Learning Techniques in Presence of Uncertainty

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Abstract. In the last few years we have witnessed increased popularity of agent systems. This popularity is the result of agents' ability to work effectively and perform complex tasks in a wide range of applications. In this paper, we highlight the importance of learning mechanisms that are essential for behavioural adaptation of agents in complex environments. We provide a high-level introduction and overview of different types of learning approaches proposed in recent years. We also argue the necessity of dynamic learning processes for handling uncertainty, and propose an uncertainty-oriented architecture of agents together with a specialized knowledge base.

1 Introduction

Agent systems are becoming increasingly popular due to wide range of applications in which they can be deployed [1]. An agent is an autonomous system that acts in a dynamic environment towards achieving its goals. In some applications, a team of agents may work together towards realization of their goals. It is common that a human supervisor provides initial knowledge to the agent. However, the built-in primary knowledge may not suffice to allow an agent to operate in a highly dynamic environment. Agents' behaviour should not be limited to actions defined and supplied by a human. Agents should be able to adapt their behaviour via a continuous learning process [2]. Such agents, referred to as "software agents", use machine learning techniques to adapt to user's demands and dynamic environments [3]. In [3], authors analyze imitation learning as the foundation behind human infants' learning ability. Their research is based on extensive studies of psychologists observing developmental progress of human infants. Typically, software agents have limited processing capability, hence employed learning mechanisms should have low computational complexity.

Learning mechanisms are essential factors enabling agents to operate in complex environments and to achieve human-like behaviour. Software agents' learning processes should provide agents with abilities to perform two important tasks. First, agents have to know how to act upon receiving new information in terms of storing the new concepts in their memory, forming links to the already known concepts, and consciously updating the information. Second, agents should be able to select appropriate actions from their repository of behavioural patterns. In this context, if the agents' old behaviours do not provide an acceptable outcome new action patterns

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have to be learned so that agents can perform their tasks correctly. This means that appropriate actions have to be learned and carried out on new situations. The ability to adapt to the changes in an environment is a necessary feature of intelligent agents.

In this paper, we provide a brief survey of some state-of-the-art learning mechanisms. Furthermore, we focus on uncertainty that is a fundamental and unavoidable feature of any environment. We emphasize the fact that uncertainty is present in discovering and analyzing information, and agents' abilities to learn should accommodate methods and techniques capable of dealing with imprecision, ambiguity, lack of full information, and limited trust in information sources. We argue that agents' knowledge bases and architectures should be suitable for storing and reasoning about uncertainty.

2 Learning Mechanisms

The basic motivation for studying learning models of agent systems stems from the strong need for an efficient learning mechanism capable of performing in complex and uncertain environments. This model would be much less complicated if agents were dealing with certain, precise and complete knowledge.

A number of different learning approaches have been developed over the last few years. These approaches target different aspects of a learning process, and use variety of learning approaches and knowledge representation schemas. This section starts with a description of two learning tools: conceptual and behavioural. The former provides an agent with facts and items related to its domain knowledge, while the latter leads to a better selection of actions to be preformed. The case-base reasoning and human involvement are discussed as important components of a learning process. The adaptive mechanisms for behavioural rules are presented next, in which the rules to be fired are identified based on pre-conditions activated by an agent's perception. We also discuss elements of reinforcement learning that are used to enhance inference of a system that is built based on truth maintenance principles. An interesting approach of learning mechanisms that compares new knowledge with the one already known to an agent is presented next. Fuzzy clustering process is described, which is used to pre-process data and prepares input to a fuzzy controller. The concept of human involvement is presented as an example of interactive learning mechanisms. Different levels of human participation are described and evaluated.

2.1 Conceptual and Behavioural Learning

Two learning mechanisms - conceptual and behavioural learning – can be used to address the adaptability of agents in dynamic environments. Architectures and functionality of two cognitive software agents, namely, CMattie (conscious Mattie) and IDA (intelligent distribution agent) are investigated in [4]. A conscious software agent is defined as a system that senses the environment through its cognitive characteristics: decision making, reasoning, knowledge perception and processing. This enables the agent to cope with unusual situations. The processes of these two agents are implemented by small pieces of codes, called codelets. The agents' architectures are composed of two main sections. In the first, a slipnet contains the agent's domain knowledge that initially consists of limited numbers of built-in concepts. In the second, a behaviour net holds a set of actions and their links to each other.

