RIGA TECHNICAL UNIVERSITY

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DEVELOPMENT OF INTERACTIVE INDUCTIVE LEARNING BASED CLASSIFICATION SYSTEM'S MODEL

Summary of Doctoral Thesis

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RIGA TECHNICAL UNIVERSITY
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DOCTORAL THESIS
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AT RIGA TECHNICAL UNIVERSITY

The defence of the thesis submitted for doctoral degree in engineering sciences will take place at an open session on October 7, 2013 in 1/3 Meza street, auditorium 202, Riga Technical University Faculty of Computer Science and Information Technology.

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APPROVAL

I confirm that I have developed this thesis submitted for the doctoral degree at Riga Technical University. This thesis has not been submitted for the doctoral degree in any other university.

Ilze Birzniece………………………………….. (signature)

Date: June 21, 2013

The doctoral thesis is written in Latvian and includes introduction, 6 sections, main results and conclusions section, bibliography, 11 appendices, 47 figures and 34 tables in the main text, 160 pages. The bibliography contains 139 references.

CONTENTS

INTRODUCTION

The growing amount of available information in the world encourages the use of automatic data processing techniques that reduce human routine work. This is the place for artificial intelligence and its subfield machine learning. The latter gives the ability to a computer program to improve its own performance, based on the past experience [1]. Classification is one of the machine learning tasks where the program learns to classify new instances from a human or environment provided facts. Classification problems arise in a number of domains, like credit scoring, pattern recognition, medical diagnostics, document classification etc.

Motivation of the research

Classification algorithms deal with numeric or nominal data which is structured. *Structured data* is organized in small, discreet units. However, in many real world situations information is organized in vague or complicated forms which are only *semi-structured* and hard to be fully structured. This aspect limits the application of traditional automatic machine learning methods and eliminates from analysis a mass of available data. In the thesis, the term *automatic classification* is used to denote a computerized classification process which does not involve the user or expert starting from the classifier's training till applying it for new instance classification (except for data preparation and adjustment of learning algorithm settings).

The problem domain the thesis is focused on is the study course compatibility analysis in higher education. Taking into consideration the number of different education institutions operating inside the global knowledge provision space this is a time consuming task if performed only manually. Although one of the main features of the Bologna process is to encourage creation of a common model for Higher Education in Europe [2], there still does not exist a generally established standard for describing study courses in all universities, and they currently appear both as semi-structured and unstructured textual descriptions. This fact creates the main difficulty for course comparison automatically.

The thesis is devoted to the development of automated (semi-automatic) classification solution which incorporates both machine learning facilities and interactive involvement of a domain expert in the classifier's applying stage for improving its results if the classifier makes uncertain classification for a new instance. With *uncertain classification* both *unclassified instances* (instances which the classifier cannot classify with its classification model) and *instances with low classification confidence* (the default threshold for accepting classification is confidence 0.5 for the decision made) are denoted. These terms are described in more detail in Sections 3 and 4.

Goal of the thesis

The goal of the thesis is to develop the model of semi-automatic classification system which allows interactivity with an expert at the classifier's applying stage if the classifier meets an object which it cannot classify or is not confident of the classification made.

Tasks

In order to achieve the goal of the thesis, the following tasks have been specified:

- To analyse computerized solutions of educational document comparison and identify problems to be solved.
- To explore the classification task in machine learning.
- To analyze existing interactive classification solutions.
- To analyze the architecture of classification systems in order to develop an interactive classification system.
- To develop interactive classification system's model which amalgamates components for creating an interactive classification system (algorithms, methods, approaches and architectures).
- To develop an extension of the interactive classification system's model which amalgamates components for creating an interactive multi-label classification system.
- To implement an interactive classification system's prototype which embodies elaborated model.
- To examine the utility of the model and usability of the prototype through practical experimenting.

Research object

The research object of the doctoral thesis is the classification task in machine learning.

Research subject

The research subject of the doctoral thesis is involvement of the expert in classification process for improving the classification results.

Constraints and assumptions

The proposed interactive classification system is intended for situations where the following *conditions* hold:

- Data to be used for classification is interpretable for the expert:
    - by its content and structure;
    - by its amount (object description is not *too* long).
- Human-expert is available.

That is, there should be an expert who can assist the classification system in classifying the instances, and the expert is able to interpret the data in problem domain. Otherwise the interactivity has no sense. The terms “expert” and “system’s user” are used with an underlying concept that the user does not have to be a domain expert to maintain classification system and browse the results, however, to assign classifications and improve the classifier one should be an expert.

Other assumption for the particular research is that the problem domain has multi-label class membership. It means that an instance can naturally belong to several classes, e.g. newspaper articles can have several labels. This constraint has been chosen due to the application domain in focus – study course comparison – where the multi-label situation is present.

For classifier building, inductive learning methods (decision trees and rule induction algorithms) are considered because they represent the classifier in a human-readable form which is important to provide insight into decision making and encourage the user to trust the classification system.

Main theses of defence

T1 A classification system that embodies the model of interactive classification system for involving an expert in classifier applying stage can reduce the number of misclassified instances, compared to automatic classification.

