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From Inductive Learning Towards Interactive Inductive Learning

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***Abstract* - Growing amount of information in the world encourage the use of automatic data processing techniques that reduce humans routine work. There is a wide range of methods used for machine learning; however inductive learning algorithms are preferable in the systems where understanding of decision making steps and further processing of results is needed, for instance the expert systems, where the rules induced by learning algorithms can be used. As the classification tasks are getting more complicated computer program may not make enough informed decision by itself. In such situations collaborative approach between machine and systems user (expert) would be useful. Inductive learning system learns classification from training examples and uses induced rules for classifying new cases. If a decision cannot be inferred from rules base, a guess is performed. Interactive inductive system in uncertain conditions could ask human for decision and improve its knowledge base with the rule derived from this human-made decision. The paper summarises approaches discussed in related works and classifies them by the phase in inductive learning process in which the human interaction appears. As a result a new approach to interactive inductive system is presented. Conceptual example of topographical map classification using this system is demonstrated.**

***Keywords:* data mining, human-computer interaction, inductive learning, interactive inductive learning, machine learning**

I. Introduction

As our ability to collect massive amounts of data increases, the machine learning and data mining take on greater importance [1]. Pham and Afify [2] mention that machine learning algorithms can be a very useful tool for the construction of knowledge-based systems.

Inductive learning algorithms are widely used in machine learning tasks and they hold a strong position as reliable classification methods that can explain their decision making process [3]. Inductive learning has more capabilities and potential to improve its performance and to extend its area of application. Still there are some problems to solve. The approaches used for dealing with non-classifiable instances do not work appropriate in all domains. The aim of this paper is to show the need for the new inductive learning system that would deal with non-classifiable examples using interaction with human.

The paper sections are organized as follows. First the importance of machine learning is described in Section II. As one of the methods for classification in machine learning inductive learning is expanded in Section III. Classification of inductive learning methods is shown to demonstrate their variety. After describing general inductive learning system, classification problem with non-classifiable examples is outlined. Then the related works of human-computer interactive learning systems are discussed in Section IV. Considering achievements and drawbacks of described approaches the new system of interactive inductive learning is proposed. Conceptual example of topographical map classification using this system is demonstrated. Conclusions of this paper follow afterwards.

II. Machine Learning

Cios and Kurgan [4] define machine learning as the ability of a computer program to improve its own performance, based on the past experience, by generation of a new data structure that is different from an old one, like production rules from input data. The demand of machine learning applications, in particular in the areas of data, image and text mining, has created an urgent need for systems that can efficiently search for regularities or data descriptions in very large information sources [5]. The ever-growing importance of machine learning in multiple fields has been highlighted in many articles, e.g. [1] – [5]. There is a wide range of methods to be used for machine learning [6], [2], e.g., artificial neural networks, Bayes classifier, K-Nearest Neighbours classifier, genetic algorithms, inductive learning etc. Although machine learning algorithms are domain independent, in many domains generated descriptions or patterns need to have not only a high predictive accuracy, but also are required to be easy to interpret and comprehend by the user. Different programs may demand different description forms, i.e. reasoning system should be able to transform types of its results. Inductive learning algorithms are preferable over other machine learning methods in systems, where understanding a decision making steps and further processing of results is needed. Expert systems are such systems where the rules induced by learning algorithms can be used [4]. The next section describes inductive learning basis to mark out the problem planned to solve.

III. Inductive Learning

Induction is a process of conversion of particular facts into general regularities. In computer science inductive learning is learning by example, where a system tries to induce a general rule from a set of observed instances [7]. This also involves classification – assigning the name of a class to every particular input. Classification is important to many problem solving tasks.

In mathematical form inductive learning can be viewed as finding the hypotheses that are closest to real function within example set [8]. Then, the generated hypotheses are applied to the new examples to predict their class membership [9].

A. Classification of Inductive Learning Methods

There are several dimensions along which learning algorithms can be classified. Depending on the way of learning, inductive learning methods can be divided in incremental and nonincremental (or static) ones (see Fig. 1). According to [10], static algorithms are appropriate for learning tasks in which a single fixed set of training instances is provided while incremental algorithms are appropriate for learning tasks in which there is a stream of training instances. In the incremental case, the algorithm revises the current concept definition, in response to each new training instance, enabling to avoid rebuilding the whole classifier each time a new instance is observed. On the other hand, it may not be worth to implement an incremental algorithm for constant learning set.

