Inductive Learning Methodology And Algorithm Through The Use Of OSHA: Exploratory Analysis

by

[Waldo Kinney]

Acknowledgement

I would take this opportunity to thank my research supervisor, family and friends for their support and guidance without which this research would not have been possible.

DECLARATION

I, [*type your full first names and surname here*], declare that the contents of this dissertation/thesis represent my own unaided work, and that the dissertation/thesis has not previously been submitted for academic examination towards any qualification. Furthermore, it represents my own opinions and not necessarily those of the University.

Signed ___________________ Date __________________

Introduction

At the moment there are a number of machine learning methods to a pre-marked data used by specialists in various fields. They are used wherever possible to use logic. They require a relatively large amount of data to produce high results. Thus, in practice, the amount of untagged data volume exceeds considerably the marked data. For example, the volume of images handwriting significantly exceeds the marked character images. The present work shows a number of new methods with partial involvement of teachers, recognition of such characters. The usage of limited Boltzmann machines and convolution neural networks that is effective for handwriting recognition. Presented algorithms outperform classical algorithm two well-known supervised learning algorithms.

A learning process includes the acquisition of new forms of knowledge: motor development and cognitive ability (through instruction or practice), the organization of new knowledge (effective representations) and the discovery of new facts and theories through observation and experimentation. Since the beginning of the computer age, research has been undertaken to implement some of these capabilities in computers. Solving this problem has been the biggest challenge for the researchers of artificial intelligence (AI). The study and modelling of learning processes in computers and its multiple manifestations constitute the main objective of the study of machine learning (Yang, C., 2012).

Background, Problem Statement and Motivation

Merriam- Webster dictionary defines accident as an unforeseen, an unexpected and unplanned event or circumstance. Safety specialists, including Usmen (1994) and Hinze (1998), argue that definition based on the fact that accidents can be foreseen and prevented, and accordingly accidents can be predicted. According to the US Department o f Commerce Census Bureau, during the first 11months o f the year 2002, the construction industry in the United States put out a total volume o f $842.3 billion o f projects with 8% increase over the same period o f the year2001, which was $782.0 billion of projects f http ://www. Census, gov/const/C3 0/newtc.html).

Construction industry has few but unique characteristics over other industries. One of those characteristics lay in the fact that the construction industry is dynamic and scattered across wide range o f specialties, and depends on local conditions including site, weather, local codes and regulations. Secondly, each o f the industry’s products is totally different even if it was built the same; each product can be considered “first full-scale prototype.” Thirdly, construction is a labor-intensive activity, and in most cases includes a diversified work-force that is seasonal and transient in nature. Due to these unique characteristics, construction industry has been suffering from the highest rate o flitigation, highest rate o f business failures, highest rates o f accidents, and lowest rates of productivity among other industries. (Usmen, 1994).The construction industry has historically had a poor record o f occupational injuries and fatalities. Incident rates in construction industry have been one the highest (Steier Dr. med. dent, L., & Steier, G., 2013).

In year 2001 fatality in construction alone constituted 21.3% o f all work-related fatalities in the U.S (http://data.bls.gov/cgi-bin/surveymost). Accident prevention is the best way to improve this record. Current construction stakeholder practices are lacking a practical methodology to understand and foresee accidents. This research establishes a methodology for better understanding o f job site accidents based on the recognition of certain hazards that cause injuries and fatalities. Simply stated, inductive learning methodology is based on learning from past experiences or examples.

There is abundance area o f information on construction accidents and injuries collected by contracting companies, insurers, and regulatory and other government agencies. A pivotal agency dealing with safety issues is the Occupational Safety and Health Administration (OSHA), which issues investigation reports containing information on accidents, violations and citations. It is possible to learn inductively about construction accidents, and citations using this information. However this information is exceedingly detailed and is not in a form that is conducive to eliciting knowledge without undertaking a systematic process. Consequently, this study aimed at establishing a systematic approach and methodology for understanding construction accidents, OSHA citations, and the relationships between factors describing these elements. Equipped with the know ledge and understanding o f these factors and their relationships, the road can be paved for further studies that might lead to reducing or eliminating accidents, and providing a safe work environment.