T2 *The method for determining the most appropriate confidence level of the classifier* helps to find the threshold at which the number of misclassified instances (*M*) is minimal taking into account the maximal expert workload parameters set by the user.

T3 It is useful to apply *the inductive learning based, interactive, multi-label classification system* for comparing university study courses.

Scientific novelty of the thesis

- The developed ***In**teractive Inductive Learning based **Cla**ssification **S**ystem’s* (InClaS) generic model which amalgamates components necessary for creating an interactive classification system.

- Developed extension of the InClaS model which amalgamates components necessary for creating an interactive multi-label classification system.

Theoretical value

Aforementioned scientific novelty includes several **theoretical results**:

- The general scheme of interactivity to be implemented into a classification system is defined;
- Structure of the interactive classification system – functional modules of the classification system, their properties and connections between them – is developed;
- Approaches for the incorporation of an expert-classified instance into the existing classifier are suggested and elaborated;
- An algorithm for detecting uncertain classification in multi-label classification tasks is defined;
- A method for determining the most appropriate confidence level of the classifier's decision at which an instance is considered to be uncertainly classified and is redirected to the expert is developed;
- An interactive classification system's design by means of modules, their inputs and outputs is developed.
- Systematized overviews on topics of classification task and educational document comparison obtained by literature analysis are done.

Practical significance

A prototype of the interactive classification system InClaS for applying it in different multi-label classification domains has been implemented. It is tailored for study course comparison in terms of more convenient user interface.

As a complementary result, an application for multi-label data transformation between different representation formats has been developed (according to diverse input requirements for *Weka* tool [3] and *Mulan* library [4]).

Approbation of the obtained results

The results of the thesis have been presented in 12 international conferences:

- November 18–23, 2012. The Fifth International Conference on Advances in Human-oriented and Personalized Mechanisms, Technologies, and Services (CENTRIC 2012) with presentation "Architecture of an Interactive Classification System". Lisbon, Portugal.

- July 16–20, 2012. International Conference on Machine Learning and Data Mining with poster presentation “Machine Learning Approach for Study Course Comparison”. Berlin, Germany.
- May 16–18, 2012. Sixth International IEEE Conference on Research Challenges in Information Science with presentation “Interactive Use of Inductive Approach for Analyzing and Developing Conceptual Structures”. Valencia, Spain.
- October 6–8, 2011. 10th International Conference on Perspectives in Business Informatics Research with presentation “Artificial Intelligence in Knowledge Management: Overview and Trends”. Riga, Latvia.
- October 13–16, 2011. 52nd International Scientific Conference of Riga Technical University with presentation “Architecture of an Interactive Classification System”. Riga, Latvia.
- July 24–26, 2011. Intelligent Systems and Agents 2011 with presentation “Interactive Inductive Learning based Classification System”. Rome, Italy.
- March 7–10, 2011. Rethinking Education in the Knowledge Society, RED 2011 with presentation “Interactive Inductive Learning Based Study Course Comparison”. Monte Verita, Switzerland.
- October 11–15, 2010. 51st International Scientific Conference of Riga Technical University with presentation “Interactive Inductive Learning: Application in Domain of Education”. Riga, Latvia.
- July 5–7, 2010. Ninth International Baltic Conference on Databases and Information Systems with presentation “Interactive Inductive Learning System: The Proposal”. Riga, Latvia.
- May 27–28, 2010. 19th Annual Machine Learning Conference of Belgium and The Netherlands with presentation “Interactive Inductive Learning Service for Indirect Analysis of Study Subject Compatibility”. Leuven, Belgium.
- April 22–23, 2010. 16th International Conference on Information and Software Technologies with presentation “The Use of Inductive Learning in Information Systems”. Kaunas, Lithuania.
- October 12–16, 2009. 50th International Scientific Conference of Riga Technical University with presentation “From Inductive Learning Towards Interactive Inductive Learning”. Riga, Latvia.

The results of the thesis have been presented in 13 international scientific papers:

- Birzniece I. Architecture of an Interactive Classification System // The Fifth International Conference on Advances in Human-oriented and Personalized Mechanisms, Technologies, and Services (CENTRIC 2012), 2012, IARIA, pp. 91-100. Indexed in: ThinkMind Digital Library.
- Birzniece I. Machine Learning Approach for Study Course Comparison // International Conference on Machine Learning and Data Mining (MLDM 2012), 2012, IBai publishing, pp. 1-13. **Received the best poster award.**
- Birzniece I. Interactive Use of Inductive Approach for Analyzing and Developing Conceptual Structures // Sixth International Conference on Research Challenges in Information Science (RCIS 2012): Conference Proceedings, 2012, IEEE, pp. 129-134. Indexed in: **Scopus**, IEEE Xplore, DBLP.
- Birzniece I. Interactive Inductive Learning Based Study Course Comparison // Proceedings of the Red-Conference: Rethinking Education in the Knowledge Society, 2011, Università della Svizzera italiana, pp. 339-347.
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- Birzniece I. Interactive Inductive Learning System // Frontiers of AI and Applications. Databases and Information Systems VI, Vol. 224, Selected Papers of Baltic DB&IS, 2011, IOS Press, pp. 380-393. Indexed in: ACM, DBLP, io-port.net.
- Birzniece I., Kirikova M. Interactive Inductive Learning Service for Indirect Analysis of Study Subject Compatibility // Proceedings of the BeneLearn, 2010, Katholieke Universiteit Leuven, pp. 1-6.
- Birzniece I. Interactive Inductive Learning System: The Proposal // Proceedings of the Ninth International Baltic Conference on Databases and Information Systems, 2010, University of Latvia Press, pp. 245-260.