Based on [4], a first step in any learning mechanism is to identify newly encountered situations by an agent. For this purpose, authors embed a function in an agent's perception module, which is triggered by observing words or phrases that have never been experienced by an agent. Next, a conceptual learning is applied as a learning mechanism that is founded on case-based memory and case-based reasoning. In conceptual learning, an agent views the newly encountered situations in terms of its past experiences. Thus, relevant functions are retrieved for the problem solving process depending on its recent activity history. The agent adds new concepts to its slipnet and creates relevant links between new and old concepts. Moreover, history of each learning process is maintained in the agent's case-based memory, which enhances the learning capabilities of the agent in future [4]. As a solution to the action selection mechanism, the authors introduce behavioural learning that helps an agent selects and performs appropriate actions based on the received information. To accomplish this task, the agent may utilize case-based reasoning that adapts solutions of old problems, and apply them to similar perceived information. As an alternative, the agent can communicate with its human supervisor to receive proper instruction. This problem is referred to as a development period. The authors argue that a development phase will be a cost-effective method for the agent to operate in its complex domain. During the development period, the agent obtains the needed knowledge of the domain. This may include observation, conversational interaction and assistance of a human supervisor.

2.2 Learning Adaptive Decision Making Rules

In [5], a real-time self-organisational algorithm is suggested for behavioural learning of an agent in autonomous systems. The authors consider a multi-agent cooperation system model. The action selection mechanism is modelled on a subsumption method [6], where an agent makes an appropriate decision based on the received perception from the environment and evaluates possible actions and their pre-conditions. The researchers only focus on single-rule scenarios and do not investigate the problem of parallel action selection which is a realistic model [5]. They argue that local behaviours and their independence to the final goal allow the agent to self-design in dynamic environments. In their approach the learning process is composed of an adaptive behavioural rules base (ABRB) component, which selects the best match in the list of possible actions by evaluating the pre-conditions. Lastly, the agent will send feedback to ABRB reporting the success of the result with the goal of improving the future cycles. See Fig. 1, redrawn from [5].

The proposed algorithm forms a tree that is composed of a limited number of Boolean expressions representing the pre-conditions. According to the received perceptions, values are assigned to each pre-condition in the tree, in order to select the action that is more likely to provide the best solution to the current perceived states of the environment.

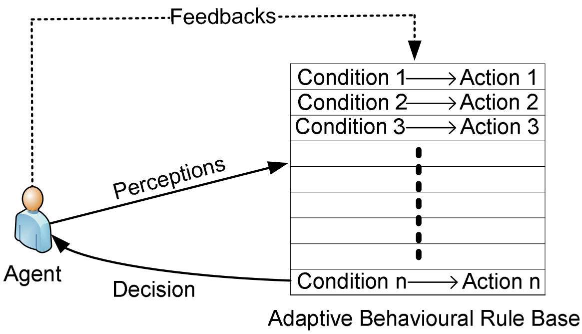

Fig. 1. Adaptive behaviour learning [5]

2.3 Relational Reinforcement Learning

The performance of a real-time learning mechanism in a highly dynamic environment is investigated in [7]. The authors enhance the adaptive logic interpreter (ADLIN) [7], which is a learning algorithm built upon relational reinforcement learning (RRL) [8]. The enhancements are due to the poor performance of ADLIN in time-constrained environments. They propose a real-time learning mechanism that combines ADLIN with a justification-based truth maintenance system (JTMS), a technique for managing the agents' beliefs [9], to enhance the inference process.

Authors argue that logical reasoning mechanisms have to be deployed carefully in intelligent agents due to their high computational complexity. JTMS makes the inference engine more efficient, by storing inferences received through interactions with inference engine, and reducing the number of RRL's states. This way, the previously seen instances that are stored in JTMS do not need to be processed by the inference engine anymore. Through experiments authors have shown that JTMS-based ADLIN outperforms both ADLIN and exhaustive inference systems in learning time. The proposed structure is shown in Fig.2.