Other option to divide inductive methods is to consider the way the classifier is obtained and described – whether it forms decision tree, generates rules or combines both (See Fig. 2. E.g., most popular algorithms in each category are [4], [2] ID3, C4.5, CART for decision tree, AQ for rules and CN2 for hybrid (quite often added to rules generating methods).

The third dimension along which the inductive learning methods can be distinguished is whether they use oblique hyperplanes to partition the data or split feature space with axis-parallel hyperplanes (see Fig. 3). Methods which construct axis-parallel separating planes are limited in their effectiveness, however, oblique hyperplanes are much complex to construct and use. Approach of constructing oblique multicategory decision trees is described in more details in [1], [11], [12].

B. General Inductive Learning System

Generally classification task with inductive learning is organized as follows. First, the classifier for particular domain is formed; afterwards it is used for automatic or semi-automatic classification of new instance. Classifier forming consists of two parts, classifier training and testing (see Fig. 4).

In the training phase an inductive learning method is used to infer description (either in form of decision tree or classification rules) from given example set, where the class for every single record is known. Example set can be accumulated form observations, generated by expert or combined. Then follows the evaluation of description accuracy for unseen examples from the same domain. The class is assigned to every test example in accordance with description gained in training step. As the test example's true class is known, one can rate the accuracy of predictions and classifier overall accuracy. Also the conclusions of tree size (or rules count, length) can be drawn. If classifier accuracy is acceptable, classifier can be brought to real new classification tasks.

C. Dealing with Non-Classifiable Examples

It often happens that none of rules fits the example or tree cannot classify the incoming instance even if classifier accuracy after test results was good. There are several methods to deal with this problem. CN2 algorithm applies the default rule that predicts the most common class in particular data set if none of generated rules fits the example [9]. This approach is comprehensible and acceptable but it does not