Structure of the thesis

The thesis consists of introduction, 6 sections, main results and conclusions section, bibliography and 11 appendices.

The introduction concerns the problem to be solved, defines the goal, tasks and theses, and describes work stages, main results and contents of the thesis.

In the first section extended problem statement is given which includes state-of-the-art in computer supported curricula and course comparison and defines the scope of the thesis as well as the features of required machine learning solution for the problem to be solved.

The second section is devoted to the related works. Subsection 2.1 concerns the classification task in machine learning paying the main attention to inductive learning, multi-label classification and evaluation measures for it, the issues in classification, e.g. inability to classify a new instance. Subsection 2.2 discusses the current interactive classification approaches while Subsection 2.3 gathers and analyses information on different existing classification system architectures.

The third section provides detailed description of the developed interactive classification system's InClaS generic model with its main components – detection of instances to be transferred to the expert, the expert's knowledge incorporation into the classifier and system's structure.

In the fourth section, the generic model is extended with the components necessary for multi-label classification by defining an algorithm for detecting uncertainly classified instances and a method for determining the most appropriate confidence level of the classifier. Besides, the decisions regarding classification system's design and implementation details for university study course comparison are detailed in this section.

In the fifths section, developed components of the model are summarized and their implementation in system's prototype is described. Differences between InClaS and other tools being used in the classification are emphasized as well as the insight into prototype's functionality and user interface is given.

The sixth section provides an experimental plan and the obtained results comparing the traditional automatic classification approach and the developed interactive classification system's model as well as confirming usefulness of the proposed solution for classification tasks.

To conclude the thesis main theoretical and practical results, lessons learned and possible future works are summarized in the main results and conclusions section.

The thesis has 11 appendices:

1. Glossary of the most important terms used in the thesis.

2. The description of the preprocessing made for the study course classification using the text categorization approach.

3. Expert inquiry form for study course classification mediated by European e-competence framework.

4. Demonstration of acquisition of the formal description by direct and indirect study course comparison.

5. Results achieved by the software application that transforms multi-label data representation formats.

6. Classification of inductive learning algorithms.

7. Summary of the classification systems' design procedures.

8. Summary of the classification systems' functional models.

9. Explanation of classification algorithms and methods used in practical experiments.

10. Representation of the classifier's models for different classification algorithms.

11. All experimental results determining the most appropriate confidence level of the classifier's decision in the study course comparison task.

1. RESEARCH OBJECTIVES

The first section of the thesis unfolds the issues behind the problem to be solved and detects necessary research and development areas. First of all, constraints of applying the automatic classification in domains with incomplete and hard to formalize data are laid out. As the main area where the need for automated inductive learning based classification solution arises, higher education where compliance between different study courses or programmes is topical is analyzed. On the basis of the analysis in this domain, the necessary parameters and particular features of solution are detected.

1.1. Restrictions of automatic classification

Application domains are getting more complex in terms of data amount, representation forms, relationships within data etc. Machine learning approaches face new challenges in solving tasks which could benefit from the machine learning because they contain time-consuming manual activities but do not conform to typical machine learning application areas regarding the data amount and structure. Information is often organized in complicated forms for machine learning, like plain (unstructured) text, graphs, semi-structured text etc. The transformation from the original data to the classifier-acceptable data structures is needed, and in this process some information can get lost or mapped inaccurately. This leads to creation of an incomplete classifier that does not generalize well the problem domain and probably will not be able to make predictions for all new unseen instances when the classifier is applied. The reason for difficulties in applying automated classification solutions may come from two aspects (see also Figure 1.1).

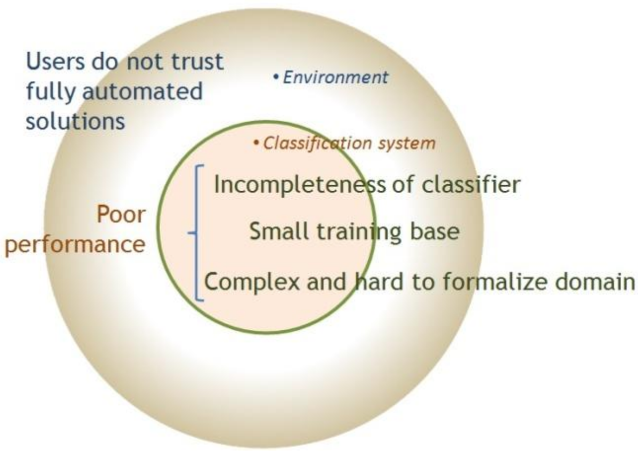

Figure 1.1. The reason for difficulties in applying classification in complex domains

One aspect is *the inner factors within the classification system* and data parameters. A semi-structured source of information makes the formal descriptions of the problem incomplete which also leads to an incomplete classifier. This consequently results in the inability to classify new instances. A small initial training base stresses the problem even more because the classifier does not achieve enough experience to learn from. This leads to a poor classifier's performance regarding different measures – e.g. precision, recall and number of misclassified instances.