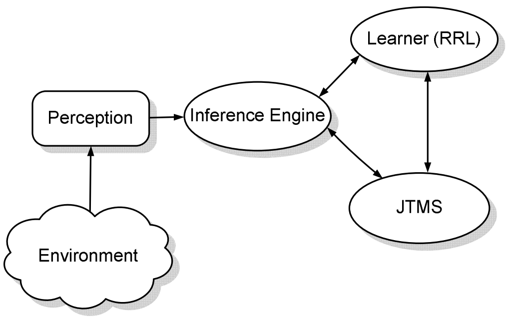

Fig. 2. Schematic of the adaptive logic interpreter (ADLIN) built based on justification-based truth maintenance system (JTMS) [7]

2.4 Participatory Learning

A quite different learning mechanism called a participatory learning mechanism is proposed in [10]. In the approach, the current knowledge of an agent participates in the learning process. This learning model is based on the features of human learning style, where the current beliefs directly affect the acceptance of newly received information. The author formulates the above learning process as a smoothing like algorithm [11], where the current observations from the environment are learned only if they are compatible to some extent with the old beliefs. For this purpose, a compatibility ratio is measured and has to be satisfied in order to consider the current observation valid. In Fig. 3 the upper feedback loop shows the participatory nature of the model, where the old beliefs and theories affect the learning process.

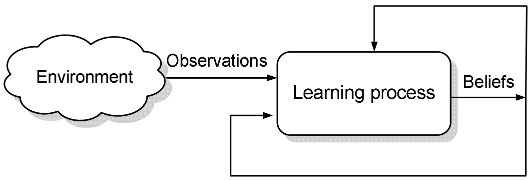

Fig. 3. Participatory learning model [10]

The learning mechanism is formulated as follows [10]:

$$V(j+1) = V(j) + \alpha\rho_i (D(j) - V(j))$$

where $V(j+1)$, $V(j)$ and $D(j)$ are vectors representing new information, old beliefs and current observations, while and ρ_i are the base rate and the compatibility rate, respectively. In [10] the impact of α and ρ_i on learning speed is shown. The author in [10] believes that this learning model is most effective when only a small change or a high compatibility exists between the new observations and the current beliefs; thus only a small change or an update happens to the current beliefs.

2.5 Online Adaptive Fuzzy Learning

In [12] an inference technique for agents' adaptation and learning in ubiquitous environments is proposed. In their model, agents learn and adapt their behaviour from a human (user) model by observing the user interactions with the environment. For this purpose, an adaptive online fuzzy inference system (AOFIS) is presented to model the user's behaviour, via a fuzzy logic controller (FLC), and to provide output actions to the environment. The proposed AOFIS technique is composed of five steps, which are shown in Fig.4.

First, agents observe the user's behaviour while capturing and labelling the inputs (from sensors and actuators) over time. Then, the sampled values are quantized into a set of fuzzy membership functions using a double clustering approach [13]. This algorithm runs iteratively to merge similar data samples based on their observed values until a predefined number of membership functions are created. In their approach, Gaussian membership functions are used as the fuzzy sets. In step 3, rules are extracted from the relationships between the set of inputs and outputs applying the learning from examples [14]. By step 4, the agent is capable of observing and controlling the environment via the learned FLC without the need for human involvement. In case of a new input arrival, the agent evaluates the input value to find which of the previously formed fuzzy sets it belongs to. Next, the proper rule is fired by the agent based on the calculated weight of the rules. In [12], the performance of AOFIS is evaluated in a real test-bed, an intelligent dormitory where 17 sensors were used as inputs and 10 actuators were used as outputs while in an interaction with a human user for five consecutive days. Through experiments it is shown that AOFIS outperforms similar soft-computing based techniques with fewer errors, and less computational complexity in online learning mode.

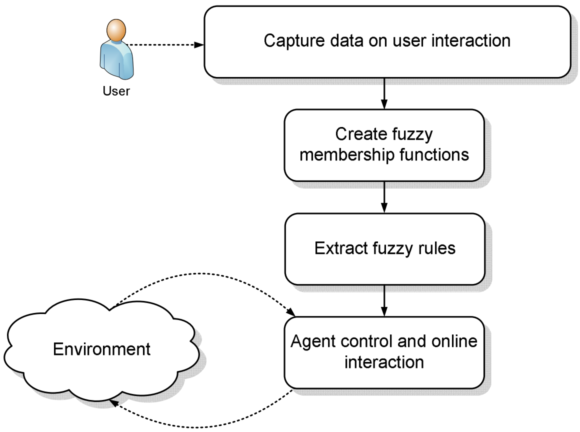

Fig. 4. Flow diagram of an adaptive online fuzzy inference system [12]