The goal of machine learning

Currently, the field of machine learning is organized on three main research foci:

Studies oriented work: - the development and analysis of systems trainees for the improvement of certain working performance.

Cognitive Simulation: - research and computational simulation of human learning.

Theoretical analysis: - a theoretical exploration of the space of possibilities methodical learning algorithms and independent domain.

As a result of much research and efforts toward these goals, progress toward a goal often leads to progress toward another. For example, a reasonable starting point for searching the space of possible methods of learning can take initiative as an example of robust learner behaviour, called human behaviour. Similarly, psychological investigations of human learning can be aided by theoretical analyzes that suggest several plausible models of learning. The need to acquire a particular form of knowledge in some job oriented studies can, by itself, generate new theoretical analyzes and propose the following question: “How humans acquire these skills (or knowledge) specific?” This challenge is a leading mutual reflection of the field of artificial intelligence, where research on expert systems, cognitive simulation and theoretical studies provide a crossing problems and ideas among scholars of this subject (Goodman, N. D., Ullman, T. D., & Tenenbaum, J. B., 2011).

Applied learning systems: a necessary practice

Currently, instruct a computer or a robot to perform a job, requires a correct and complete definition of an algorithm for this task, and then a workhorse computer program. These activities typically involve a tedious and time consuming effort by trained specialists.

At the present time, computer systems can not learn to perform a task through examples or by analogy to a similar previously solved work. They can not improve their performance significantly through their past mistakes, or acquire skills by observation and / or imitation. Research in machine learning strive to open up the possibility of instructing computers in new ways, and thus promise to ease the burden that programmers due to the increased complexity of the information. The rapid expansion of applications and availability of computers currently make this option more attractive and desirable.

When we approach an acquisition of knowledge oriented work, we must ensure that the computational result is interacting with humans, being compatible with their skills. The traditional argument that an ingenious approach does not accurately reflect human or biological application is not really applicable to machine learning. Learning machines should interact with the people who will handle them and, consequently, the concepts and skills they acquire (not necessarily their internal mechanisms) should be understood by humans (Cohen, J., Ferguson, R., Goldenson, D., McCurley, J., Stoddard, R., & Zubrow, D., 2013).

Machine learning as a science

The doubt about the abilities of gifted genetics in a biological system (versus skill or knowledge acquired), has fascinated biologists, psychologists, philosophers and researchers in Artificial Intelligence. A strong candidate for the invariant cognition in humans is the learning mechanism - the innate ability to acquire facts, skills and many abstract concepts. So understanding human learning well enough to reproduce aspects of learner behaviour in a computer system is a worthy scientific goal. The computer can render substantial assistance to cognitive psychology can be used to test the consistency and “completeness” of learning theories, forcing a commitment to high level of detail, avoiding in this way, meaninglessness, tautology or untested theories.

The study of the human learning process is of considerable practical and meaningful. Not surprisingly, research on computers educated with intelligence, with emphasis on development of tutoring systems which share many of the goals and perspectives of research in machine learning. A particular and interesting development is on computers tutoring systems that incorporate skills to infer models of student competence by observing their performance. Inferring the scope of a student’s knowledge and skill in a particular area, it becomes more effective and individualized teaching.

An equally basic scientific goal of machine learning is the exploration of alternative mechanisms of learning, including the discovery of different induction algorithms, the scope and limitations of certain methods, the information must be available to the learner, the generation of data incorrect values and the creation of techniques applicable in many fields of work. There is no reason to believe that the method of human learning is the only way to acquire knowledge and skill. Indeed, common sense suggests that human learning is just one point of the large space of possible learning methods - a point that through the evolutionary process is particularly well placed to win the physical environment we live. Many theoretical works in machine learning has focused on the creation, characterization and analysis methods for global learning, with greater emphasis on general analysis and plausible psychological performance.