Another aspect is *the factors of system's usage* and its environment. Experts who well know the complexity of the problem domain usually do not believe in a fully automatic approach [5] which provides poor classification performance. However, they are ready to invest some effort towards a more suitable solution [5].

This leads to the main objective of the research – find the tradeoff between capabilities given by the automatic classification system on the one hand and the domains which are complex and are so far mainly served by human intellect on the other hand. The solution is proposed through creation of a semi-automatic classification system to give the expert a wider control over the classification process and use his/her knowledge for gradual improving of it.

The usage of terms "classifier" and "classification system" has to be explained. In the context of the thesis, the classifier means the exact classification model or rule set according to which a new unseen instance can be classified, whereas the classification system is an extended functional structure which allows to pre or post-process data and applies the classifier. Designing of the classification system includes designing the classifier. The latter is produced by a machine learning method, in this case learning algorithm which induce the classification model in the form of a decision tree or If-Then rules. Thus, the classification system is a classifier and its peripherals which ensure the classification process.

The overall problem and the proposed solution statement are given in Figure 1.2. Part A depicts the current automatic classification solution with its shortcomings for complex problem domains – inability to classify new instances or a large number of misclassified instances. Part B suggests the intended interactive solution which extends the classification system with elements for (1) detecting unclassified instances or instances which are classified with low confidence (calling them uncertain classification) and (2) interaction handling with an external expert.