2.6 Interactive Artificial Learning

The issue of effectiveness in interactive artificial learning (IAL) is addressed in [15]. It is accomplished by comparing interactive learning method to traditional and conventional learning methods. The effectiveness of a learning method is measured as the ratio of the agent capability over the amount of inputs and skills from a human (designer or end-user). Several other metrics for measuring the quality of a learning method are also investigated in [15]. The authors explain two drawbacks of traditional learning methods as the significant amount of trial and error cycles in order to evaluate the agent's behaviour in a dynamic environment, and the need for a domain expert in addition to a system designer to encode the agent. Furthermore, in conventional learning methods agents operate more independently than in traditional learning methods, yet require human involvement to some extent. Also, conventional learning methods suffer from a slow learning process. Another drawback in conventional

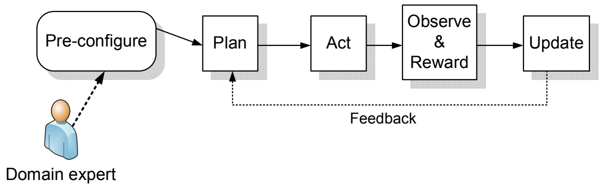

Fig. 5. Conventional learning steps

learning techniques is that the domain expert's role in pre-configuration step, consisting of system's parameter adjustment, reward structure, and learning mechanisms development, is considerably affecting the successfulness of the learning process. Fig. 5 shows a typical conventional learning process.

IAL is a new learning method that recently attracts many researchers' attention. In [15], the authors describe IAL as the learning method in which a human iteratively interacts with the agent during the learning process. The main goal of IAL is to keep the overall human involvement minimal. A general view of IAL learning steps is depicted in Fig. 6. As can be seen the end-user, not necessarily a domain expert, interacts in each step of the learning process thus diminishing the required work on the pre-configuration step [15]. Furthermore, IAL provides mutual understanding and exchange of knowledge between the end-user and the agent which facilitates the end-user's responsibility to provide more efficient inputs to the agent. The authors in [15] discuss the potential benefits of IAL learning on each particular learning step as shown in Fig. 6. Through simulations it is shown that traditional and conventional learning methods require more human involvement in the learning process that leads to a lower learning effectiveness than IAL method.

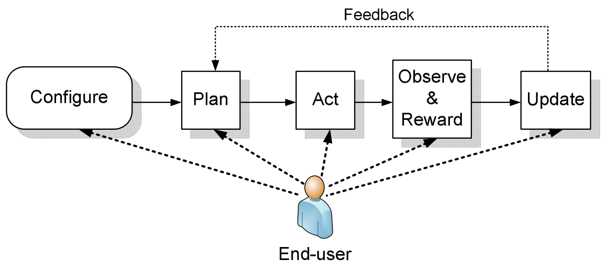

Fig. 6. Interactive artificial learning steps

2.7 Comparison and Discussion

All the discussed mechanisms are efficient learning processes equipped with different capabilities and features. They support various tasks, such as interactive learning, reinforcement learning, fuzzy reasoning, agent's feedback loops, and adaptive decision making. Table 1 provides a comparison of the discussed methods. As can be seen, in all of the mentioned approaches agents are able to adapt online in order to meet real-time needs. Another important observation is that approaches presented in [4] and [15] are the only techniques exploiting continuous human involvement as a vital element during the learning process. In other cases, the agent only relies on the initial knowledge provided by a human.

Table 1. Learning approaches for intelligent agents

Learning mechanisms	**Learning model**	**Multi-agent cooperation**	**Real-time adaptation**	**Uncertainty management**	**Human interaction**
Conceptual and behavioural leaning [4]	Conceptual, behavioural learning	No	Yes	No	Yes
Adaptive decision making rules [5]	Subsumption model learning	Yes	Yes	No	No
Relational reinforcement learning [16]	Relational reinforcement learning	No	Yes	No	No
Participatory learning [10]	Participatory learning	No	Yes	No	No
Online adaptive fuzzy learning [12]	Fuzzy inference learning	No	Yes	No	No
Interactive artificial learning [15]	Interactive artificial learning	Yes	Yes	No	Yes

As it can be observed, none of the above methods consider adapting the learning approach due to uncertainty observed by the agent. In fact, uncertainty is a factor that always exists in any complex and dynamic environment. We believe that there exists a relation between the level of agent's uncertainty and the agent's ability to learn. This is due to the fact that levels of uncertainty influence agent's confidence during the learning process.

