Chapter 16
Application Areas of AI Systems

Before we discuss the issue of the possibility of constructing an intelligent artificial system in the last chapter, we now summarize practical results concerning application areas of AI systems.[1] As we have mentioned in a previous chapter, designers of such systems do not model a *general intelligence*, rather they focus on methods simulating particular human cognitive/mental abilities and corresponding constructs such as knowledge representation models. Application areas of AI systems will be discussed on the basis of human cognitive abilities identified after the analysis of psychology models of intelligence discussed in the previous chapter.

16.1 Perception and Pattern Recognition

Intelligent behavior depends on *perception* of the external world to some extent. Although a human being perceives with the help of five senses, i.e., sight, hearing, taste, smell, and touch, only the first two senses are simulated in most AI systems. From a technical point of view, both sound and image are treated one- or two-dimensional signals. (Sometimes 3D signals, if a spatial model of the world is defined in the system.)

In AI systems the task of perceiving sound or image is divided into two main phases. The first phase concerns of receiving a corresponding signal with the help of a sensory device (e.g., a camera or a microphone), its preprocessing, and its coding in a certain format. The methods used in this phase belong to conventional[2] areas of computer science (also automatics and electronics) such as *signal processing theory* and *image processing theory*. Both theories were developed remarkably in

[1] In the monograph we do not present specific AI systems, because they are continuously being introduced in the software market. So, this chapter had to be updated each year.

[2] *Conventional* means here that they do not need the support of AI techniques.

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the second half of the twentieth century. They allow us to implement systems which surpass human beings in some aspects of sensory perception.[3]

In the second phase of perception, in which sensory information is ingested thoroughly, AI systems can use methods belonging to three groups of models that have been introduced in the monograph, namely *pattern recognition*, *neural networks*, and *syntactic pattern recognition*. Let us notice that also in these areas a lot of efficient techniques have been developed. Optical Character Recognition (OCR) systems, vision systems of industrial robots, optical quality control systems in industry, analysis of satellite images, military object identification systems, and medical image systems are some examples of practical applications of such systems. Recently research has been carried out into constructing systems which are able not only to identify objects, but also to understand (interpret) them [297]. Image understanding is especially useful in the area of advanced medical diagnostics [214, 296].

There are, however, still challenges in this area. Automatic learning is a crucial functionality of pattern recognition systems. In the case of classical pattern recognition and neural networks, models contain adaptive techniques of learning. On the other hand, in syntactic pattern recognition the issue of a system self-learning is more difficult, since it relates to the problem of formal grammar induction. In this area research is still in a preliminary phase.

The second problem concerns *intelligent* integration of information sent by various sensory devices at the same time (e.g., a camera and a microphone) in order to obtain a synthetic sensation.[4] We will return to this problem in the next chapter.

16.2 Knowledge Representation

The problem of adequate *knowledge representation* has been crucial since the very beginning of developments in the AI area. An intelligent system should be able to adapt to its environment, according to our definition formulated in Sect. 15.2. Thus, it should be able to acquire knowledge which describes this environment (*declarative knowledge*), then to store this knowledge in a form allowing a quick and adequate (intelligent) response to any stimulus generated by the environment. Patterns of such responses, represented as *procedural knowledge*, should be stored in the system as well.

A taxonomy of knowledge representation models can be defined according to two basic criteria: the form of knowledge representation and the way of acquiring knowledge.

According to the first criterion, knowledge representation models can be divided into the following three groups.

[3] Certainly the reader has seen crime films in which a blurry photograph made while moving has been processed by a computer system in order to restore a sharp image of a killer.

[4] Such a functionality in the system corresponds to St. Thomas Aquinas' *sensus communis* introduced in the previous chapter.

- *Models of symbolic knowledge representation formulated in an explicit way*. Let us notice that the basic models of this group, i.e., *conceptual dependency graphs*, *semantic networks*, and *scripts* have been introduced by psychologists Roger Schank, Allan M. Collins, and Robert P. Abelson, respectively. Where procedural knowledge is concerned, *rule-based systems* are the most popular representation model. In this book we have also introduced other specific representations for such knowledge, e.g., formal grammars, representations based on mathematical logic, models in reasoning systems, and schemes in Case-Based Reasoning systems.
- *Models of symbolic-numeric knowledge representation formulated in an explicit way*. These models are used if the notions which are the basis for the representation model are fuzzy, i.e., they are ambiguous or imprecise. Bayesian networks, models based on fuzzy sets, and models based on rough sets introduced in Chaps. 12 and 13 are good examples of such models.
- *Models of knowledge representation formulated in an implicit way*. This form is applied if knowledge is represented in a numeric way. It is typical for pattern recognition methods and neural networks. Such representations are of the form of clusters consisting of vectors, sets of parameters (in pattern recognition), and weight vectors (in NNs). Here, representation in an *implicit way* means not only that we lack access to these vectors or parameters. Even if we read these strings of numbers, we could not relate them to the meaning of knowledge coded in such a way. In other words, we are not able to interpret them in terms of the problem description.