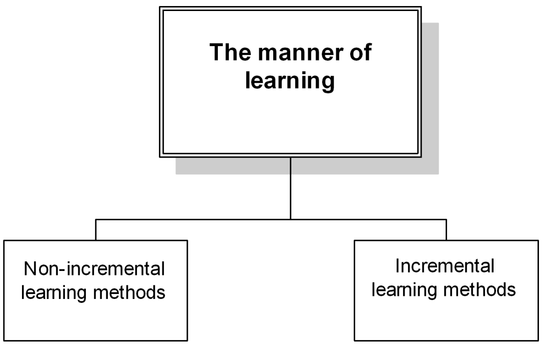

Fig. 1. Division based on learning manner

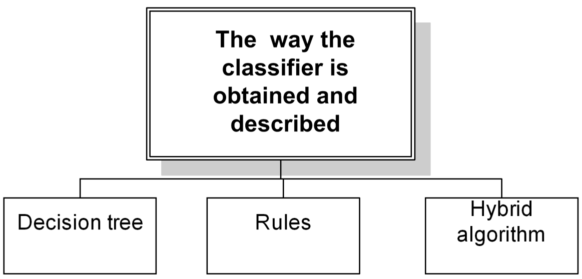

Fig. 2. Division based on classifier form

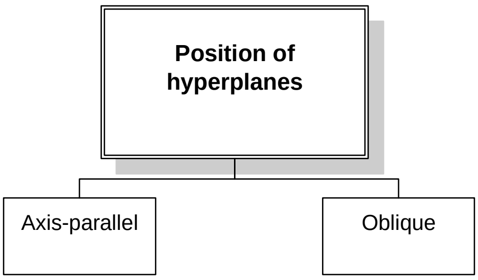

Fig. 3. Division based on position of hyperplanes

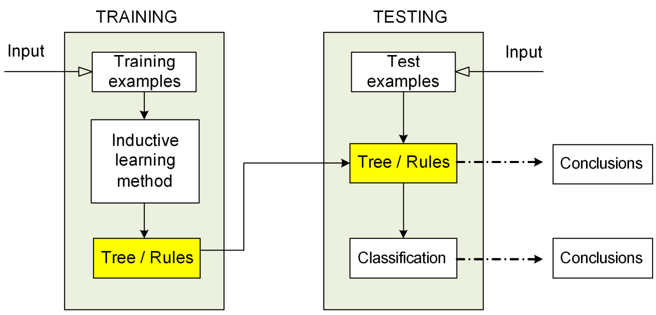

Fig. 4. Steps of classifier forming

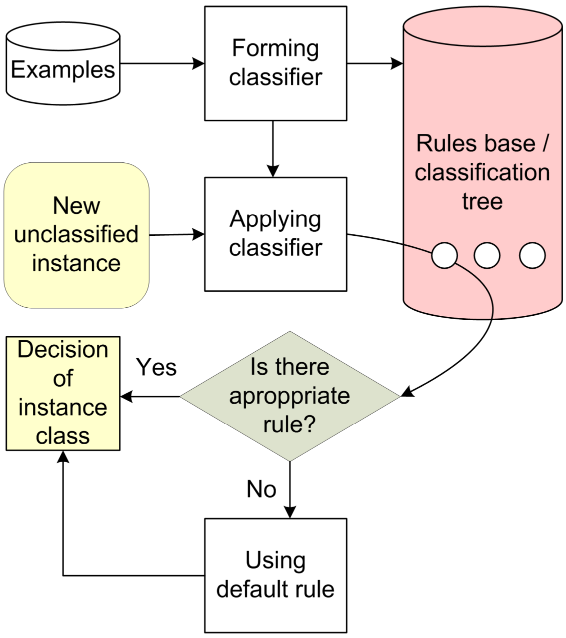

Fig. 5. Automatic classification

work well if data set contains many classes and all of them occur equally frequently. Within the domains where one class is more critical to be detected than the others, e.g. medical diagnosis, this most relevant class is usually assigned, when classification can't be clearly made, not to make a serious mistake. Yet such a method is not appropriate for all situations. In Fig. 5 traditional process of classification is depicted.

"Classifier forming" block includes both training and testing phases. Here and forth the term "rules" is used to denote classifier, either in form of decision tree or IF-THEN rules. When no rule for example classification is found, a guess is performed. Most frequently the default rule is used.

As the classification tasks are getting more complicated, computer program often meets the situations when classification can't be made with existing rules base. Leaving a decision making to some predefined algorithm is not always the best solution, and it is also not the only opportunity. Some machine learning systems attempt to eliminate the need for human interaction, while others adopt a collaborative approach between human and machine. In situation when example can't be unequivocally classified collaborative approach between machine and systems user (or expert) would be useful. The paper proposes to construct new inductive learning system that could ask user to make a classification in previously described situation. This interactive inductive system in uncertain conditions could ask human for decision and improve its knowledge base with rule derived from this "experience".

IV. Related Works

There are different papers in last twenty years referring to concept „interactive inductive learning" or exploring idea of user interaction in concept learning process. Systems and approaches proposed are from distinct fields and suggest different levels of user interaction. There are the following levels of interaction described in [13] – [18]:

1. Systems where user feedback is asked to evaluate only the given result (decision or prediction).
2. Systems that learn concept classification based on human classification.
3. Human first is giving his/her knowledge to system and affirming rules induced by the system afterwards.
4. Human evaluates and selects rules induced by system in classifier forming phase.
5. Learning systems where human is the learner and computer should be able to interact in user-friendly way.

WWW Search Engines usually return a hit-list including many irrelevant pages because of not enough specific query input from user. Okabe and Yamada [13] propose a system which uses the interactive process called "relevance feedback" to create a query specific filter. This filter is a set of rules, each of which helps to decide whether to show page to the user or not. The filter is made by the inductive learning algorithm FOIL. After getting a hit-list from a search engine, the user is asked to evaluate their relevancy. System stores those pages as training pages, analyzes them, generates filtering rules and does the re-search.

Tanumara, Xie, and Au [14] present approach where computer learns colour concepts taking examples one by one categorised by human. Computer hasn't ability to create or modify category by its own. Human interaction is done at the same time as learning. Computer learns colour identity and category by building layers of neural network. Though it isn't an inductive learning algorithm that is trained this way, the idea can be applied much broadly (including inductive learning). The outcome of [14] demonstrates that it's possible to achieve good results toward human-like knowledge and intelligence without imitating human perception in complicated way.

Buntine and Stirling [15] argue that "induction should be interactive so that both further subjective information can be input to the induction process and the final induction product can gain the expert's acceptance". They talk about eliciting information from an expert during knowledge acquisition. In this approach induction is not viewed as an automatic process. The authors explain that induction has never been isolated from human actions while expert is that who defines categories and chooses features taken in count. Buntine and Stirling don't find it a problem or drawback to involve humans in several phases of induction process. In defined system interaction with humans is used for the following purposes:

- To acquire knowledge from expert (in addition to examples available).
- To get acceptance for knowledge (rules) induced.