While theoretical analyzes provide a means of space exploration methods for learning, task-oriented approach provides a vehicle for testing and improving the performance of functional learning systems. By building and testing systems applied to apprentices, we can determine the actual cost and limitations of learning. In this way, individual data points in the space of possibilities of systems trainees are explored, and the space becomes better understood.

Knowledge acquisition versus refinement of skills

There are two basic forms of learning: knowledge acquisition and refinement of skills. When we say that somebody learned physics, we say this person acquired concepts of physics, understood these concepts and understand the relationship of each with the physical environment. The essence of learning in this case is the acquisition of knowledge, which includes descriptions and models of physical systems and their behaviour, incorporating a variety of representations - from simple and intuitive models, examples and images to complete tests of mathematical equations and physical laws. A person is said to have learned more if your knowledge explains a broad scope of situations, it is more accurate, and is skilful to predict the behaviour of the physical world. This form of learning is called knowledge acquisition. So, knowledge acquisition is defined as learning new symbolisms along with the ability to apply this information effectively.

The second form of learning is gradual motor and cognitive development of a skill through practice (like riding a bike or playing the piano). Acquiring knowledge from a book or learn how to perform these activities is only the initial stage of skill development. The centre of the learning process is the refinement of skill, mental or motor, by repetition and correction of deviations from the desired behaviour. This form of learning is called learning by refining skills, differing in many ways of the knowledge acquisition process. So the essence of knowledge acquisition can be a conscious process that results in the creation of new structures and mental models of symbolic knowledge, whereas the refinement of skills occurs at a subconscious level by virtue of the practice of repetition. Many human learning are a mixture of both activities, with the previous attempt to favour intellectually and motor coordination, improving further work.

Taxonomy of machine learning research

The classification of learning of computing systems can be done in several ways. We chose three dimensions of classification:

Classification learning strategy used: they are ordered according to the amount of inference of the learning process.

- Classification type of representation of knowledge or skill acquisition by the learner.
- Rank in terms of system performance according to the application domain.

Each point in the space defined by dimensions corresponds to a particular learning strategy, employing a special representation of knowledge about a specific domain. There are, and then learning routines that employ multiple representations and processes, many have been applied for more than one domain, with systems being characterized for various points in space.

The subsections below describe the values explored in each of these dimensions. The wide space of all the possibilities for learning are partially explored and understood. There learning systems corresponding to small portions of space because they are a small number of combinations of possible values.

Classification based on learning strategy

Since we distinguish learning strategies for the importance of the learner's inference on the information available, we consider two extremes: no inference implementation and execution with a substantial amount of inference. If a computer is programmed directly, your knowledge is increased, but this shall not have any inference; entire cognitive effort is up to the programmer. Conversely, if a system discovers new theories or invents new concepts independently, it performs a substantial amount of inference. An intermediate point on this spectrum may be a student looking to solve a math problem solved by analogy to examples from the book - a process which requires inference, but much less to find a branch of mathematics without being guided by a teacher or a book (Wild, C. J., Pfannkuch, M., Regan, M., & Horton, N. J., 2011).

The more inference the learner is able to increase, unless the teacher or the external environment needs to do. It is more difficult to program a computer to perform a complex task to instruct a person to perform the same work; programming requires explicit specification of all required details, but a person receiving instruction can use knowledge and judgment to complete the most mundane details. The taxonomy below captures this notion of the amount of effort required of the learner and the teacher:

Learning and direct deployment of new knowledge: no inference or other processing knowledge is required on the part of the learner. Variations of this method include:

- Learn the planning, construction or modification by an external entity, requiring no effort on the part of the learner (e.g. conventional programming).
- Learning by memorization of facts and data without inference of input information (eg bank run by primitive data systems).