Where the second criterion, i.e., the way of acquiring knowledge, is concerned, representation models can be divided into the following two groups.

- *Models in which knowledge can be acquired by the system automatically.* First of all, models of knowledge representation formulated in an implicit way belong to this group. Both pattern recognition methods and neural networks can be self-learning in the case of unsupervised learning techniques. For pattern recognition we use cluster analysis. In the case of symbolic representations such learning is performed via induction, for example grammatical induction in syntactic pattern recognition.
- *Models in which knowledge representation is defined and entered into the system by a knowledge engineer.* Most models of knowledge representation formulated in an explicit way belong to this group.

Summing up, automatic acquisition of knowledge in models based on symbolic knowledge is the crucial issue in this area. An automatic conceptualization is the main problem here and it has not been solved in a satisfactory way till now. Learning methods will be discussed in a more detailed way in Sect. 16.8.

16.3 Problem Solving

We define the area of *problem solving* as research into constructing *generic* methods that can be used for solving general problems. *General Problem Solver, GPS*, constructed by Allen Newell and Herbert A. Simon described in Chap. 1 is a good example of this area of Artificial Intelligence. The dream of AI researchers to construct such a system has not come true yet. Therefore, this problem has been divided into a variety of subproblems such as reasoning, decision making, planning, etc., which are discussed in the next sections.

Returning to the problem of constructing a *general problem solver*, let us notice that *heuristic search methods* and their extension in the form of *evolutionary computing*[5] are good candidates for such a purpose.

Nevertheless, systems based on a search strategy do not solve problems in an autonomous way, but in *cooperation* with a human designer. Let us notice that there are two phases of problem solving with the help of a search strategy, namely:

- a phase of constructing an *abstract model of the problem*, which is the basis for defining states in the state space (cf. Sect. 4.1) and
- a phase of searching the state space.

Methods of searching a state space concern only the second phase. The first phase is performed by a human designer. The development of methods which allow an AI system to autonomously construct an abstract model of a problem on the basis of perception (observation) of the problem seems to be one of the biggest challenges in the area of simulating cognitive/mental abilities.

16.4 Reasoning

Artificial Intelligence systems work perfectly, where *deductive reasoning* is concerned.[6] Deductive reasoning is a type of reasoning in which on the basis of a certain general rule (rules) and a premise, we infer a conclusion (cf. Appendix F.2). Systems based on mathematical logic are the best examples of such reasoning. In Chap. 6 we have introduced two basic models for constructing such systems, namely *First-Order Logic* and *lambda calculus*.

Rule-based systems presented in Chap. 9 are one of the most popular types of reasoning systems. They are applied in business, medicine, industry, communications, transport, etc. In case we deal with imperfect knowledge or fuzzy notions, AI systems based on *non-monotonic logic* introduced in Chap. 12 are constructed or we apply *fuzzy logic* presented in Chap. 13.

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[5] In fact *evolutionary computing* can be treated as an efficient version of a search strategy.

[6] In this section by reasoning we mean deductive reasoning, whereas later when we discuss the area of machine learning we discuss both deductive and inductive inference.

Thus, in Artificial Intelligence in the area of deductive reasoning we are able to simulate human abilities better than in the case of the remaining cognitive/mental abilities. This results from the dynamic development of mathematical and logic models in the period preceding the birth of Artificial Intelligence. This concerns especially the excellent development of mathematical logic in the first half of the twentieth century. Its models have been used successfully for defining effective algorithms of reasoning.

16.5 Decision Making

Supporting a process of *decision making* was one of the first applications of AI systems. The natural approach based on a simulation of succeeding steps of a decision process performed by a human expert is used in *expert rule-based systems*. A simple example of a simulation of such a decision process has been presented in Sect. 9.2. Let us notice that in order to apply such an approach, *explicit* knowledge in the form of rules representing partial decisions which can be used in any reasoning scenario should be delivered by a human expert. These rules are the basis for constructing an expert system.