Hadjimichael and Wasilevska in [16] propose the probabilistic inductive learning system where user takes an integral part in learning cycle by, first, supplying conditions to the system and then selecting conditions for further use from the suggested conditions by the system. User role is similar to decision tree subtree pruning in other approaches. The system outputs all generated rules and lets the user decide which rules to save and which to discard. This way user can see all information compiled by the learning system before deciding which rules to discard, whereas ordinary tree pruning removes information and it is forever lost for the user.

Interactive computer learning is used in interactive inductive logic programming (ILP), discussed by Wong and Leung [17]. ILP uses background knowledge and a set of examples represented as a logical database of facts to derive hypothesised logic program. Between other inputs an interactive ILP system is provided with a teacher that can answer questions generated by the system. The system named CLINT is mentioned that generates its own learning examples and asks human to classify them. It is important that the system has the ability to check integrity constraints.

In systems where human-computer interaction is a part of human learning, like in ambient intelligent learning [18], interaction between learners and computer should be natural enough, without human bothering about computer technologies.

In the next section the approaches described will be discussed in the context of flexibility to dealing with non-classifiable examples in inductive learning.

V. Discussion

Various inductive systems involving human have been presented. System which uses the “relevance feedback” [13] interacts with user in the rearmost moment of a learning process. For dealing with non-classifiable examples in inductive learning this moment is too late, because the user is involved after the decision of classification is already done.

System proposed by Hadjimichael and Wasilevska [16] is promising, however the problems with its applicability start when model underlying input data is complicated and generated rules are many and/or long, because it takes much effort to human expert to compare even tens of rules, not talking about hundreds.

Although Buntine and Stirling [15] are right and human intuition cannot be entirely eliminated from learning process, since the system's designer must specify data representation,

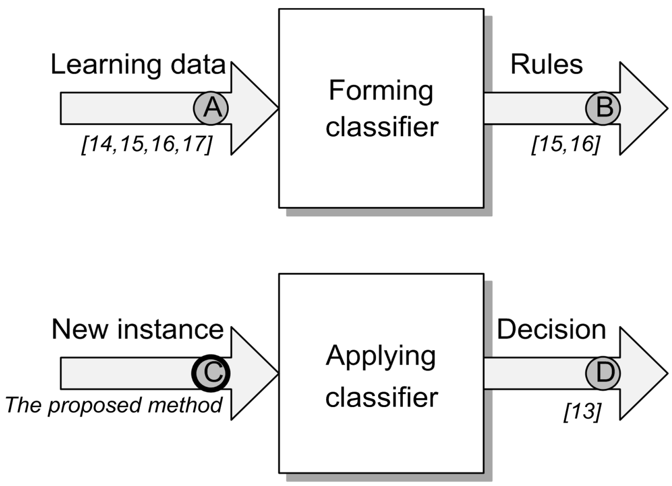

Fig. 6. Moments when user interacts with classifier

creation of such a system takes too much of human time and attention if classifier could be obtained more automatically. The same can be said about the system that learns colour concepts directly from a human [14]. Besides this system represents other field in machine learning – artificial neural networks.

The system described in [17] is quite close to expectations of user help with complicate example classification. Nonetheless this system asks for human answers in learning phase (what does not eliminates the possible arrival of non-classifiable example in classifier applying phase) and it uses inductive logic programming, not inductive learning method.

Systems like described in [18] are not close to subject because they employ human-computer interaction as a regular operation and a learner is mainly human, less computer.

It is clear from the previous section that interaction with a human is held in a different phases of learning. Depending on phase in inductive learning process where user interaction is expected, the diagram (see Fig. 6) for abstract comprehension of different existing approaches to interactive inductive learning has been created.

In classifier forming stage training and testing data are passed and rules are given to output. In classifier applying stage new instance (instances) with no classification is provided to the classifier and a decision of its class is expected to receive. The following learning phases are decompounded:

A. Forming of classifier learning data, data selection for input.
B. Extraction, processing, and selection of rules.
C. New instance handling in classifier applying.
D. The decision handling after classification of new instance.

The circles with letters in Fig. 6 denote the particular phase in inductive learning where the interaction is expected.