Learning by instruction - to acquire knowledge from a teacher or another source such as a book, requires that the learner become aware of the language input to an internal representation, and this new information must be integrated with prior knowledge for effective use. Then, the learner is required to perform some inference, but a large fraction of the obligation is for the teacher, who must be present and must arrange everything so that increases the learner's prior knowledge. Learning by parallel instruction is the most formal educational method. So the job of machine learning is a form of construction that can accept instructions or advice guarding and applying this knowledge efficiently.

Learning by analogy - to acquire new facts or skills for the transformation and growth of knowledge bringing existing strong similarity to the new concept or skill required in an efficient and usual way in new situations. E.g. a person who has never driven a truck, but have led some car should turn the current skill to new situation. Similarly, learning by analogy should be applied to convert an existing program to another computer running a close but different function of the original function. Learning by analogy requires more inference on the part of the learner than learning by instruction. A fact or a similar ability is an important parameter that must be retrieved from memory, so the recovered knowledge must be transformed, applied to new situations and saved for future use.

Learning from examples: (a special case of inductive learning) - Taking a number of examples and counter-examples of a concept, the learner induces a general description that describes all the positive examples of the concept. Learning by example is a method that has been heavily investigated in artificial intelligence. A portion of the inference performed by the learner is much larger than the learning by running and something greater to learn by analogy. Learning from examples can be subjected according to the origin of the examples:

- The source is a teacher who knows the concept and generalize sequences of examples to help as much as possible the knowledge of the learner. If the teacher infers the state of knowledge of the learner, the examples can be selected to optimize the convergence to the desired knowledge.

- The source is the learners themselves. The learner typically knows their state of knowledge, but clearly does not know the concept to be acquired. Then the learner can generate models (having an external entity such as environment, or a teacher classifying the samples as positive or negative) on the basis of information, and relies on the discrimination argued concept. Eg a learner acquiring the concept of ferromagnetic substance, generalizing the possible candidates as all metals. Testing an object of copper and other metals with a magnet, the learner discovers that copper is a counterexample, then, the concept of ferromagnetism ceases to be generalized to all metals.

- The source is an external environment: in this case, the process of generalization of the sample is random; the learner must rely on observations that are available to you. Eg an astronomer who knows the concept of a shooting star, but may not know when and where it will occur, nor can induce this phenomenon.

A possible classification of learning can be the kind of example available to the learner:

- Only positive examples: positive examples provide instances of concepts to be acquired. They do not provide information that prevents super generalization of the concept inferred. In this case learning should be careful and seek to consider the minimum possible generalization or rely on prior knowledge to restrict the concept to be inferred.
- Examples of positive and negative: in this situation, positive examples force generalization while negative examples prevent the super generalization (induced concept can never be so general as to include some of the negative examples). This is the most typical form of learning by examples.

Learning from examples can be experimental or incremental process. In the first case, all the examples are presented only once. In the latter case, the system should form one or more hypotheses of the concept (or set of concepts) consistent with the available data, refining the assumptions before considering additional examples. The nearest incremental approach to human learning allows the learner to use partially learned concepts (for performance or to guide the process of generalization), and enables the teacher to focus on the basic aspects of the new concept before bringing to the smallest details. On the other hand, the step by step approach is less suitable for learning a path that generates a fair choice of initial examples for the formulation of the new concept.

Learning from observation and discovery (called unsupervised learning): this is a very general form of inductive learning that includes discovery systems, forming theories, creation of classification criteria to form hierarchies and similar work without the help of an external teacher. This form of learning requires the learner a greater degree of inference than previous forms of learning. The learner has no examples of a particular concept, or has access to any source of examples of classification generalization (positive or negative examples). In addition, focusing on a simple concept at a time, the observations may detect other concepts that need to be acquired, introducing a severe focus of attention to the problem. There is a possible sub classification of learning by observation in accordance with the extent of interaction with the external environment. The extreme points of these dimensions are:

Passive observation: the learner classifies observations of multiple aspects of the environment;

Active experimentation: the apprentice disturbs the environment to observe the results of this disruption. The trial may be random, focused in accordance with the general criteria of interest, or strongly guided by theoretical constraints. As the system acquires knowledge, a theoretical hypothesis can be directed to confirm or contradict a theory, and then the environment can be exploited by applying different strategies of observation and experimentation. Often this form of learning involves the generation of hypotheses to test samples or acquire partial concepts.