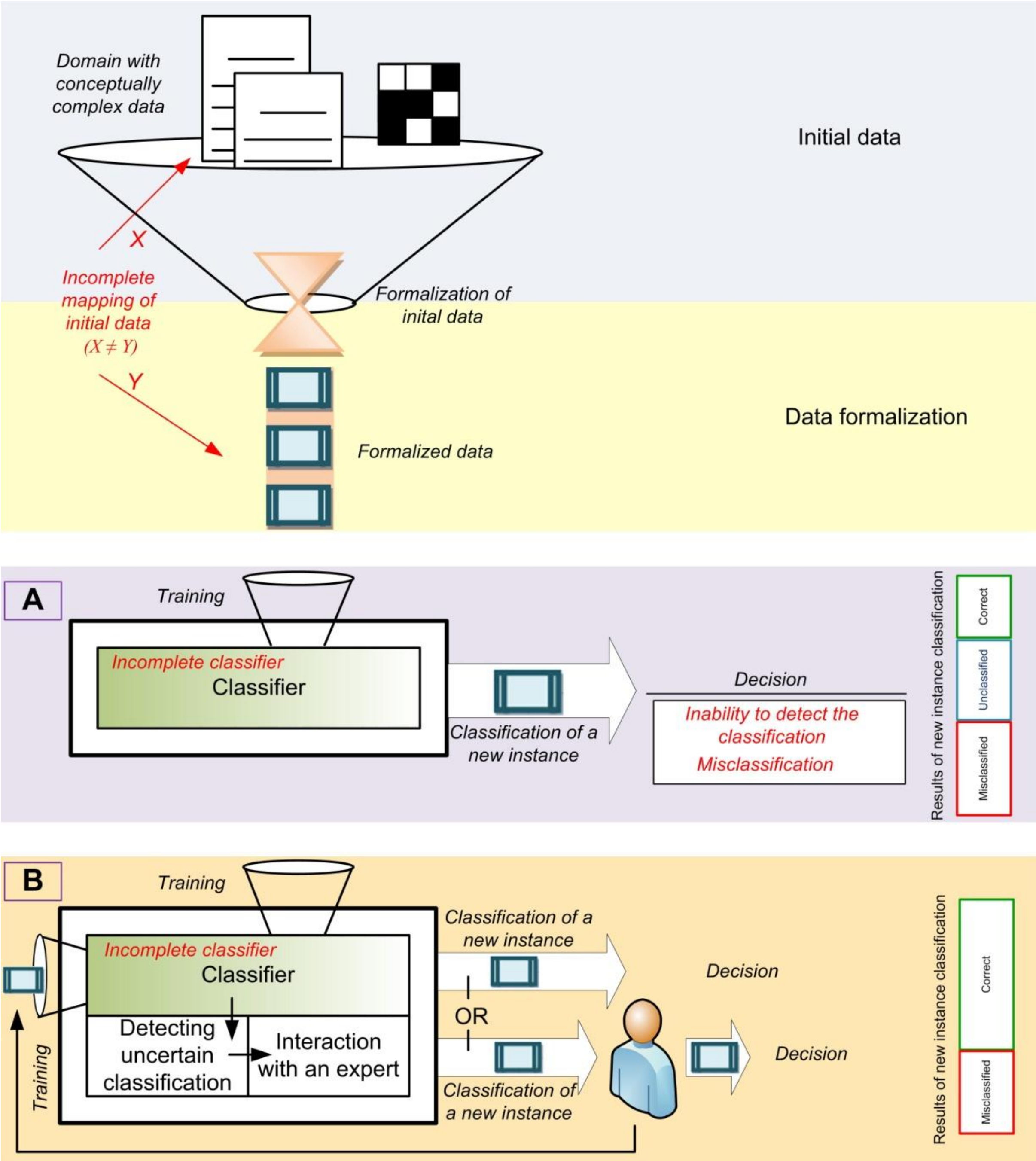

Figure 1.2. Automatic (A) or interactive (B) classification in case of incomplete learning data

Before specifying the interactive classification in more details, the state of the art in computer supported classification tasks in curricula management is analyzed to ascertain the need for semi-automatic approach.

1.2. Classification tasks in higher education

The need for computers to support the process of educational document comparison has been highlighted in literature and stated by practitioners in higher education. A term *educational document* is used to denote different types of materials for educational content and assessment, including course descriptions, teaching materials, academic credentials etc. The necessity to compare educational documents appears in different forms and can be conditionally divided into three categories [6-13].

- Study course comparison for student exchange programmes, further education, academic transcript interoperation and other needs.
- New curriculum development which is related to comparison with other similar study programmes.
- Teaching material and learning object categorization for, e.g. e-learning systems to provide corresponding content to the learner.

As claimed in [9], comparative analysis of educational documents is a complicated task both for experts and computer systems. Therefore automation of this process requires specific approaches and expert participation. Semi-structured document representation requires the use of various information extraction methods. Authors of Academic e-Advising system [9] point out that system's results could undoubtedly be improved by expanding the size of the training corpora and involving an expert. The system would also benefit from the implementation of an easy mechanism for manual inspection and augmentation of the extracted data to improve data quality for further use. To extend the training corpora, significant expert contribution is needed as only an expert can prepare training examples for the system; accordingly, the available training set will always be limited and the main constraint for improving classification is a workload an expert can devote. Analysis of related works shows that educational document comparison requires automated but not automatic approach to receive reliable results. It is also worth noting that despite the fact that different study programmes do not have the same granularity and content distribution between courses [10, 11], the course similarity has been considered only using one-to-one correspondence. None of the presented systems so far deals with the possible one-to-many correspondences between courses or uses multi-label classification approach. Although the need for expert involvement has been emphasized, methods used so far do not foster collaboration with an expert.

Thus, the domain analysis point out improvement directions and existing constraints to implement some extent of automation in educational document comparison. Concluding on issues in this domain, target of the thesis is defined as development of *inductive learning based interactive multi-label classification system for supporting study course comparison*.

Specifics of the problem domain can be defined by the following ***features which intended machine learning solution should take into account:***

- Understanding decision making steps is important for the classifier's user and the expert.
- Available initial learning base is small.
- Initial data is semi-structured or unstructured.
- Domain defines many classes with equal frequency.
- Each object can have a multi-label class membership.

The meaning and consequences of these features are to be explained in more details. For classification purpose, the inductive learning approach is chosen because it holds a strong position as a reliable classification method group that can explain its decision making process [14]. By inductive learning one should understand decision trees and rule induction learning. A multi-label class membership requires the use of appropriate and more sophisticated classification methods. As the classification task is complicated because of insufficient amount of training examples and possibly incomplete formalized study course descriptions, the automatic classifier may not make enough informed decision on its own. It may happen that none of the rules fit or the tree cannot classify the new instance when the classifier is applied. There are several methods to deal with this problem. Inductive learning systems with a low number of non-classifiable instances usually apply a default rule for classifying new instances that none of the rules in the rule base can classify [15]. A default rule comes from CN2 [15] and AQ [16] algorithms and predicts the most common class in a particular data set. If a data set contains many classes and, moreover, if all of them occur equally frequently, assigning one certain class to all unclassified instances will not lead to a high accuracy of the classifier. Even more, most of nowadays classification algorithms do not admit their inability to classify instance but classify it anyway (correctly or incorrectly) making it harder for the system's user to detect the boundary of "real knowledge" of the classifier. Therefore, the interactive semi-automatic approach which takes into account confidence with which the classifier makes its decision is to be developed.

1.3. Interpretation of the education domain task in machine learning context

This subsection clarifies the study course comparison as a classification task. To do it, we need to define attributes and classes. Attributes must be not only representative but also available. Study course description does not naturally possess well-defined attributes. This task is also not trivial for application of machine learning methods directly because of mixture of domain features. Due to the natural overlapping of course contents, course from one study programme can be similar to several other courses of another study programme. To deal with possible one-to-many correspondences between courses, the use of multi-label classification approach is necessary. The task of machine learning algorithm in this case is to adopt experience from a human expert in deciding whether two courses are corresponding or not. The initial data is study course descriptions in such form as the educational institution has published them. To apply inductive learning or other classification methods, a formalized attribute-value based representation is to be achieved.

