

CONTEMPORARY ARTIFICIAL INTELLIGENCE





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Preface

Over the years my view of an artificial intelligence (AI) course has changed significantly. I used to view it as a course that should discuss our efforts to develop an artificial entity that can learn and make decisions in a complex, changing environment, affect that environment, and communicate its knowledge and choices to humans; that is, an entity that can think. I would therefore, cover the weak AI methods that failed to scale up. However, as strong methods that solved challenging problems in limited domains became more predominant, my course increasingly concerned these methods. I would cover backward chaining, forward chaining, planning, inference in Bayesian networks, normative decision analysis, evolutionary computation, decision tree learning, Bayesian network learning, supervised and unsupervised learning, and reinforcement learning. I would show useful applications of these methods. These techniques have come to be as important to a computer science student's repertoire as techniques such as divide-and-conquer, greedy methods, branch-and-bound, etc. Yet a student would not see them unless the student took an AI course. So my AI course evolved into a course that undergraduate students would take either concurrently or following an analysis of algorithms course, and would cover what I viewed as important problem-solving strategies that have emerged from the field of AI. I feel such a course should be a standard component of every computer science curriculum just like data structures and analysis of algorithms.

No text satisfied my needs for the course I taught for two reasons:

- AI is a vast field that has included the development of many and varied techniques in the past 50 years. Current texts tried to include most of what has been going on rather than simply providing useful methods and algorithms.
- No current text was accessible to students at a mainstream university like Northeastern Illinois University. I had this same problem with my analysis of algorithms course, and was the reason I wrote Foundations of Algorithms.

So I taught the course using my own Bayesian network texts and class notes. I finally decided to turn these notes into this textbook so professors at other mainstream universities could provide a similar course. This text is not meant to be an encyclopedia or history of AI, but rather is meant to be a text that

xii CONTENTS

can be covered in one semester; and, in the amount of time one semester allows, provide the student with what I consider the most useful techniques that have emerged from AI. These techniques include the following:

- 1. Logic-based methods
- 2. Probability-based methods
- 3. Evolutionary computation and methods based on swarm intelligence
- 4. Language understanding

The text clearly reflects my own bias. I have not discussed neural networks, fuzzy logic, support vector machines, and many other endeavors in AI. I also do not include searching because most searching techniques appear in data structures and algorithms texts. Almost half the text is about probabilistic methods. This is perhaps partially due to the fact that I know these methods best because they are my own area of research, but also due to the fact that I view them as most important (that is why they are my area of research).

I have written the material in the order I teach it. So I recommend simply covering the chapters from first to last. If there is not time to cover the entire book, I recommend leaving out Sections 8.3 through 8.7 where I have explored more advanced topics in decision analysis, and Section 12.3 which concerns causal learning. Sections marked with a \bigstar contain material that is inherently more difficult than the other material in the text. However, they do cover important topics and should not be skipped if the students have the sophistication to grasp them.

I thank Dawn Holmes and Kevin Korb for reading the manuscript and providing useful comments. I also thank Prentice Hall for allowing me to include excerpts from my text *Learning Bayesian Networks*, and Morgan Kaufmann for allowing me to include excerpts from my texts *Probabilistic Methods for Financial and Marketing Informatics* and *Probabilistic Methods for Bioinformatics*. Finally, I thank Relu I. Jianu for designing an attractive and thought-provoking cover.

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About the Authors



Richard E. Neapolitan is a professor of computer science at Northeastern Illinois University. His research interests include probability and statistics, expert systems, cognitive science, and applications of probabilistic modeling to fields such as medicine, biology, and finance. Dr. Neapolitan is a prolific author and has published in the most prestigious journals in the broad area of reasoning under uncertainty. He has previously written five books, including the seminal 1990 Bayesian network text *Probabilistic Reasoning in Expert Systems*; *Learning Bayesian Networks* (2004); *Foundations of Algorithms* (1996, 1998, 2003, 2010), which has been translated into three languages; *Probabilistic Methods for Financial and Marketing Informatics* (2007); and *Probabilistic Methods for Bioinformatics* (2009). His approach to textbook writing is innovative; his books have the reputation for making difficult concepts easy to understand while still remaining thought-provoking.