The classifications of learning strategies above help compare various learning systems in terms of their mechanisms, the source of information available and in terms of the extent of reliance on previously organized knowledge.

Classified according to the type of knowledge gained

A learning system can acquire rules of behaviour, descriptions of physical objects, heuristic problem solving, and classification on a sample space of possibilities and many other kinds of useful knowledge in a variety of task performance. The list below presents types of knowledge acquired, primarily depending on the type of representation of this knowledge:

Parameters in algebraic expressions - learn this concept is the numerical parameters set in algebraic expressions or coefficients of a fixed functional form to obtain the desired performance.

Decision trees - some systems purchase decision trees to discriminate between classes of objects. The nodes in a decision tree correspond to attributes of the selected objects, and the edges correspond to certain alternative values for these attributes. The leaves of the tree correspond to the values of objects of identical classes.

Formal grammars - learning experience for recognizing languages (usually artificial), formal grammars are induced sequences of expressions in the language. These grammars are typically represented as regular expressions, finite automata, rules of grammar rules or context-free processing.

Production rules - a rule of production is a pair condition -> action {c => a}, where ‘c’ is one or more conditions and is a sequence of actions. If all conditions of the production rule are satisfied, then the sequence of actions is executed.

Because of this simplicity and ease of interpretation, production rules are widely used in knowledge representation of systems trainees. The four basic operations where production rules can be acquired and improved are:

- Creation: a new rule is built for a system or acquired from a third party;
- Generalization conditions are decreased or made less restrictive being applied to a greater number of situations;

Specialization: Additional conditions are added to the group, or made more restrictive, being applied to a smaller number of cases (specific cases).

Composition: two or more rules that are applied in sequence are composed in a single rule, and then form a process “compiled” that eliminates any redundancy condition or action. Formal logical expressions and related formalisms - these representations of general plan has been used to Formulate descriptions of individual objects (input apprentice system) and to Formulate Resulting descriptions of concepts (output apprentice system). These representations take the form of formal logic expressions in which the components are arbitrary predicate propositions, finite variable values restricting claims series of variables (such as a number between 1 and 9) or logical expressions fit.

Graphs and networks - in many fields, graphs and networks provide a more convenient and efficient way of representing que logical expressions, through the expressive power of representation of the network is comparable to que of formal logic expressions. Some learning techniques exploit Wedding and transformation of graphs for comparison and knowledge efficiently indexing schemes.

Frames and schemas these types of representation provide larger units of representation queue simple logical expressions or rules of production Frames and schemas can be viewed the collections of labelled entities (slots), each slot has a certain prescribed in the task representation. They have been used in many applications of artificial intelligence. For example, the system acquires queue general plans must be able to represent and manipulate some plants the units through its internal structure queue must be arbitrarily complex. In addition, experiential learning, past successes, untested alternatives, causes of failure, and other information and Compared Should be recorded in induction and refinement of various rules of behaviour. “Schemes” Provide an Appropriate formalism.

Computer programs and other procedural codes the goal of the learning system is to acquire the ability to delete a specific process efficiently, before pondering about its internal structure. Many systems of automatic programming fail in this category In addition to computer programs, procedural codes include human motor skills (like riding a bike), sequences of instructions for robotic manipulation, and other “compiled” human or machine skills. Unlike logical descriptions, networks and frames, the detailed internal structure of the Resulting procedural code need not be understood by humans or by automated reasoning systems. Only the external behaviour of procedural skill acquired needs to be understood by reasoning system.

Taxonomies - learning by observation can result in global structures of domain objects in a hierarchy or taxonomy. Amounts of description of objects in categories proposed formation of hierarchical classification and require the system to Formulate relevant classification criteria.