3 Learning and Uncertainty

The definition of learning – *knowledge or skill acquired by instruction or study* – indicates that learning is a process of assimilating information that contributes to the overall knowledge and experiences of an individual. The pivotal element of the learning process is gaining knowledge. Assimilated knowledge can be evaluated from three different perspectives: its *source*, its *quality*, and its *novelty*. A newly acquired knowledge has to be analyzed in the context of an agent's knowledge base, and then integrated with this base. This process resembles a decision-making activity in which pieces of knowledge are chosen and combined with the existing knowledge. Each of the above perspectives, as well as decision-making mechanisms are potential source of uncertainty. Therefore, the process of learning has to be equipped with procedures suitable for handling uncertainty.

3.1 Knowledge Sources

In general, the web is a large uncensored network to which anyone can contribute by providing truthful as well as false information. Knowledge can be acquired from websites that can have different degrees of reliability. Recently, a lot of attention is dedicated to the issue of trust [17, 18]. In the initial structure of the semantic web [19], the importance of trust is recognized via defining a trust and proof layer as the top layers of the semantic web architecture. Some research activities are focused on different methods for assigning trust values to different sources, as well as methods dedicated to aggregation and inference of trust values. A number of different trust strategies have been proposed to rationale about trust: optimistic, pessimistic, centralized, trust investigation, and trust transitivity [18]. Each of these approaches deals with uncertainty and tries to discover aspects of the environment that are relevant to reduce uncertainty. Overall, the issue of trust in knowledge sources is related to the uncertainty associated with learning processes.

Another important aspect is quality of knowledge. The quality of knowledge relates to the amount of missing or ambiguous information. The quality-based knowledge uncertainty can be divided into three categories: non-specificity (imprecision), fuzziness (vagueness), and strife [20]. Non-specificity is manifested when two or more pieces of information are left unspecified. This may be the result of generalization, simplification, imprecision, or simply time constraints imposed on knowledge collecting processes. Fuzziness is characterized by the lack of definite or sharp distinction among pieces of information and may result from vagueness or any variety of indecisiveness. In some cases, especially for linguistic-based knowledge representation, terms and facts can be ambiguous due to differences in meaning as perceived by authors of the information. Strife or discord is an uncertainty characterized by disagreement in a selection process among pieces of information. This may happen due to dissonance, incongruity, discrepancy, and conflict. There is no doubt that quality of knowledge contributes to the uncertainty associated with the acquired knowledge.

In learning processes, the concept of uncertainty is also associated with novelty of knowledge – new knowledge introduces and changes uncertainty. In general, acquired knowledge can be of different levels of novelty. We can distinguish three scenarios of how acquired knowledge contributes to an agent's knowledge base and how it influences uncertainty.

- Updating existing knowledge – increases confidence in facts, skills and behavioral patterns already known to an agent. The agent's beliefs are modified and its uncertainty about correctness of facts decreases; the information that is "used" for this purpose can be associated with different levels of uncertainty, and it modifies the uncertainty levels of known information to a different degree.
- Modifying existing knowledge – includes changes in facts and skills that an agent currently believes in. The execution of those changes requires the agent's confidence in incoming knowledge; modifications should depend on estimated levels of uncertainty.
- Increasing existing knowledge – means assimilation of acquired knowledge that is new by an agent. This process needs procedures able to handle uncertainty; regulations are required to determine up to what degree of uncertainty an agent accepts new pieces of information.

The mentioned scenarios confirm that uncertainty is a crucial element of a learning process. Agents' learning mechanisms should be properly selected depending on environments. Also, agents should be able to take advantage of new information to increase their knowledge.

Based on presented above aspects, we claim that uncertainty is a part of a learning process and without it the learning would look quite different. Uncertainty is associated with the following issues:

- <u>uncertainty triggers learning:</u> a state of ambiguity forces an individual to search for more information and facts to resolve the vagueness;
- <u>uncertainty enables adaptability:</u> a constant state of not being sure means that an individual has to be prepared for a possible change of his/her opinion, in such a case it is easier to accept a change;
- <u>uncertainty prevents misjudgement:</u> processes of induction and deduction of new facts should have the ability to deal with situations which are not clearly true or false, it is not desirable to simplify everything to those two values;
- <u>uncertainty leads to more accurate models of reality:</u> the real world is not just "black and white", it is full of "gray areas", i.e., vagueness and ambiguity – any models real phenomena should be able to accommodate uncertainty.

