hayes, 1977). The two are independent, and the way in which the processor infers need not be an automated theorem prover. The neat–scruffy dispute overlaps another dispute about the goals of AI: so-called weak AI tries to "simulate" human intelligent behavior without attempting to do it in precisely the way humans do, without attempting to be psychologically accurate; so-called strong AI tries to "emulate" human intelligent behavior, to be psychologically accurate (Searle, 1980). Thus, perhaps, the real issue in the neat–scruffy debate is a dispute over the level at which logic or psychology enters into the analysis and solution of problems in AI. [But see Cherniak (1984) for a recent argument concerning computational limitations on neatness, and see Levesque (1987), Nilsson (1991), and Birnbaum (1991) for recent neat–scruffy debates.]

GUIDE TO LOGIC ARTICLES IN THIS ENCYCLOPEDIA

The following articles provide more references and more detailed discussions of logic, reasoning, and inference, and their relations to AI:

Abduction
Argument comprehension
Bayesian inference methods
Belief revision
Belief representation systems
Church's thesis
Circumscription
Completeness
Constraint logic programming
Logic programming
Logic, propositional
Mental models
Meta-knowledge, meta-rules, and meta-reasoning
Parallel logic programming languages
Presupposition
Problem solving
Reasoning, case-based
Reasoning, causal
Decision theory
Deductive database systems
Fuzzy sets and fuzzy logic: an overview
Fuzzy logic: applications to natural language
Fuzzy sets and fuzzy logic
Induction, mathematical
Inductive inference
Inheritance hierarchy
Knowledge representation
Logic and depiction
Logic, conditional
Logic, higher order
Logic, modal
Logic, order sorted
Logic, predicate
Reasoning, commonsense
Reasoning, default
Reasoning, memory-based
Reasoning, nonmonotonic
Reasoning, plausible
Reasoning, spatial
Reasoning, temporal
Recursion
Resolution
Rule-based systems
Self-reference
Semantic theory
Theorem proving
Truth maintenance
Turing machines
Unification
Z-Modal quantification logic

BIBLIOGRAPHY

L. Birnbaum, "Rigor Mortis: A Response to Nilsson's 'Logic and Artificial Intelligence'," *Artifi. Intell.* **47,** 57–177 (1991).

C. Cherniak, "Computational Complexity and the Universal Acceptance of Logic," *J. Philos.* **81,** 739–758 (1984).

D. Gabbay and F. Guenthner, *Handbook of Philosophical Logic,* 4 vols., D. Reidel, Dordrecht, 1983.

P. J. Hayes, "In Defence of Logic," *Proceedings of the Fifth International Joint Conference on Artificial Intelligence,* Cambridge, Mass., Morgan-Kaufmann, San Mateo, Calif., 1977, pp. 559–565.

D. Kahneman, P. Slovic, and A. Tversky, *Judgment under Uncertainty: Heuristics and Biases,* Cambridge University Press, Cambridge, U.K., 1982.

G. Kolata, "How Can Computers Get Common Sense?" *Science* **217,** 1237–1238 (1982).

H. Levesque, ed., "Taking Issue/Forum: A Critique of Pure Reason," *Comput. Intell.* **3,** 147–237 (1987).

A. Newell, J. C. Shaw, and H. A. Simon, "Empirical Explorations with the Logic Theory Machine: A Case Study in Heuristics," in E. A. Feigenbaum and J. Feldman, eds., *Computers and Thought,* McGraw-Hill, New York, 1963.

N. J. Nilsson, "Logic and Artificial Intelligence," *Artif. Intell.* **47,** 31–56 (1991).

N. Rescher and R. Brandom, *The Logic of Inconsistency: A Study in Non-Standard Possible-World Semantics and Ontology,* Rowman and Littlefield, Totawa, N.J., 1979.

J. A. Robinson, *Logic: Form and Function; The Mechanization of Deductive Reasoning,* Elsevier North-Holland, New York, 1979.

J. R. Searle, "Minds, Brains, and Programs," *Behav. Brain Sci.* **3,** 417–457 (1980).

General References

J. McCarthy, "Epistemological Problems of Artificial Intelligence," *Proceedings of the Fifth International Joint Conference* on *Artificial Intelligence,* Cambridge, Mass., Morgan-Kaufmann, San Mateo, Calif., 1977, pp. 1038–1044.

R. C. Moore, "Problems in Logical Form," *Proc. ACL* **19,** 117–124 (1981).

P. Wallich, "AI Specialists Debate Logic at Conference," *IEEE The Institute* **7,** 2 (Nov. 1983).

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LOGIC AND DEPICTION

Logic-based tools have been widely used in artificial intelligence. Many cognitive areas, for example, language understanding, robot planning, commonsense reasoning, and problem solving (qv) have benefited from various uses of logic. However, the perceptual areas, such as computational vision have not generally been seen as amenable to logic-based approaches. In this article, a theory of depiction is outlined within a framework for image interpretation tasks (Reiter and Mackworth, 1989). The theory has two sets of goals: scientific and engineering. The scientific goals include understanding the concept of an interpretation of an image and understanding the role constraint satisfaction (qv) plays in image interpretation. The engineering goals include the provision of tools for specifying the behavior of image interpretation systems and tools for verifying that a system meets its specification. Potential benefits include the advantages of a common framework for vision and graphics systems and the provision of more modular and portable systems.