Multiple representations disappears acquisition systems use some knowledge representation schemes for the newly acquired knowledge More remarkable, some discoveries and theoretical systems queue acquire concepts, these concepts and operations of heuristic rules for the new domain must select Appropriate combinations of representation schemes applicable to different forms of knowledge acquired (Prasad, T. V., 2012).

Classification by Application Domain

A common form of classification of learners systems is in the area of application. The list below specifies areas where the scope of existing learning systems has been applied. The sequence of presentation does not reflect any significance of the result of machine learning.

- agriculture
- chemistry
- Cognitive modelling (simulation of human processes)
- computer programming
- education
- expert systems (high-performance, domain-specific programs)
- Games (chess, poker, etc.)
- General methods (in specific field)
- image recognition
- mathematics
- medical diagnosis
- music
- Natural language processing
- physical characterization of objects
- physics
- Troubleshooting

- robotics
- prediction of sequences
- speech recognition

A theory and methodology of inductive learning

This theory shows the inductive learning as a heuristic search through the space of symbolic descriptions, generated by applying various rules of inference about the characteristics observed. The rules of inference rules include generalization, which perform transformations in conventional descriptions and deductive rules with preservation of originality. Applying these rules of inference is descriptions is restricted by the problem of prior knowledge, and guided by criteria of quality evolution inductive assertions generated.

Based on this theory, a general methodology for learning structural descriptions from examples, called STAR, is described and illustrated by a problem in the area of conceptual data analysis.

The ability of people to make accurate Generalizations of scattered facts or discover models in seemingly confusing collections is a fascinating research topic. Understanding this ability is now growing practical Importance Also because it is the key to the development of methods by which computers can acquire knowledge. The need for development is evidenced by colleagues acquisition of knowledge is at present the most limited “bottleneck” in the development of knowledge-intensive models of Artificial Intelligence systems. Achieved Greater skill is by a process called inductive learning, i.e., inductive inference of facts provided by the teacher or external environment. The study and modelling of this form of learning is one of the main topics of machine learning.

Before we discuss this topic, we will first discuss the potential application of inductive learning systems. One possible application is in automatic construction of knowledge bases for expert systems. This approach to building the knowledge base involves the tedious process of formalizing and encoding expert knowledge in some knowledge representation systems, such as production rules or semantic networks. Inductive learning programs can provide improvements in the techniques of current programming and a basis for the development of alternative methods of acquiring knowledge.

In small and selected domains, inductive programs are now able to determine decision rules induction of examples of expert Decisions. Noticeably this process simplifies the transfer of knowledge from an expert to a machine. The practicality of some forms of inductive knowledge acquisition has Been Demonstrated in expert system PLANTS / ds, for the diagnosis of soybean diseases. In this system, the rules for diagnosis were tested in a few hundred cases patients. Another example is in inductive acquisition of decision rules for the game of chess.

A less direct but potentially promising use of inductive learning is for the refinement of knowledge bases developed INITIALLY by human experts. Here, inductive learning programs can be used to detect and rectify inconsistencies, removes redundancies, close gaps and to simplify decision rules derived from an expert. Applying the program of inductive inference for data, consisting of original rules and examples of correct and incorrect results from the application of these rules to new situations, the data can be incrementally improved with little or no human assistance.

Another important application is inductive programs in various fields of science (seen above). Here, they help the user to detect interesting conceptual models or reveal structures in collections of data. The wide data analysis techniques used in mathematics and statistics as regression analysis, numerical rating is not sufficient for the potential of this work. Methods for analysis of conceptual data are needed in the fields in which the results are not merely mathematical formulas, but characterization of data in terms of high-level, human-oriented concepts and relationships. One such application is the META-DENDRAL, which infers rules of division to mass spectral simulation.

There are two basic ways in which inductive programs can be used: as interactive tools for acquiring knowledge of specific facts or examples, or as part of machine learning systems. In the first mode, a user supplies the machine learning examples and exercises strong control over the way in which the program is used.