User interaction in classifier training (phase A in Fig. 6) has been practised in two ways: as learning from the examples and categories only shown by the user [14] or learning from human answers to questions generated by the system [17]. Systems described in [15] and [16] ask for the human advice both in forming of input data and evaluating training results (phases A and B in Fig. 6). According to [13], the user feedback is asked after decision to improve the search results (phase D in Fig. 6).

None of methods discussed provides appropriate model of interactivity for solving the inductive learning problem with classifying examples that do not fit any of rules in knowledge base. As stated in section “Dealing with non-classifiable examples” previously, current approaches to this problem does not work well in all situations. Therefore, resuming achievements and drawbacks of approaches to user involving into inductive learning the new system dealing with non-classifiable examples can be proposed.

VI. The Proposed System

The proposed system would interact with human in order to classify unknown example in phase C (Fig. 6) only if it is needed. The system meets two requirements:

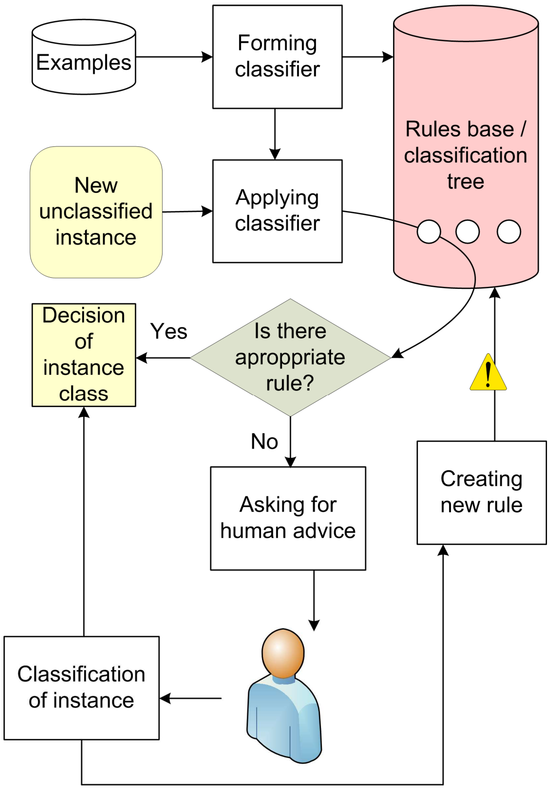

Fig. 7. Classification with user interaction

- System is not dependent on human; it in principle operates by itself.
- Human isn't bended to the system to answer its questions systematically.

Those both properties are expected from automatic inductive system.

The proposed system only involves user when it meets new example not consistent with the rules base (see Fig. 7).

Using expert knowledge will not only lead to more correct classification of every single instance but also to more complete rules base as the human-given advice is being saved and formed as a new rule. However, there is a hidden threat within human-based rules. It is important to feature the system with integrity constraints and a control mechanism for rule consistency check between existing knowledge base and new input information.

VII. An Illustration

The interactivity of proposed inductive system will be demonstrated with the following example. Classification task involves assigning the one of four predefined categories to a topographical map. Maps are being stored in a spatial data base and features can be extracted. A map instance [19] is depicted in Fig. 8.

Every map is described with 4 categorical attributes (chosen by human expert) and its difficulty level for orienteering should be detected. Features and their possible values as well as class values are given in Table 1. Feature extraction and conversion to categorical form from spatial data is done by computer system that utilizes expert defined instructions.

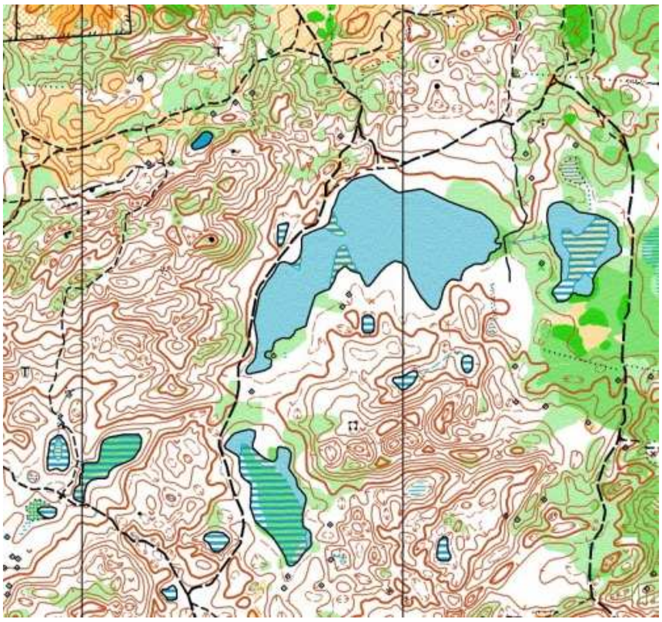

Fig. 8. Topographical map for orienteering [19]