In case such knowledge is unavailable an approach based on *pattern recognition* or *neural networks* can be used. Then we build a general specification of a problem with the help of numerical features, as has been presented in Chap. 10. The problem is characterized by a vector of numerical values. The possibility of equating the set of possible decisions with the set of classes determined by the vectors of a learning set is a condition of using such an approach.

If we apply a pattern-recognition-based approach for constructing a system which supports decision making, then *statistical pattern recognition* using the Bayes classifier (cf. Sect. 10.5) can be especially convenient. In such a case a system does not propose one decision in a deterministic way, but it suggests several possible decisions, assigning probability measures to them. As we have mentioned in Sect. 10.5, we can generalize the Bayes classifier by assuming that in case of making erroneous decisions there are various consequences with various costs of an error. The function of the cost of an error together with the *a posteriori* probability is used for defining the function of the risk corresponding to various decisions. Of course, the Bayes classifier tries to minimize the risk function.

If a decision process can be divided into stages, then we can apply a classifier based on *decision trees*, which has been presented in Sect. 10.6.

In case we have to solve a decision problem on the basis of knowledge which is uncertain, imprecise, or incomplete, we should use the methods introduced in Chap. 12, i.e., *Bayes networks* or *Dempster-Shafer Theory*. If a decision problem is described with fuzzy notions, then *fuzzy rule-based systems*, introduced in Chap. 13, or hybrid systems based on fuzzy set theory and model-based reasoning [152], introduced in Chap. 9, can be used.

At the end of the twentieth century effective methods of decision making were developed on the basis of advanced models of decision theory, game theory, and utility theory. Decision support systems are applied in many application areas. Typical application areas include, e.g., economics, management, medicine, national defence, and industrial equipment control.

16.6 Planning

Planning consists of defining a sequence[7] of activities which should result in achieving a predefined target. Simulation of this mental ability seems to be very difficult. It contains a crucial element of *predicting* consequences (results) of taking certain actions. This task is especially difficult if it is performed in a real-time mode and in a changing environment, which is typical in practical applications. Then, a system has to modify (very quickly) a plan which has been already generated, in order to keep up with the changing environment.

Planning methods can be based on a scheme of *state space search*,[8] which has been introduced in Chap. 4. The final state represents a goal which should be achieved as a result of a sequence of activities. Possible activities are defined by transition operators in the state space, and states represent the results of performing these activities. However, defining these intermediate results is a crucial problem. Let us notice that, for example, in case of using a search strategy for problems concerning artifacts, like various games, predicting results of activities is trivial. For example, if a system playing chess makes a decision to make the move *Ra5-h5*, then the result of this activity is obvious, i.e., *Rook* moves from *a5* to *h5*.[9] In this case the predictability of the result of the activity arises from the precise rules in the "world of chess". However, if a system functions in the real world, then the consequences of performing an activity sometimes cannot be determined. For example, if somebody has said something unpleasant to me, I can plan the activity of making a joke of it. Such an activity can result in easing the tension, which is the goal of my activity. However, it can also result in further verbal aggression, if my joke is treated as showing disrespect to my opponent. Thus, predicting consequences of planned activities is a very difficult issue.

Planning in the real world is sometimes connected with some circumstances, facts, or situations which limit the possibility of our activity in the sense of time, space, other conditions related to the physicality of the world, preferences concerning the way of achieving a goal, etc. Then, a planning problem can be expressed as a

[7] We use the term *sequence* in the definition of a planning task. However, it can be a *complex* of activities, which consists of many activity sequences that are performed in a parallel way.

[8] This scheme can be extended to *evolutionary computing* introduced in Chap. 5.

[9] Unless the opponent has been irritated and he/she has knocked the chessboard down from the table. However, if we assume that our opponent is well-bred, we can eliminate such a "result" from our considerations.

Constraint Satisfaction Problem, CSP, which has been introduced in Sect. 4.5. In such a case a planning strategy can be based on one of the CSP search methods.

In the area of Artificial Intelligence planning problems are very important, because of their various practical applications [311]. Therefore, many advanced methods which are based of such models as *temporal logic*, *dynamic logic*, *situation calculus*, and *interval algebra* have been defined in this area recently.