Xia Jiang is an assistant professor in the Department of Biomedical Informatics at the University of Pittsburgh. She has over 13 years of teaching and research experience in Bayesian network modeling, machine learning, and algorithm design. She is the co-author of the book *Probabilistic Methods for Financial and Marketing Informatics* (2007). Dr. Jiang is currently focusing on developing novel algorithms/systems that improve the computational efficiency of large data analysis, and network modeling of cancer genome data.

Contents

Pı	efac	е					xi
A	bout	the A	uthors				xiii
1	Intr	oducti	ion to Artificial Intelligence				1
	1.1	Histor	y of Artificial Intelligence				2
		1.1.1	What Is Artificial Intelligence?				2
		1.1.2	Emergence of AI				4
		1.1.3	Cognitive Science and AI				4
		1.1.4	Logical Approach to AI				5
		1.1.5	Knowledge-Based Systems				6
		1.1.6	Probabilistic Approach to AI	'n,	٠,		7
		1.1.7	Evolutionary Computation and Swarm Intelligence			•	7
		1.1.8	A Return to Creating HAL			•	8
	1.2	Conte	mporary Artificial Intelligence				8
т.	т.		T1-11!				
Ι	Lo	gicai	Intelligence				11
2	Pro	positio	onal Logic				13
	2.1	Basics	s of Propositional Logic				14
	+:	2.1.1	Syntax		٠.		14
		2.1.2	Semantics				16
		2.1.3	Tautologies and Logical Implication				20
		2.1.4	Logical Arguments				22
		2.1.5	Derivation Systems				25
	2.2	Resolu	ıtion				28
		2.2.1	Normal Forms				28
		2.2.2	Derivations Using Resolution				31
		2.2.3	Resolution Algorithm				34
	2.3	Artific	cial Intelligence Applications		٠,		35
		2.3.1	Knowledge-Based Systems				35
		2.3.2	Wumpus World				48
	2.4	Discus	ssion and Further Reading				56