Although there are attempts to put it this way [6, 11], study course comparison does not fully belong to the problem of text classification. The study course description most often is a semi-structured text which usually includes sections like “prior knowledge”, “learning outcomes” etc. It is important to distinguish between these sections. Besides, a semi-structured text has a significantly richer and more complex structure than a plain-text, and the relation among semi-structured documents is harder to be fully utilized if only text categorization is used [17, 18]. Here could help the study course comparison approach which uses formalized semantically meaningful attributes. The study course is an issue that does not naturally possess well defined attributes relevant for the comparison of course contents. Course topics are not always available. Meaningful and usually accessible attributes are learning outcomes, study level and the number of credit points. Learning outcomes can be described in different ways; hence, a need for unification arises. Therefore, learning outcomes could be mapped to common representation form, e.g. European e-Competence Framework (e-CF) [19], and compared indirectly. As a result, course attributes are represented in a formal description.

For practical experiments in university course comparison two main settings are chosen – direct and indirect comparison. For direct comparison, text classification approach is applied which makes use of word vectors obtained from full course descriptions. Indirect comparison involves mediating framework for extracting semantically meaningful information from course descriptions.

For the training set, an expert defines classes (i.e. detects correspondences) to unknown study courses. Note that the expert can assign more than one class since the courses can overlap.

Figure 1.3 demonstrates an overview of way for achieving formalized course attributes and detected classes in direct and indirect comparison. Formalization is done in order to prepare appropriate input data format for machine learning algorithms.

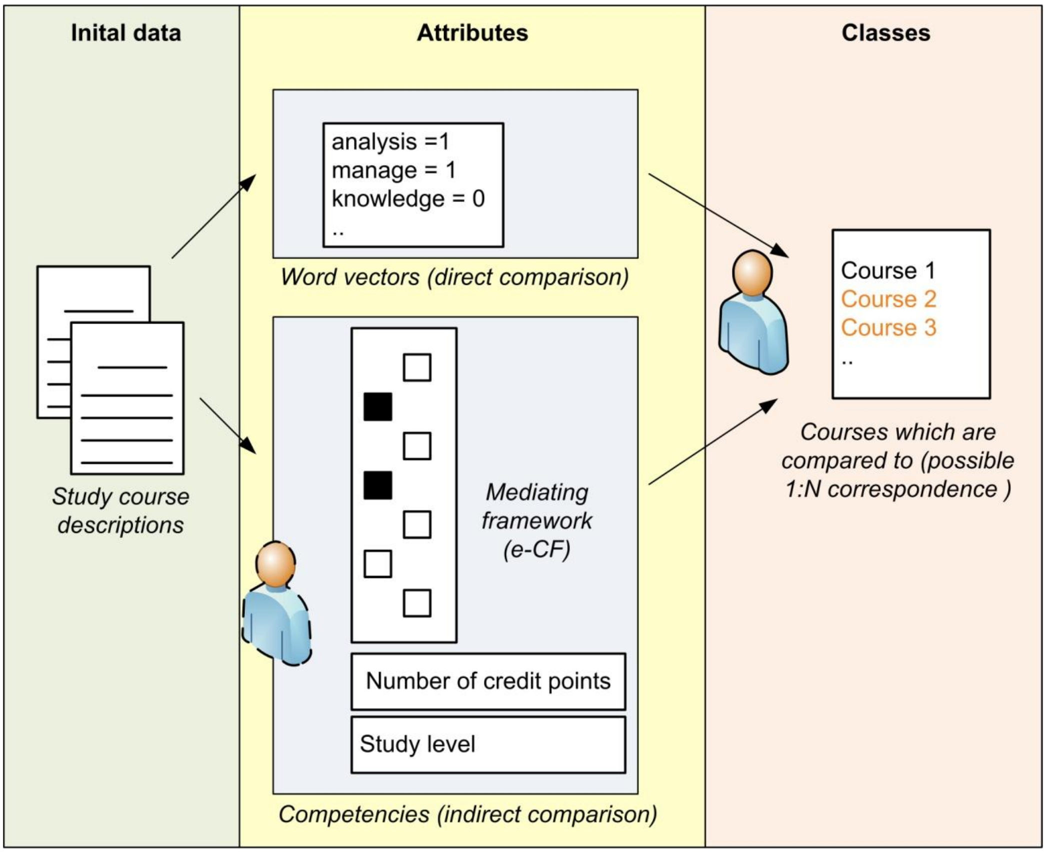

Figure 1.3. Approach for formalizing study course comparison

It is worth noting that the attribute selection in this task is not predefined. Data sets extracted in direct and indirect comparison are used separately; therefore, practical experiments can demonstrate the classifier's ability to generalize from provided attributes in both representations and provide a justification for preferring one or another.

2. RELATED WORK: PRECURSES AND CURRENT ISSUES

This section concerns related works and theoretical foundations in various aspects of classification. Subsection 2.1 relates to the classification task in machine learning paying the main attention to inductive learning, multi-label classification and evaluation measures for it, the issues in classification, e.g. inability to classify a new instance. Subsection 2.2 discusses current interactive classification approaches while Subsection 2.3 summarizes and analyses different existing classification system architectures to adopt the best practices in implementing the interactive classification system.