16.7 Natural Language Processing (NLP)

The research area of *Natural Language Processing, NLP*,[10] should be divided into two subareas. The first subarea includes problems which can be solved by an analysis of a language on the syntactic (and lexical) level. For example, text proofreading, extraction of information from a text, automatic summarizing, Optical Character Recognition (OCR), speech synthesis (on the basis of a text), simple *question-answer* dialogue systems, etc. belong to this group. The second subarea contains problems which can be solved by analysis of a language on the semantic level. For example, automatic translation from a natural language into another natural language, speech/text understanding, systems of human-computer verbal communication, etc. belong to this group. This division has been introduced because nowadays only problems belonging to the second group are challenging in Artificial Intelligence.

The Chomsky theory of *generative grammar* introduced in Chap. 8 is a referential model in this area. Although the Chomsky model is sometimes criticized in the area of NLP, since it has not fulfilled all the expectations of NLP researchers, it is usually the point of departure for defining models of NLP such as, e.g., *metamorphosis grammars* [58], *Definite Clause Grammars, DCGs* [225], and *Augmented Transition Networks, ATNs* [318].

At the end of the twentieth century a statistical approach to language analysis was developed. It makes use of *text corpora*, which are large referential sets of texts in a given language. A system refers to a text corpus during a text analysis with the help of stochastic models in order to determine statistical characteristics of the text, which relate to, e.g., possible contexts in which a word occurs, possible uses of a given phrase in the text corpus, etc.

Another approach consists of the use of the generative grammar model together with probability theory, which results in defining *stochastic grammars* and *stochastic automata* introduced in Chap. 8. Such a model is equivalent to the *Markov chain model* (cf. Appendix B.2), which is also used in advanced methods of NLP.

In the models mentioned above a syntax is assumed as a point of departure for language analysis. Such an approach is sometimes not sufficient in case of problems

[10]The notion of *natural language* is used in computer science in relation to such languages as English, German, Chinese, etc. in order to distinguish the issue of computer processing of such languages from the problem of computer processing of *artificial languages*, which is much easier. Artificial languages include, for example, programming languages, and formal languages, which have been presented in Chap. 8.

in which concept understanding is necessary. Then, in order to interpret the semantics of sentences in a proper way, an AI system should have additional knowledge in the form of a world model. This problem can be solved by defining an *ontology*, which has been introduced in Chap. 7. Let us recall that *semantic networks* are one of the most popular formalisms for defining ontologies.

In computerized semantic analysis of spoken language we cope with a much more difficult problem. Communication is the main function of spoken language. From the point of view of this function *non-verbal aspects of a language*[11] such as intonation, stress, etc. are essential. For example, the sentence: "I did not testify under oath that I had seen Cain killing Abel." can be interpreted in a number of ways, depending on which phrase is stressed. Possible interpretations include (the stressed phrase is marked):

- "*I did not testify* under oath that I had seen Cain killing Abel."—the basic interpretation,
- "I did not testify *under oath* that I had seen Cain killing Abel."—I testified, but not under oath,
- "I did not testify under oath that I *had seen* Cain killing Abel."—I overheard the event,
- "I did not testify under oath that I had seen *Cain* killing Abel."—I saw somebody killing Abel, but it was not Cain,
- "I did not testify under oath that I had seen Cain killing *Abel*."—I saw Cain killing somebody, but it was not Abel.

Passing a message in one specific sense reveals the intention of its sender. He/she passes this sense by stressing the proper phrase. However, the ability to understand the correct sense of the message on the basis of stress, intonation, etc. relates to social intelligence. Although in this case we mean elementary social intelligence, it is very difficult to embed this kind of intelligence in an AI system.

Summing up, Natural Language Processing can be considered a well-developed area of AI. *Chatbots*, mentioned in Chap. 1, where we have presented *ELIZA* designed by Joseph Weizenbaum, simulating human speakers are good examples of successes in NLP. On one hand, some chatbots simulate an intelligent conversation quite well. On the other hand, they still cannot pass the *Turing test*.

16.8 Learning

Learning models in Artificial Intelligence can be divided into two basic groups:

1. experience generalization models,
2. models transforming a representation of a problem domain.

[11] Here we distinguish *non-verbal aspects of a language* from *non-verbal communication*, which includes, e.g., body language and facial expression.