3.2 Decision Making

The existence of uncertainty means that any decision-making mechanism has to cope with it. The processes of selecting what actions should be performed or which pieces of information should be integrated with the existing agent's knowledge should use a degree of uncertainty as an input. Decision-making mechanisms should be able to derive a conclusion in the presence of uncertainty, and provide the results that are "labelled" with degrees of uncertainty. Combining uncertainty with decision-making processes is not new. There are a number of different methods and techniques that can be applied here. These methods embrace probabilistic approaches – Bayes nets and Markov Models, possibilistic logic, preference and utility theories, as well as elements of game and auction theories [21-26].

An interesting investigation of decision models and uncertainty has been conducted in [27]. Authors use the bounded rationality concept to describe human decision strategy. They believe in a strong connection between agent rationality and agent model uncertainty. For clarifying this relation, four aspects of decision models are defined where the agent makes the best possible decision based on its knowledge base. These four aspects include: information availability, sampling of alternatives before the decision, the measure of assessment before the decision, and selection of an alternative. Each of those aspects can be associated with different levels of uncertainty. The selected decision will be optimum when the agent has full information with no ambiguity. This will result in full rationality (un-bounded), but it is not a realistic model for making decisions in real-world situations.

The ability to make decisions under uncertainty and to estimate the uncertainty of concluded decisions is a must for an adaptive intelligent agent. The methods and techniques for building and updating agents' knowledge bases with indications about uncertainties of acquired or induced knowledge should be part of learning processes.

4 Uncertainity-Oriented Agent Architecture

Overall, agents should be equipped with multiple learning mechanisms that are utilized depending on the agents' environments and levels of uncertainty associated with acquired information. In order to make it possible we propose an ontology-based uncertainty-oriented architecture for intelligent agents, and a special structure for their knowledge bases, Fig. 7.

Before we describe the architecture in detail, we need to explain the structure and the role of an agent's knowledge base (KB). The base is built based on three different forms of knowledge representations: ontology, causal nets, and belief structures. The ontology provides the basis for expressing facts, their definitions, and different types of relations that can exist among them. One of these relationships is a cause-effect relation. This relation is a fundamental relation of causal nets that are used to express conditional (in)dependence (causal relations) between facts in ontology. Additionally, a belief structure is imposed on ontology facts. It is represented by assessment of beliefs distributed among relevant facts. It can be said that the agent's KB is a multi-dimensional base able to embrace a multi-facet character of information. Furthermore, a number of if-then rules can be built using facts and their definitions contained in the base. The agent's KB has two essential parts: *temporary KB*, and *primary KB*. The *temporary KB* serves as a working memory and is used to store information that is still being retrieved and evaluated. Based on the estimated levels of uncertainty associated with different pieces of information from the *temporary KB*, the information and inferred facts that satisfy pre-defined confidence levels are moved into the *primary KB*. The *primary KB* contains information that has been analyzed via mechanisms of approximate reasoning. There are two parts of the *primary* KB – *facts-part* and *definitions-part*.

- The *facts-part* contains concrete pieces of information; it resembles individuals defined in the semantic web definition of ontology.
- The *definitions-part* contains general knowledge – definitions of things, concepts, and different relations between them; it resembles the definition part of the semantic web ontology. Facts from the *facts-part* and definitions from the *definitions-part* are connected by the "instance-of" relation. Facts and their definitions are associated with belief values that all together constitute a belief structure. Two important elements of the *definitions-part* are relations and rules:
  - o *relations* express different types of relations that exist among facts/definitions; each fact is just an instance of a single definition; the relations are built through observing relations among facts and then are generalized to the level of definitions;
  - o *rules* are if-then rules of arbitrary complexity built using facts, definitions, and relations between them.