2.1. Classification task in machine learning

Classification is important in many problem solving tasks. To perform classification, it is necessary to implement some kind of reasoning. There is a wide range of methods used for classification in machine learning, e.g. artificial neural networks, K-nearest neighbour algorithm, Bayes classifier. However inductive learning algorithms are preferable in systems where understanding of decision making steps and further processing of results is needed. Inductive learning algorithms in a form of decision trees and rule induction are widely used in machine learning tasks and they hold a strong position as reliable classification methods that can explain their decision making process [20]. Further in the thesis the term "rules" is used to denote the induced classification model both in form of classification rules and decision trees since the trees can be transformed into rules afterwards. 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 concept description $c: X \rightarrow L$ from a set of observed instances $X = \{x_1, ..., x_i\}$ with a known set of class labels $L = \{l_1, ..., l_j\}$. Each instance x consists of attribute-value pairs $\{(a_1, v_{a1}), ..., (a_n, v_{an})\}$. Inductive learning and classification is broadly examined in Bachelor and Master thesis of the author [21, 22]. Figure 2.1 shows the classification process as classifier building or training, testing and applying stages.

Classification tasks vary on several parameters, one of which is number of classes or categories assigned to each object. The majority of classification approaches do not consider assigning multiple class labels to each object. A traditional classification algorithm tries to extract only one class associated with the most obvious rule.

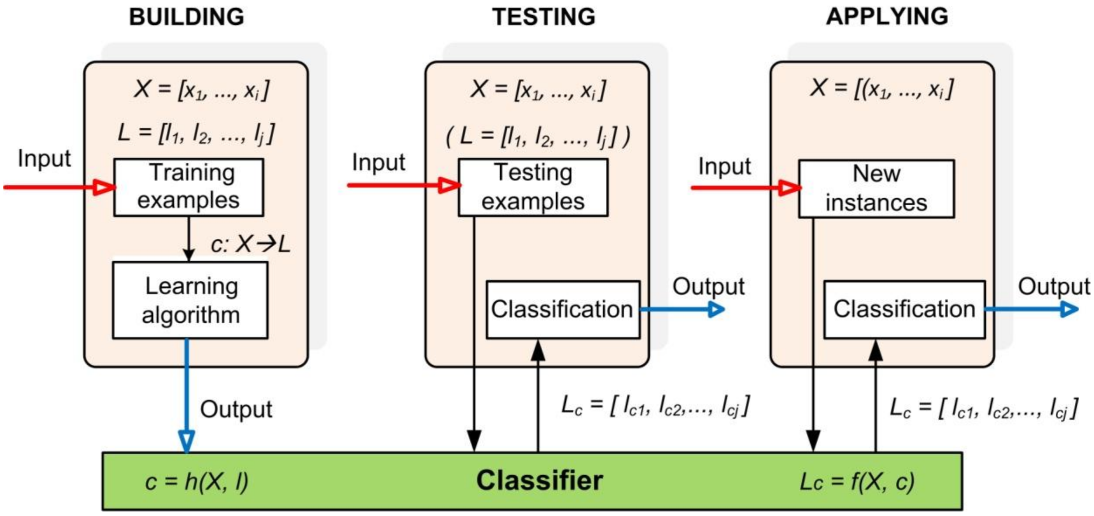

Figure 2.1. Process of classification

However, multi-label classification may be useful in practice, when an object naturally belongs to more than one category [23]. The need for multi-label classification appears in fields such as bioinformatics, scene classification and text categorization. In multi-label classification, examples are associated with a set of labels $Y \subseteq L$ where L is a set of labels in contrast with the traditional single-label classification where examples are associated with a single label l from L, $|L| > 1$. It is also feasible to calculate the ranking of labels relevance with respect to a current instance [24]. Multi-label data can be processed in two ways – (1) through problem transformation to one or more single-label classification tasks (e.g. using the *binary relevance* method or creating a *label powerset*) or (2) algorithm adaptation to deal with multi-label tasks directly [25]. It depends on the nature of the problem domain whether classification in multiple classes simultaneously is avoidable or, on the contrary, advisable. Although slightly similar to fuzzy classification regarding the ability to assign more than one class label to an instance, multi-label classification differs from it since an object is not a fuzzy member of several classes (due to ambiguity) but is a full member of each assigned class with a membership value 1. Fuzzy logics are used as a means to cope with ambiguity in the feature space between multiple classes for a given object not as the end for achieving multi-label classification [26]. Table 2.1 depicts potential classification results of a single-label, multi-label and fuzzy classification.

Within the thesis, a multi-label classification is concerned since the main discussed application area – study course comparison – can benefit from using the multi-label class assignment due to course content overlapping and possible one-to-many course correspondence between different educational institutions.