In *experience generalization models* we assume the availability of a *learning set* $U = ((\mathbf{X}^1, \mathbf{u}^1), (\mathbf{X}^2, \mathbf{u}^2), \ldots, (\mathbf{X}^M, \mathbf{u}^M))$, where a pair $(\mathbf{X}^j, \mathbf{u}^j)$, $j = 1, \ldots, M$, consists of a *stimulus* $\mathbf{X}^j$, which represents a certain fact occurring in a system environment, and a *response* $\mathbf{u}^j$, which should be generated by the system as a result of receiving this stimulus. In other words, a learning set represents experience gained. An AI system is confronted with this experience, which is formalized in such a way. As a result it should define, via induction (generalization), a response function f such that for each $\mathbf{X}^j$, $j = 1, \ldots, M$, the following rule holds: $f(\mathbf{X}^j) = \mathbf{u}^j$. We say that the response function f is a generator of a proper reaction of the system for the observation (stimulus).

Generalized learning in AI is connected with the behavioral approach in psychology. Such learning is treated as gaining experience, which is done in order to modify the system's behavior. Following this approach, we have trained *neural networks* in Chap. 11 and *classifiers* for pattern recognition in Chap. 10. In both cases a stimulus $\mathbf{X}^j$ is of the form of a vector of numbers, which is used for coding a problem. The scheme for constructing a classifier based on a *decision tree* introduced in Sect. 10.6 belongs to this approach as well.

In the case of neural networks and classifiers we have also discussed models of *unsupervised learning*. Then, a learning set is of the form $U = (\mathbf{X}^1, \mathbf{X}^2, \ldots, \mathbf{X}^M)$. This means that the required reaction is not determined. The system should divide a set of stimuli into groups (subsets) itself. *Cluster analysis* introduced in Sect. 10.7 and *Hebbian learning* presented in Sect. 11.1 are good examples of such learning.

In *experience generalization learning* a stimulus $\mathbf{X}^j$ usually consists of a complex of parameters. However, such learning can also be applied to symbolic representations. The scheme *grammar induction—automaton synthesis* is a good example here. Then the response function f takes the form of a formal automaton.

Models transforming a representation of a problem domain correspond instead to models of *cognitive psychology*. In this case, an AI system should construct a world representation, i.e., an *ontology* introduced in Chap. 7. Then the system should *transform* it on the basis of the new knowledge gained. Thus, a learning process can be divided into two phases, ontology construction and ontology transformation.

In order to *construct* an ontology the system should, firstly, define *concepts* on the basis of observations of the world. Then, it should define structures which describe semantic relations among these notions. Unfortunately, AI systems are not able to perform such a task nowadays.[12]

However, AI systems are able to learn by transforming ontologies predefined by a human designers. In this case the system extracts knowledge from the ontology by transformation operations. For example, if there are the following two rules in our knowledge base[13]:

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[12]It seems that in order to perform such a task, a system should be able to learn via insight into the heart of the matter. Such a way of learning, however, results from *understanding* the heart of the matter.

[13]In the example we assume that the ontology is constructed with the help of First-Order Logic.

$$C = aunt(A) \quad \Leftrightarrow \quad [\, \exists B \; B = mother(A) \;\wedge\; C = sister(B) \,] \\ \vee \quad [\exists B \; B = father(A) \;\wedge\; C = sister(B)] \;,$$

and

$$B = parent(A) \quad \Leftrightarrow \quad [\, B = mother(A) \;\vee\; B = father(A) \,] \;,$$

then the system can infer a new rule:

$$C = aunt(A) \quad \Leftrightarrow \quad [\, \exists B \; B = parent(A) \;\wedge\; C = sister(B) \,] \;.$$

In fact, systems based on models which transform a representation of a problem domain simulate a cognitive activity. However, referring to the St. Thomas Aquinas definition of three generic operations of the intellect (cf. Sect. 15.1), this cognitive activity is limited to the third one, i.e., *reasoning* only.[14] In other words, the system extracts new knowledge from knowledge which is already stored in its knowledge base. Nevertheless, a human designer has to construct an ontology with the help of the two remaining cognitive operations, i.e., defining concepts (*simple apprehension*) and pronouncing judgments. Let us notice that system learning via an ontology transformation is possible only if the human designer is able to *encode* semantic knowledge into its syntax in a precise and unambiguous way.[15] Unfortunately, at present this is impossible for many application areas.

Syntactic pattern analysis systems introduced in Chap. 8 are AI systems which are able to generate a *structural representation* of some aspects of the world in an automatic way. However, such a representation is limited to *physical objects* which are extracted from an image and to *spatial-topological relations* among them. These systems perform neither abstraction processes nor conceptualization. Thus, there is no ontology construction in this case either.