TABLE 1
Attributes, Class and Their Values

Relief {mountainous, hilly, plain}
Network of roads {intense, intermediate, rare}
Movement {hard, bothered, easy}
Visibility {good, intermediate, poor}
Difficulty level {very high, high, intermediate, easy}

TABLE 2
Rules Base

No.	RULE
1.	IF **relief** = mountainous AND **movement** = hard THEN **difficulty level** = very high
2.	IF **relief** = mountainous AND **movement** = intermediate AND **network of roads** = intermediate THEN **difficulty level** = high
3.	IF **relief** = hilly AND **network of roads** = rare AND **visibility** = good THEN **difficulty level** = intermediate
4.	IF **network of roads** = intermediate AND **movement** = easy THEN **difficulty level** = easy
5.	IF **network of roads** = intense AND **relief** = plain THEN **difficulty level** = high
Default rule	IF "whatever" **difficulty level** = intermediate

Classification rules form existing data base items are induced and they are depicted in Table 2. Classifier forming (phase A and B in Fig. 6) has not been demonstrated in this example. Inductive learning algorithm used to form the classifier creates IF – THEN rules of attribute – value pair conjunctions.

If the default rule was used at the end of rules base to capture unclassified examples, it would use the most frequent class in training data base. In this case it is difficulty level = intermediate.

Using these rules the new maps are tried to be classified. Arrives map (example) with such a description:

Relief = mountainous, **network of roads** = rare **movement** = hard, **visibility** = poor.

This example can be classified with difficulty level = very high on 1st rule basis as the relief is mountainous and movement is hard.

The following example arrives next:

Relief = mountainous, **network of roads** = intense **movement** = bothered, **visibility** = poor.

None of rules satisfy attribute values entirety. In this situation request for human classification is performed (what corresponds to phase C in Fig. 6). Human is provided with attributional information and bench-mark data (visual map). While human is thinking of classification, system can either idle and wait or classify other examples (if such are available). User has decided to classify unknown map as very hard for orienteering. Such classification is assigned to last map. Now the new rule consistent with existing knowledge base could be formed. The incremental inductive learning algorithms should be considered. Designing this part of system is one of future tasks.

Let's consider what would happen if other approaches would be used to assign class to this example. If a default rule had been used, the class assigned would be "intermediate" that differs from human opinion quite much. As there is no crucial class, also assigning one predefined class to all non-classifiable examples wouldn't lead to acceptable results in long term.

Considering help by system's user, in phases A or B (in Fig. 6) no one knew that such an example would arrive, so direct help from user side can't be provided. On the other hand, user interaction in those earlier stages could possibly lead to more precise or more complete rules base and such non-classifiable example could be classified by one of rules form rules base. However, such approach does not eliminate the possible arrival of non-classifiable example in classifier applying phase.

If user would be involved in phase D (Fig. 6), it would be already too late. The user could evaluate the decision (made by default rule) and accept or reject it, but more effective technique would be to ask for human advice exactly when the problematic example arrives – neither earlier nor later.

VIII. Conclusions

This paper discussed inductive learning as a valuable tool in machine learning. Inductive learning has more capabilities and potential to improve its performance. The research has contributed the following results:

- One of the problems and several of its existent solutions in inductive learning have been defined. It often happens that the classifier cannot classify the incoming instance and the existing methods to solve this problem do not work acceptable in all situations. Dealing with non-classifiable instances as area of development is considered.
- A proposal to deal with non-classifiable examples using computer-human interaction has been made.
- Interactive approaches to inductive learning or similar learning methods reviewed in the literature have been discussed. None of the methods found can help to deal with non-classifiable examples directly. Most of systems described tend to involve human in learning process so much that induction can hardly be defined as automatic.
- The diagram for abstract comprehension of different existing approaches to interactive inductive learning has been created depending on phase in inductive learning process where user interaction is expected. It is found that interaction with human has been used in all most relevant classifier forming and applying stages except new instance processing. However, this is the most appropriate phase for dealing with non-classifiable examples.
- The paper proposes to construct new inductive learning system that could ask human expert for decision in uncertain conditions and improve its knowledge base. Inductive system works automatically and uses the help of human only in classifier applying phase when the incoming instance can't be classified using rules in the knowledge base.
- The interactivity of proposed inductive system has been demonstrated with a conceptual example. The advantages over other existing and possible approaches in handling non-classifiable examples have been shown.