The methods proposed are based on a two-domain theory of perception. For any perceptual task at least two domains must be distinguished: the signal domain and the referent domain (or, for deconstructionists, the signifier and the signified). For vision the image domain and the scene domain are initially distinguished. All objects are either image objects or scene objects. Given those domains axioms can be written down in, say, first-order logic, constraining the image and scene objects. For a given application there are three classes of general axioms: image axioms I, scene axioms S, and mapping axioms M. Axioms in I mention only image domain objects and their attributes and relations. Similarly, axioms in S are confined to describing legitimate scenes. Each axiom in M mentions objects in both domains; it may use a reserved predicate $\Delta(i,s)$ signifying that image object i depicts scene object s. If the theory is to be used for image interpretation axioms that describe the particular image to be interpreted, I_0 are also required. The theory states that an interpretation of an image corresponds to a logical model of the set of axioms $I_o \cup I \cup S \cup M$. This provides a formal task specification for image interpretation. This specification is then refined by model-preserving transformations to a provably correct implementation that computes all or some of the interpretations of the image.

The theory is illustrated with a specification in first-order logic of a simple sketch map interpretation task. Consider the sketch maps shown in Figure 1. For this task each region must depict a land area or water area and each chain of line segments must depict a road, a river, or a shore. Roads and rivers appear only on land; shores separate land and water. Rivers must flow into other rivers or shores. Given that background knowledge the image in Figure **1a** depicts one of three possible scenes. Either regions r_1 and r_2 both depict land while chain c_1 depicts a road; r_1 depicts land (an island), r_2 depicts water, and c_1 depicts a shore; or finally, r_1 depicts water (a lake), r_2 depicts land, and c_1 depicts a shore. For this application I consists of taxonomy axioms (eg, "each image object is a chain or a region"). I_o consists of a description of the image in terms of primitive predicates ("chain c_1 bounds region r_1") and closure axioms (eg, "c_1 is the only chain"). S consists of taxonomy axioms ("each linear-scene-object is a road, a river, or a shore"), and general scene knowledge ("the inside area of a shoreline is land if and only if its outside is water" and "rivers lead to other rivers or shores"). The mapping knowledge M includes axioms such as "each image object i depicts a unique scene object $\sigma(i)$," "depiction holds only between image and scene objects," "a chain depicts a linear-scene-object," and the like. Given that specification it is possible to refine it to an equivalent formula in propositional logic by eliminating the quantifiers over finite domains and various other database-oriented transformations. To find all the visual interpretations it is necessary only to find all the logical models of that formula using standard SAT or CSP techniques (see CONSTRAINT SATISFACTION).

For the map domain these models all share in common fixed extensions of all the image, scene, and mapping predicates except $ROAD(.)$, $RIVER(.)$, $SHORE(.)$, $LAND(.)$ and $WATER(.)$. For the example in Figure **1a** the three models correspond to the descriptions:

$$LAND(\sigma(r_1)) \wedge LAND(\sigma(r_2)) \wedge ROAD(\sigma(c_1))$$

$$WATER(\sigma(r_1)) \wedge LAND(\sigma(r_2)) \wedge SHORE(\sigma(c_1))$$

$$LAND(\sigma(r_1)) \wedge WATER(\sigma(r_2)) \wedge SHORE(\sigma(c_1))$$

For the map shown in Figure **1b** there are four possible interpretations corresponding to:

$$LAND(\sigma(r_1)) \wedge LAND(\sigma(r_2)) \wedge ROAD(\sigma(c_1)) \wedge ROAD(\sigma(c_2)) \wedge ROAD(\sigma(c_3))$$

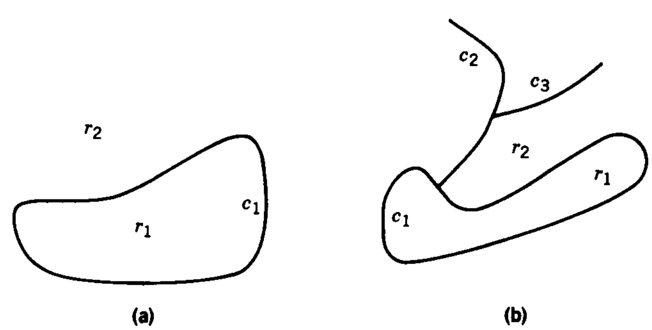

Figure 1. Two simple maps.