vi CONTENTS

3	Firs	t-Order Logic 6	31
	3.1		62
		3.1.1 Syntax	62
		3.1.2 Semantics	65
		3.1.3 Validity and Logical Implication 6	69
		3.1.4 Derivation Systems	71
		3.1.5 Modus Ponens for First-Order Logic	75
	3.2	Artificial Intelligence Applications	79
		3.2.1 Wumpus World Revisited	79
		3.2.2 Planning	80
	3.3	Discussion and Further Reading	84
4	Cer	tain Knowledge Representation 8	39
	4.1	Taxonomic Knowledge	90
		4.1.1 Semantic Nets	90
		4.1.2 Model of Human Organization of Knowledge	92
	4.2	Frames	92
		4.2.1 Frame Data Structure	92
		4.2.2 Planning a Trip Using Frames	93
	4.3	Nonmonotonic Logic	96
		4.3.1 Circumscription	96
		4.3.2 Default Logic	97
		4.3.3 Difficulties	99
	1 1	D'accident I Devile Devile	00
	4.4	Discussion and Further Reading	99
TT			
11		robabilistic Intelligence 10	
II 5	Р	robabilistic Intelligence 10 bability 10	01
	Р	robabilistic Intelligence 10	01
	P Pro	robabilistic Intelligence 10 bability 10 Probability Basics	01 03 06 06
	P Pro	robabilistic Intelligence 10 bability 10 Probability Basics	01 03 06 06 06
	Pro 5.1	robabilistic Intelligence 10 bability 10 Probability Basics	01 03 06 06 09 12
	P Pro	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem 11 Random Variables 10	01 03 06 06 09 12
	Pro 5.1	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 11	03 06 06 09 12 13
	Pro 5.1	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables 115	03 06 06 09 12 13 13
	Pro 5.1	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables Meaning of Probability 12 13 14 15 16 17 17 18 18 19 19 10 10 10 10 10 10 10 10	01 03 06 06 09 12 13 18 22
	Pro 5.1	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables Meaning of Probability 5.3.1 Relative Frequency Approach to Probability 12	03 06 06 09 12 13 13 18 22 22
	Pro 5.1	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables 12 5.2.2 Independence of Random Variables 13 Meaning of Probability 14 5.3.1 Relative Frequency Approach to Probability 15 5.3.2 Subjective Approach to Probability 15	03 06 06 09 12 13 18 22 22 25
	Pro 5.1	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 11 5.2.1 Probability Distributions of Random Variables 12 5.2.2 Independence of Random Variables 13 5.2.2 Independence of Random Variables 14 5.3.1 Relative Frequency Approach to Probability 15 5.3.2 Subjective Approach to Probability 15 Random Variables in Applications 16	03 06 06 09 12 13 18 22 22 25
	Pro 5.1 5.2 5.3	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables 12 5.2.2 Independence of Random Variables 13 Meaning of Probability 14 5.3.1 Relative Frequency Approach to Probability 15 5.3.2 Subjective Approach to Probability 15	01 03 06 06 09 12 13 18 22 22 25 27
	Pro 5.1 5.2 5.3 5.4 5.5 Uno	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables Meaning of Probability 5.3.1 Relative Frequency Approach to Probability 5.3.2 Subjective Approach to Probability Random Variables in Applications Probability in the Wumpus World 13 14 15 16 17 18 18 19 19 19 19 19 19 19 19	01 06 06 06 09 12 13 18 22 25 27 31
5	Pro 5.1 5.2 5.3 5.4 5.5 Uno 6.1	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables 15 5.2.2 Independence of Random Variables 15 5.3.1 Relative Frequency Approach to Probability 15 5.3.2 Subjective Approach to Probability 15 Random Variables in Applications 16 Probability in the Wumpus World 17 Rertain Knowledge Representation 18 Intuitive Introduction to Bayesian Networks 19	01 06 06 09 12 13 13 18 22 25 27 31 37
5	Pro 5.1 5.2 5.3 5.4 5.5 Uno	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables 11 5.2.2 Independence of Random Variables 12 Meaning of Probability 13 5.3.1 Relative Frequency Approach to Probability 15 5.3.2 Subjective Approach to Probability 15 Random Variables in Applications 16 Probability in the Wumpus World 17 18 Properties of Bayesian Networks 18 Properties of Bayesian Networks 19	01 06 06 09 12 13 18 22 25 27 31 39 42
5	Pro 5.1 5.2 5.3 5.4 5.5 Uno 6.1	robabilistic Intelligence bability Probability Basics 5.1.1 Probability Spaces 5.1.2 Conditional Probability and Independence 5.1.3 Bayes' Theorem Random Variables 5.2.1 Probability Distributions of Random Variables 5.2.2 Independence of Random Variables 15 5.2.2 Independence of Random Variables 15 5.3.1 Relative Frequency Approach to Probability 15 5.3.2 Subjective Approach to Probability 15 Random Variables in Applications 16 Probability in the Wumpus World 17 Rertain Knowledge Representation 18 Intuitive Introduction to Bayesian Networks 19	01 03 06 06 09 12 13 18 22 25 27 31 37 42 42

CONTENTS vii

	6.3	Causal Networks as Bayesian Networks
		6.3.1 Causality
		6.3.2 Causality and the Markov Condition 149
		6.3.3 Markov Condition without Causality 154
	6.4	Inference in Bayesian Networks
		6.4.1 Examples of Inference
		6.4.2 Inference Algorithms and Packages 157
		6.4.3 Inference Using Netica
	6.5	Networks with Continuous Variables
		6.5.1 Gaussian Bayesian Networks
		6.5.2 Hybrid Networks
	6.6	Obtaining the Probabilities
		6.6.1 Difficulty Inherent in Multiple Parents 166
		6.6.2 Basic Noisy OR-Gate Model
		6.6.3 Leaky Noisy OR-Gate Model
		6.6.4 Further Models
	6.7	Large-Scale Application: Promedas
	0	2016 Sould Tippinoution Tiomeday
7	Adv	vanced Properties of Bayesian Network 177
	7.1	Entailed Conditional Independencies
		7.1.1 Examples of Entailed Conditional Independencies 178
		7.1.2 d-Separation
	7.2	Faithfulness
		7.2.1 Unfaithful Probability Distributions 186
		7.2.2 Faithfulness Condition
	7.3	Markov Equivalence
	7.4	Markov Blankets and Boundaries
8		ision Analysis 199
	8.1	Decision Trees
		8.1.1 Simple Examples
		8.1.2 Solving More Complex Decision Trees 204
	8.2	Influence Diagrams
		8.2.1 Representing with Influence Diagrams 217
		8.2.2 Solving Influence Diagrams
		8.2.3 Techniques for Solving Influence Diagrams
		8.2.4 Solving Influence Diagrams Using Netica
	8.3	Modeling Risk Preferences
		8.3.1 Exponential Utility Function
		8.3.2 Assessing r
	8.4	Analyzing Risk Directly
		8.4.1 Using the Variance to Measure Risk
		8.4.2 Risk Profiles
		8.4.3 Dominance
	8.5	Good Decision versus Good Outcome
	8.6	Sensitivity Analysis
	8.7	Value of Information