The proposed system would be preferable over traditional inductive learning approach for the classification tasks where the following conditions hold:

- Expected need for human interaction is occasional; however, obtaining the right classification is relevant.
- The human expert is available at the time when classification tasks are executed.
- It is complicate to define the features in the problem domain and there is suspicion that not all the best features are selected.
- The problem area tends to change its nature; objects to classify can be very different in their initial form.

Future areas of research exist. More related works should be summarized. The information about problem domains where the proposed system could benefit need to be gathered. Process of creating and adding a rule to the rules base after human-made decision of classification has to be studied in details.

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She has been working at Department of Systems Theory and Design, Riga Technical University, Latvia since 2007. Her research interests include inductive learning, data mining and pattern recognition.

Ilze Birzniece. No induktīvās apmācības uz interaktīvu induktīvo apmācību
Pieaugošais informācijas apjoms pasaulē ir veicinājis tādu automātisku datu apstrādes tehniku attīstību, kas spēj atvieglot cilvēka rutīnas darbu. Mašīnapmācībā tiek izmantots plašs metožu klāsts, tomēr sistēmās, kur cilvēkam nepieciešams saprast lēmuma pieņemšanas ceļu, kā arī tālāk apstrādāt iegūto rezultātu, ir novērtējamas induktīvās apmācības metožu priekšrocības. Piemēram, ekspertu sistēmu zināšanu bāzēs var tikt izmantoti induktīvās apmācības iegūtie likumi. Induktīvā apmācība ir mācīšanās no piemēriem, kad no konkrētiem gadījumiem tiek inducēts vispārīgs klasifikators, kuru iespējams izmantot jaunu piemēru klases piederības noteikšanai. Klasifikācijas uzdevumiem kļūstot arvien sarežģītākiem, induktīvās apmācības rezultātu uzlabošanai var tikt izmantota sadarbība ar sistēmas lietotāju (ekspertu). Ja jauna piemēra klasifikācijai nepietiek ar apmācībā iegūtajām zināšanām, sistēmai jāveic minējums. Interaktīvas induktīvās apmācības gadījumā sistēma varētu vaicāt padomu cilvēkam situācijā, kad nav iespējams pārliecinoši veikt klasifikāciju, kā arī papildināt savu likumu bāzi ar jauniegūtajām zināšanām. Šajā rakstā apkopotas dažādas literatūrā aprakstītas pieejas interaktīvam apmācību procesam, kā arī veikta to klasifikācija, atkarībā no apmācības etapa, kurā cilvēka iesaistīšana notiek. Tiek piedāvāta jauna sistēma interaktīvas induktīvas apmācības veikšanai, kā arī demonstrēts konceptuāls piemērs, kurā šī sistēma klasificē topogrāfiskas kartes.

Илзе Бирзниеце. От индуктивного обучения к интерактивному индуктивному обучению
В мире всё прирастающий объём информации способствовал развитие таких автоматических техник обработки данных, которые облегчают рутинную работу человека. В машинномобучении используется обширный круг методов, однако в системах, в которых человек должен понять последовательность принятия решения, а также дальше обрабатывать полученный результат, проявляются преимущества методов индуктивного обучения. Например, в экспертных системах, база знаний может пополнятся за счет законов полученных в индуктивном обучении. Индуктивным обучением является обучение на примерах, когда на основе конкретных случаев индуцируеться общий классификатор, который можно использовать для определения принадлежности класса новых примеров. Для улучшения результатов индуктивного обучения при возврастании сложности заданий классификации можно использовать сотрудничество с пользователем (экспертом) системы. Если для классификации нового примера знаний полученных в обучении недостаточно, система должна строить предложение. В случае интерактивного индуктивного обучения система могла бы просить совет пользователя в ситуации, когда нельзя убедительно классифицировать, а также дополнить свою базу законов новоприобретёнными знаниями. В данной статье обобщены различные подходы к процессу интерактивного обучения описанные в литературе, а также проведена их классификация в зависимости от этапа обучения, на котором происходит вовлечение человека. Предлагается новая система для реализации интерактивного индуктивного обучения, а также демонстрируется концептуальный пример, в котором эта система классифицирует топографические карты.