In the second mode, an inductive program is a component of an integrated learning system where other components generate the necessary learning samples. Some examples are positive and negative feedback from the system attempts to perform a desired task. An example of the second mode is the learning system LEX symbolic integration, where a “generalizing” module performs inductive inferences in instances provided by a “critic” module.

From the viewpoint of application, as an aid in building expert systems or conceptual analysis of experimental data, the most relevant is the conceptual inductive learning. We use this term to describe a type of inductive learning that are symbolic descriptions on high end products, human-oriented terms and formats. The descriptions are typically applied to objects or phenomena in the real world, preferably abstract concepts or computational mathematics.

The most frequent type of learning is studied learning examples (called knowledge acquisition), where the task is to induce general descriptions of concepts of specific instances of these concepts. An important variant of the learning examples is the concept of incremental refinement, where the input information includes, in addition to examples, hypotheses previously learned, or initial hypotheses provided by humans that can be partially incorrect or incomplete. Another type of conceptual inductive learning is the concept of learning by observation (or descriptive generalization), concerned with the expanse of new concepts or theories characterizing acquired facts. This area includes some topics such as automatic formation theories, the discovery of relationships between data, or construction automatic taxonomy. Differences between the concept of learning from examples and concept learning by observation are discussed in more detail in the next section.

Conclusion

A theory of inductive learning has been shown targeting both learning and heuristic search through the space of symbolic descriptions, generated by the application of rules of inference to Certain Observed the baseline characteristics (the teacher generates examples of concepts or the environment Provides facts). The process of generating the target statement - the preferred inductive assertion depends on universal and complementary operations of specialization or generalization of the statement, ordered to accommodate new facts the domain of prior knowledge has been shown to be the Necessary component of inductive learning, Which Provides restrictions, guidance, and the Criterion for selecting the most Desired assertion.

The characterization of inductive learning is conceptually simple, and is a theoretical framework for the description and comparison of learning methods, as well as developing new methods. The methodology for learning structural descriptions of examples represents a general approach for acquiring concept can be implemented in a variety of ways and applied to different problem domains.

There are many topics of inductive learning queue has not been covered here. Among them is the learning of incomplete or uncertain information, descriptions containing errors learning, learning with multiple forms of observation, as well as inductive assertions based on multiple models, and general learning rules with exceptions. The problem of discovering new concepts, descriptors, and usually several, multi-level description of the initial space transformations (i.e., the problem of constructive inductive learning) has been only superficially covered.

References

Steier Dr. med. dent, L., & Steier, G. (2013). SUCCESSFUL DENTAL IMPLANT PLACEMENT SURGERIES WITH BUCCAL BONE FENESTRATIONS. *Journal of Oral Implantology*.

Roy, A., Khanra, K., Mukherjee, A., & Bhattacharyya, N. (2013). Asbestos: A potential food contaminant and associated safety risks to consumers. *Journal of Science, 3*(1), 241-243.

Occupational Safety and Health Administration. (2013). Basic Program Elements for Federal employee Occupational Safety and Health Programs and related matters; Subpart I for Recordkeeping and Reporting Requirements. Final rule. *Federal register*, *78*(150), 47180.

Yang, C. (2012). *Knowledge and learning in natural language* (pp. 1680-1681). Springer US.

Goodman, N. D., Ullman, T. D., & Tenenbaum, J. B. (2011). Learning a theory of causality. *Psychological review, 118*(1), 110.

Cohen, J., Ferguson, R., Goldenson, D., McCurley, J., Stoddard, R., & Zubrow, D. (2013). 9 Quantifying Uncertainty for Early Lifecycle Cost Estimation (QUELCE). *Results of SEI Line-Funded Exploratory New Starts Projects*, 104.

Wild, C. J., Pfannkuch, M., Regan, M., & Horton, N. J. (2011). Towards more accessible conceptions of statistical inference. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *174*(2), 247-295.

Prasad, T. V. (2012). Hybrid Systems for Knowledge Representation in Artificial Intelligence. *arXiv preprint arXiv:1211.2736*.