viii CONTENTS

		8.7.1	Expected Value of Perfect Information	49
		8.7.2	Expected Value of Imperfect Information 2	52
	8.8	Discuss	sion and Further Reading	53
		8.8.1	Academics	54
		8.8.2	Business and Finance	54
		8.8.3	Capital Equipment	54
		8.8.4	Computer Games	
		8.8.5	Computer Vision	
		8.8.6	Computer Software	
		8.8.7	Medicine	
		8.8.8	Natural Language Processing	
		8.8.9	Planning	
		8.8.10	Psychology	
		8.8.11	Reliability Analysis	
		8.8.12	Scheduling	
		8.8.13		
			Vehicle Control and Malfunction Diagnosis	
		0.0.11	remote control and manufaction bloghoods	01
II	I E	merg	ent Intelligence 26	35
9			ary Computation 20	67
	9.1		cs Review	
	9.2	Geneti	c Algorithms	
		9.2.1	Algorithm	
		9.2.2	Illustrative Example	
		9.2.3	Traveling Salesperson Problem	
	9.3		c Programming	
		9.3.1	Illustrative Example	
		9.3.2	Artificial Ant	88
		9.3.3	Application to Financial Trading 2	
	9.4	Discus	sion and Further Reading	94
	~			
10				97
	10.1		vstem	
			Real Ant Colonies	
			Artificial Ants for Solving the TSP 2	
	10.3	Discus	sion and Further Reading	06
IV	<i>7</i> T	earni	ng 90	20
Τ ۷	L	earm	ng 30	Jy
11	Lear	rning I	Deterministic Models 3	11
		_	rised Learning	
			sion	
	11.2	11 9 1	Simple Linear Regression	12
		11.2.1	omple Linear regression	14

CONTENTS ix

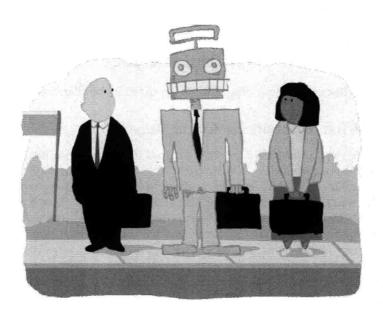
		11.2.2	Multiple Linear Regression		315
			Overfitting and Cross Validation		
	11.3		ng a Decision Tree		
			Information Theory		
			Information Gain and the ID3 Algorithm		
			Overfitting		
12			Probabilistic Model Parameters		331
	12.1		ng a Single Parameter		
			Binomial Random Variables		
			Multinomial Random Variables		
	12.2		ng Parameters in a Bayesian Network		
			Procedure for Learning Parameters		
		12.2.2	Equivalent Sample Size		339
	12.3	Learni	ng Parameters with Missing Data $^{\bigstar}$		341
13	Lear	ning I	Probabilistic Model Structure		351
10	13.1	Structi	ure Learning Problem		352
	13.2	Score-1	Based Structure Learning	•	353
	10.2		Bayesian Score		
			BIC Score		
			Consistent Scoring Criteria		
			How Many DAGs Must We Score?		
			Using the Learned Network to Do Inference		
			Learning Structure with Missing Data★		
			Approximate Structure Learning		
			Model Averaging		
		13.2.9	Approximate Model Averaging★		380
	13.3	Constr	raint-Based Structure Learning		383
			Learning a DAG Faithful to P		
		13.3.2	Learning a DAG in which P Is Embedded Faithfully		389
	13.4	Applic	ation: MENTOR		390
		13.4.1	Developing the Network		390
		13.4.2	Validating MENTOR		394
	13.5	Softwa	re Packages for Learning		394
	13.6		Learning		
			Causal Faithfulness Assumption		
		13.6.2	Causal Embedded Faithfulness Assumption		397
		13.6.3	Application: College Student Retention Rate		401
	13.7		Probability Trees		
			Theory of Class Probability Trees		
			Application to Targeted Advertising		
	13.8		sion and Further Reading		
			Biology		
			Business and Finance		
			Causal Learning		
		13.8.4	Data Mining		411