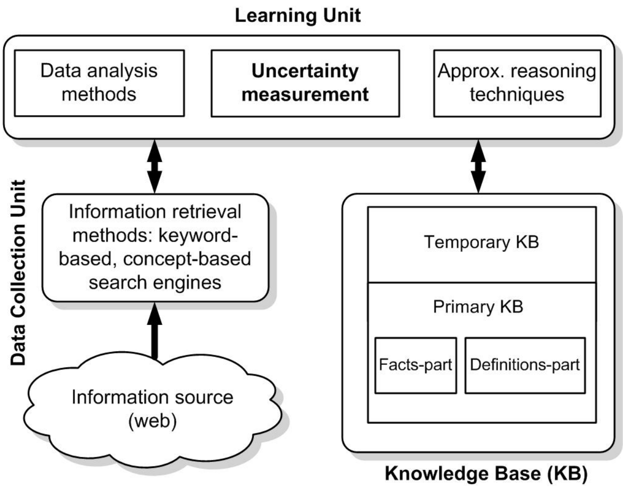

Fig. 7. The proposed uncertainty-oriented agent's architecture

The presented agent's architecture, Fig. 7, can be described in the following way. Information is retrieved from the web using different keyword- and concept- based information retrieval methods. This acquired knowledge is stored in the *temporary KB* and analyzed using variety of methods such as NLP-based pre-processing, different unsupervised and supervised techniques, and ontology-based processing (identification of facts included in ontology, synonyms, and ontology-defined relations). These analyses are integrated with processes leading to estimation of quality- and novelty- based uncertainties – "uncertainty measurement" unit in Fig. 7. The obtained uncertainties are combined with trust values associated with sources of information. This process results in determining belief values that are assigned to the acquired pieces of knowledge. The new information together with uncertainty values is stored in the agent's *primary KB*, and to be more precise, in its *facts-part*.

However, the learning process is far from done. Depending on available data and beliefs assigned, different methods will be used in order to find patterns and rules (association mining, decision tree construction, and supervised learning); to identify groups of items that exhibit similarity (unsupervised and semi-supervised learning); and to award/punish agent's decision and actions (reinforcement learning with possible involvement of a human). These processes will be performed on a regular basis. The levels of uncertainty associated with different facts, definitions and relations will influence the invoked learning mechanism and determine if an additional gathering of information is still needed in order to achieve a satisfying level of uncertainty.

It is worth noting that a human can play a distinct and significant role in almost every part of the agent's architecture by providing raw information to the agent, being involved in decision making processes, assisting the agent in estimating knowledge uncertainty or in building agent's knowledge base.

The importance of dealing with uncertainty and the justification of the proposed architecture can be illustrated with a simple, almost naïve example. Let us define a scenario in which two agents, "A" and "B", operate independently in the same environment. The agent "B" is designed such that it is capable of representing and reasoning under uncertainty, while the agent "A" is not able to do it. The assigned task from an end-user to these two agents is to organize a trip to Disneyland. Firstly, the agents start discovering the location of Disneyland on the web. The agent "A" looks through a number of hits (determined by its configuration parameters) and accepts the results without any doubt. The agent "B" estimates the uncertainty associated with the results, and is able to perform more search, i.e., to find more possibilities related to the trip's destination.

Secondly, once the destination is determined, the agents try to identify the most suitable hotel at a given location. Once again, the agent "A" is more rigid – it only does what is determined by its parameters – number of selection criteria, number of alternative hotels. The agent "B", on the other hand, is more flexible and is able to adapt and modify the selection process in the case the information about alternatives involves imprecision and ambiguity – it increases the search, looks for more criteria that were used in the past. Conclusively, the agent "B" accomplishes the task but the agent "A" struggles to finish it and needs human intervention.

As can be inferred from this example, the agent's ability to understand uncertainty and properly act based on it lead to increased "curiosity" and adaptation in the process of exploring the environment. A large set of available options is evaluated until the agent becomes certain whether its selections and decisions match the preferences of the requested task.

5 Conclusion

Learning is a key feature that converts an ordinary agent into one that intelligently interacts with its environment. This means that an agent is capable of dealing with different situations while adjusting its tactical strategies during operation in a dynamic environment. A brief survey of a number of state-of-the-art learning mechanisms is presented in this paper. The discussed methods address different features of a learning process and types of required knowledge. We have argued that the agent's ability to update its learning schema in the presence of uncertainty is an essential element of learning mechanisms of an intelligent system. This leads to greater flexibility in the agent's functionality in dynamic environments.

We also proposed a new architecture with the focus on uncertainty for intelligent agents. The architecture reflects the importance of: assessing levels of uncertainty, storing the uncertainty values in the agent's knowledge base, and using these values for decision making and learning processes. A new knowledge base structure is also proposed which addresses the issue of knowledge representation with uncertainty. Among different uncertainty management approaches – such as probabilistic models or the Dempster-Schaefer theory – we strongly believe in appropriateness of the fuzzy set theory. This opinion is also shared by the author of [20] who believes that the fuzzy set theory is the most appropriate tool for modeling human decision making processes due to the fact that the fuzzy set theory is inherently suitable for modeling information with imprecision – a situation that is normal for complex environments.

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