$$WATER(\sigma(r_1)) \wedge LAND(\sigma(r_2)) \wedge SHORE(\sigma(c_1)) \wedge ROAD(\sigma(c_2)) \wedge ROAD(\sigma(c_3))$$

$$WATER(\sigma(r_1)) \wedge LAND(\sigma(r_2)) \wedge SHORE(\sigma(c_1)) \wedge RIVER(\sigma(c_2)) \wedge ROAD(\sigma(c_3))$$

$$WATER(\sigma(r_1)) \wedge LAND(\sigma(r_2)) \wedge SHORE(\sigma(c_1)) \wedge RIVER(\sigma(c_2)) \wedge RIVER(\sigma(c_3))$$

Image interpretation is just an instance of the task of evidential reasoning. In general, suppose there is a system S whose system description is available as a set of first-order sentences SD. Given a set of observations of the system Obs the task is to determine a description of the system's internal state $State$ chosen from a set of possible internal states $States$. This characterization of evidential reasoning tasks covers, for example, both image interpretation and diagnosis.

There are essentially two competing logical frameworks for solving such tasks: consistency based and abductive (Poole, 1989a). The consistency-based approach allows any $State \in States$ such that $SD \cup Obs \cup \{State\}$ is consistent (Reiter, 1987; de Kleer and co-workers, 1990). The abductive approach imposes the stronger requirements that $SD \cup \{State\}$ be consistent and $SD \cup \{State\} \models Obs$. The logical framework for depiction and image interpretation described above is a consistency-based theory. The abductive approach is typified by Theorist (Poole and co-workers, 1987). Poole (1989b) describes how to implement in Theorist a system for map interpretation using essentially the same image domain, scene domain, and mapping knowledge.

BIBLIOGRAPHY

J. de Kleer, A. K. Mackworth, and R. Reiter, "Characterizing Diagnoses," in *Proceedings of the Ninth National Conference on Artificial Intelligence*, Boston, AAAI, Menlo Park, Calif., 1990, pp. 324–330.

D. L. Poole, "Normality and Faults in Logic-Based Diagnosis," in *Proceedings of the Eleventh IJCAI*, Detroit, Mich., Morgan-Kaufmann, San Mateo, Calif., 1989a, pp. 1304–1310.

D. L. Poole, "A Methodology for Using a Default and Abductive Reasoning System," TR89-20, Department of Computer Science, University of British Columbia, Vancouver, B.C., 1989b.

D. L. Poole, R. G. Goebel, and R. Aleliunas, "Theorist: A Logical Reasoning System for Defaults and Diagnosis," in N. Cercone and G. McCalla, eds., *The Knowledge Frontier: Essays in the Representation of Knowledge*, Springer-Verlag, New York, 1987, pp. 331–352.

R. Reiter, "A Theory of Diagnosis from First Principles," *Artif. Intell.* **32,** 57–95 (1987).

R. Reiter and A. K. Mackworth, "A Logical Framework for Depiction and Image Interpretation," *Artif. Intell.* **41,** 125–155 (1989).

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LOGIC, CONDITIONAL

Conditional logic examines the proof theory and semantics for ordinary conditionals in natural language. Contemporary work in this area is motivated by the so-called paradoxes of material implication and by the apparent non truth-functionality of many ordinary conditionals. A standard formal language for representing the logical structure of conditionals has been developed, and several conditional logics have gained widespread attention. Both possible worlds and probabilistic semantics have been proposed as alternatives to the classic truth functional account of conditionals. Within the artificial intelligence community there have been several efforts to develop nonmonotonic reasoning systems based on conditional logic (see REASONING, NONMONOTONIC).

PROBLEMS WITH MATERIAL IMPLICATION

The typical conditional has the structure "If A, then C" where A is called the antecedent and C the consequent of the conditional. The classic treatment of conditionals translates ordinary language conditionals into *material conditionals*. A material conditional, represented $A \supset C$, is a compound expression of which the truth value is a function of the truth values of its antecedent and consequent as defined by Table 1. $A \supset C$ is true whenever A is false or C is true, and this is the source of the so-called paradoxes of implication. Where A is the false sentence "Shakespeare didn't write *Hamlet*" and C is the sentence "Someone other than Shakespeare wrote *Hamlet*," both the material conditional $A \supset C$ and the corresponding English conditional

1. If Shakespeare didn't write *Hamlet*, then someone else wrote *Hamlet*

are true. But if the mood of sentence 1 is changed from indicative to subjunctive, the resulting English conditional

2. If Shakespeare had not written *Hamlet*, then someone else would have written *Hamlet*.

is at least improbable. Perhaps indicative conditionals can be represented as material conditionals, but most conditionals in the subjunctive mood cannot. The problem is not that the material conditional is the wrong truth function for representing English subjunctive conditionals; these conditionals cannot be represented by any truth function. Consider the following four conditionals:

Table 1.

A	C	$A \supset C$
t	t	t
t	f	f
f	t	t
f	f	t