EN	II	7
	L/\	ENI

			Medicine		
		13.8.6	Weather Forecasting		. 412
14	Mor	e Lear	ning		417
	14.1	Unsup	ervised Learning		. 417
			Clustering		
			Automated Discovery		
	14.2		rcement Learning		
			Multi-Armed Bandit Algorithms		
		14.2.2	Dynamic Networks★		. 423
	14.3	Discus	sion and Further Reading		. 436
					. 200
T 7	т.		TT 1		400
\mathbf{V}	La	angua	ge Understanding		439
15	Nat	ural La	anguage Understanding		441
	15.1	Parsing	g		. 442
		15.1.1	Recursive Parser		. 445
			Ambiguity		
			Dynamic Programming Parser		
*		15.1.4	Probabilistic Parser		. 454
			Obtaining Probabilities for a PCFG		
			Lexicalized PCFG		
	15.2		tic Interpretation		
			ot/Knowledge Interpretation		
	15.4	Inform	ation Extraction		. 461
			Applications of Information Extraction		
		15.4.2	Architecture for an Information Extraction System		. 463
	15.5		sion and Further Reading		
Bi	bliog	raphy			467
III	\mathbf{dex}				493

Chapter 1

Introduction to Artificial Intelligence



In 1990, I (Richard Neapolitan) was relatively new to the field of **Artificial Intelligence** (**AI**). At the 6th Conference on Uncertainty in Artificial Intelligence, which was held at MIT, I met Eugene Charniak, who at the time was a well-known researcher in AI. During a conversation while strolling along the campus, I said, "I heard that the Japanese are applying fuzzy logic to AI." Gene responded "I don't believe the Japanese have been any more successful at AI than us." This comment substantiated that which I had already begun to realize, namely that AI seemed to be a dismal failure.

Dr. Charniak's comment was correct in 1990 and it is still correct today. If we consider AI to be the development of an artificial entity such as the Termi-

nator in the movie by the same name or HAL in the classic sci-fi movie *Space Odyssey*, then we have not developed anything close. The Terminator and HAL are artificial entities that can learn and make decisions in a complex, changing environment, affect that environment, and communicate their knowledge and choices to humans. We have no such entities.

So why does the field of AI persist, and why was this book written? In their efforts to develop artificial intelligence, researchers looked at the behavior/reasoning of intelligent entities such as humans, and developed algorithms based on that behavior. These algorithms have been used to solve many interesting problems, including the development of systems that behave intelligently in limited domains. Such systems includes ones that can perform medical diagnosis, diagnose problems with software, make financial decisions, navigate a difficult terrain, monitor the possible failure of a space shuttle, recognize speech, understand text, plan a trip, track a target, learn an individual's preferences from the preferences of similar individuals, learn the causal relationships among genes, and learn which genes affect a phenotype. This book concerns these algorithms and applications. Before discussing the content of this book further, we provide a brief history of AI.

1.1 History of Artificial Intelligence

We start by discussing early efforts to define artificial intelligence.

1.1.1 What Is Artificial Intelligence?

Abandoning the philosophical question of what it means for an artificial entity to think or have intelligence, Alan Turing [1950] developed an empirical test of artificial intelligence, which is more appropriate to the computer scientist endeavoring to implement artificial intelligence on a computer. The **Turing test** is an operational test; that is, it provides a concrete way to determine whether the entity is intelligent. The test involves a human interrogator who is in one room, another human being in a second room, and an artificial entity in a third room. The interrogator is allowed to communicate with both the other human and the artificial entity only with a textual device such as a terminal. The interrogator is asked to distinguish the other human from the artificial entity based on answers to questions posed by the interrogator. If the interrogator cannot do this, the Turing test is passed and we say that the artificial entity is intelligent.