Learning models which transform a problem domain have been developed dynamically in AI since the 1980s. The most popular methods include *Explanation-Based Learning, EBL* [205], *Relevance-Based Learning, RBL* [3], and *Inductive Logic Programming, ILP* [207].

16.9 Manipulation and Locomotion

As we have discussed in the previous chapter, *kinesthetic intelligence* related to both manipulation and locomotion abilities has been identified in the *sensimotor stage* of cognitive development of an infant (from birth to about age two) by Jean Piaget. Since we do not remember this stage of our life well, we do not realize the difficulty of acquiring these abilities. The simulation of these abilities is one of the most difficult problems in Artificial Intelligence, strictly speaking in *robotics*, which

[14] In the sense of proceeding from one proposition to another according to logical rules.

[15] As has been done in our genealogy example above.

is an interdisciplinary research area making use of models of automatic control, mechatronics, mechanics, electronics, cybernetics, and computer science.

Firstly, manipulation and locomotion abilities of robots (or similar devices) depend strongly on functionalities of other systems such as perception/pattern recognition systems, problem-solving systems, or planning systems. Successes and challenges in these research areas have been discussed in previous sections.

Secondly, manipulation and locomotion abilities of robots also depend on the technological possibilities of execution devices, such as effectors, actuators, etc. Let us notice that in this case sometimes we do not want to simulate human abilities. For example, where locomotion is concerned, some animals have a clear advantage over humans. Therefore, mobile robots for military or search-and-rescue applications are often constructed on the basis of the locomotion abilities of insects (hexapod robots), snakes (snakebots), or four-limbed animals (e.g., the BigDog quadruped robot), not to mention intelligent aerial mobile robots (drones) and underwater drones. Generally, in the area of locomotion constructors of mobile robots and devices have achieved amazing achievements recently.

Manipulation abilities of robots surpass those of humans in certain applications, especially if high precision, manual dexterity, or high resistance to tiredness are required. Manipulation microsurgical robots and robots aiding microbiology experiments are good examples here. Of course, these robots are telemanipulators (or remote telemanipulators) which are controlled by operators (e.g., surgeons). Summing up, there have been remarkable results in the area of intelligent manipulators and one can expect further successes in this field.

In spite of the fact that there are some interesting and usually spectacular results in the area of humanoid/android robotics, we still await robots which can simulate a violin virtuoso or a prima ballerina.

16.10 Social Intelligence, Emotional Intelligence and Creativity

At the end of the twentieth century research into simulating both social intelligence and emotional intelligence in AI systems began. This has concerned synthetic aspects of the problem, e.g., expression of emotions by a robot face, as well as analytic aspects, e.g., recognizing human mood on the basis of speech intonation. Simulating human abilities in the analytic aspect is, of course, more difficult. In order to analyze facial expression and features of speech (intonation, stress, etc.) advanced pattern recognition methods are applied. Rule-based systems are used for the purpose of integrating vision and sound. Surely, research in this area is very important, since its results, together with achievements in robotics, can be applied in medicine, social security, etc. *Distinct* emotional messages sent by humans via, e.g., facial expressions are recognized quite well nowadays by AI systems. Will robots be able to recognize them in case these messages are not clear? We must await for the answer.

In 2010 the first International Conference on Computer Creativity was organized at the prestigious University of Coimbra, which was established in 1290. The issue of the possibility of simulating human creativity discussed during the conference is really controversial. It seems that a view of Margaret Boden,[16] who distinguishes two types of creativity, can be helpful in this discussion [32]. *Exploratory creativity* consists of searching a predefined conceptual space.[17] However, if we deliberately transform or transcend a conceptual space, then we deal with *transformational creativity*. Simulation of transformational creativity in artificial systems is a really challenging task in the AI area.

Creative AI systems are implemented for solving general problems, generating music and visual art, etc. Various AI methods such as state space search, neural networks, genetic algorithms, semantic networks, and reasoning by analogy are used for these purposes.

Bibliographical Note

The issue of simulation of various human mental/cognitive abilities is usually discussed in fundamental books on Artificial Intelligence. The following monographs are recommended [18, 19, 55, 147, 189, 211, 241, 256, 261, 262, 273, 315].

[16] Margaret Boden—a professor of cognitive science at the University of Sussex. Her work concerns the overlapping fields of: psychology, philosophy, cognitive science, and AI. She was the Vice-President of the British Academy.

[17] Let us notice that this type of creativity can be simulated via cognitive simulation, i.e., searching a state space.