Note that the Turing test avoids physical interaction between the interrogator and the artificial entity; the assumption is that physical interaction is not necessary for intelligence. For example, HAL in the movie *Space Odyssey* is simply an entity with which the crew communicates, and HAL would pass the Turing test. If the interrogator is provided with visual information about the artificial entity so that the interrogator can test the entity's ability to perceive and navigate in the world, we call the test the **total Turing test**. The Terminator in the movie of the same name would pass this test.



Figure 1.1 The Chinese room experiment.

Searle [1980] took exception to the Turing test with his **Chinese room** thought experiment. The experiment proceeds as follows. Suppose that we have successfully developed a computer program that appears to understand Chinese. That is, the program takes sentences written with Chinese characters as input, processes the characters, and outputs sentences written using Chinese characters. See Figure 1.1. If it is able to convince a Chinese interrogator that it is a human, then the Turing test would be passed.

Searle asks "Does the program literally understand Chinese, or is it only simulating the ability to understand Chinese?" To address this question, Searle proposes that he could sit in a closed room holding a book with an English version of the program, and adequate paper and pencils to carry out the instructions of the program by hand. The Chinese interrogator could then provide Chinese sentences through a slot in the door, and Searle could process them using the program's instructions and send Chinese sentences back through the same slot. Searle says that he has performed the exact same task as the computer that passed the Turing test. That is, each is following a program that simulates intelligent behavior. However, Searle notes that he does not speak Chinese. Therefore, because he does not understand Chinese, the reasonable conclusion is that the computer does not understand Chinese either. Searle argues that if the computer is not understanding the conversation, then it is not thinking, and therefore it does not have an intelligent mind.

Searle formulated the philosophical position known as **strong AI**, which is as follows:

The appropriately programmed computer really is a mind, in the sense that computers given the right programs can be literally said to understand and have other cognitive states.

Based on his Chinese room experiment, Searle concludes that strong AI is not possible. He states that "I can have any formal program you like, but I still understand nothing." Searle's paper resulted in a great deal of controversy and discussion for some time to come (See, for example, [Harnad, 2001]).

The position that computers could appear and behave intelligently, but not necessarily understand, is called **weak AI**. The essence of the matter is whether a computer could actually have a mind (strong AI) or could only simulate a mind (weak AI). This distinction is of greater concern to the philosopher who is discussing the notion of consciousness [Chalmers, 1996]. Perhaps facetiously, a philosopher could even argue that emergentism might take place in the Chinese room experiment, and a mind might arise from Searle performing all his manipulations. Practically speaking, none of this is of concern to the computer scientist. If the program for all purposes behaves as if it is intelligent, computer scientists have achieved their goal.

1.1.2 Emergence of AI

Initial efforts at AI involved modeling the neurons in the brain. An artificial neuron is treated as a binary variable that is switched to either on or off. This notion was first proposed in [McCulloch and Pitts, 1943], and was furthered by Donald Hebb [1949] when he developed **Hebbian learning** for **neural networks**. In 1951, Marvin Minsky and Dean Edmonds built SNARC, the first neural network computer.

Following this accomplishment and Turing's development of the Turing test, researchers became increasingly interested in the study of neural networks and intelligent systems, resulting in John McCarthy¹ organizing a 2-month workshop involving interested researchers at Dartmouth University in 1956. He coined the term *Artificial Intelligence* at that workshop. Attendees included Minsky, Claude Shannon (the developer of information theory), and many others. AI emerged as a new discipline whose goal was to create computer systems that could learn, react, and make decisions in a complex, changing environment.

1.1.3 Cognitive Science and AI

Cognitive science is the discipline that studies the mind and its processes. It concerns how information is represented and processed by the mind. It is an interdisciplinary field spanning philosophy, psychology, artificial intelligence, neuroscience, linguistics, and anthropology, and emerged as its own discipline somewhat concurrently with AI. Cognitive science involves empirical studies of the mind, whereas AI concerns the development of an artificial mind. However, owing to their related endeavors, each field is able to borrow from the other.

¹ John McCarthy developed the LISP programming language for AI applications and is considered by many to be the father of AI.