Table 2.1

Single-label, multi-label and fuzzy classification

Approach	Object (its attributes)	Class labels assigned				Decision
		A	**B**	**C**	**D**	
Single-label classification	a1 = 1, a2 = 1, a3 = 0	**1**	**0**	**0**	**0**	Object belongs to class A
Multi-label classification		**1**	**0**	**1**	**0**	Object belongs to a set of classes {A, C}, does not belong to a set of classes {B, D}
Fuzzy classification		**0.5**	**0.1**	**0.3**	**0.1**	Object belongs to class A with the highest membership value

Before applying the induced classifier to new instance classification, it should be evaluated. Evaluation methods for multi-label classification differs from those used in single-label classification. The most common multi-label evaluation metrics [24, 27-29] are encompassed.

Classification and inductive learning confronts several issues to be successfully applied, e.g. data preprocessing. Still there are some problems to be solved. Issues regarding new instance classification are discussed and conclusion made that the interactive classification approach with expert involvement for reviewing instances classification of which are not certain to the classifier could help in approvement of classification results.

2.2. Interactivity in classification and inductive learning

Before presenting a new approach of interactivity in classification, the author of the thesis has summarized [30, 31] different papers referring to the concept “interactive inductive learning” or exploring the idea of user interaction in a concept learning process [32-37]. Depending on phase in the classification process where a human interaction is expected, a diagram for abstract comprehension of different existing approaches to the interactive inductive learning has been created (see Figure 2.2). In the stage of classifier building, data is passed to the learning algorithm (phase A) and rules are given to output (phase B). In the stage of classifier applying, a new instance (instances) with no classification is provided to the classifier (phase C) and a decision of its class is expected to be received (phase D). Methods described in the related work provide interaction with an expert in phases A, B or D which is either too early or too late to handle new instances that the classifier cannot classify, but not in phase C when a particularly hard-to-classify instance arrives.

Special methods of interactive classification – active learning [38] and Ripple Down Rules [39] – are also discussed in the thesis.

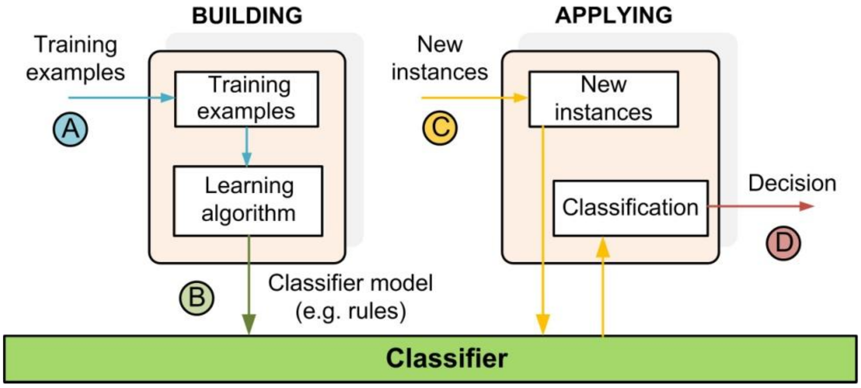

Figure 2.2. Phases when an expert can interact with the classifier

2.3. Architecture of classification systems

To develop architecture of an interactive classification system, different existing architectures by means of (1) the stages of system design and (2) the model of system's functioning (components) of "non-interactive" classification systems [40-49] are reviewed to reuse ideas and best practices from former approaches where appropriate. The review results are published in [50]. Differences between architectures are determined mainly by the scope or the intended application area. Descriptions of classification system architectures usually are either in terms of general classifier building guidelines or a summary of the very abstract components. More detailed architectures of classification systems are domain specific and hard to reuse for other purposes, and every new case requires a problem domain analysis with respective design decisions. Therefore, also the interactive classification system has to be designed on demand taking into account the specificity of the need for computer-human interaction in the final architecture. The situation is different with models of classification systems' design process itself. Most of the design cycles give a great weight to the initial stage which is called either a problem statement and formulation of hypothesis, identification of the problem, application identification or a feasibility study. Another common thing is that the design process of the classification system in some form should contain analysis for choosing the best solution for a particular task. Creating a classification system for a new application is rarely the case of one-way direct software implementation; therefore, the search for appropriate classification system elements (algorithms, methods, parameters etc.) is done either in analytical way or carrying out experiments, or implementing a prototype. In general, the design process of an interactive classification system does not differ from a design of a non-interactive system, therefore, in this context no need for a new approach arises.

3. INTERACTIVE INDUCTIVE LEARNING BASED CLASSIFICATION SYSTEM'S (INCLAS) GENERIC MODEL

Introducing interactivity into a classification system could not only lead to more accurate classification but also provide a system's user with an insight into classification's process. In order to offer such an interactivity model which ensures expert involvement if the classifier meets an object which it cannot classify or is not confident of the classification made, various components extending traditional classification system are developed. These components which have been detailed in the author's publications [30, 50-53] are amalgamated in the **In**teractive Inductive Learning Based **Cla**ssification **S**ystem's (**InClaS)** model. The following components are essential for developing an interactive classification system (see Figure 3.1):

- General scheme of interactivity to be implemented (see Section 3.1).
- Definition regarding an *uncertain classification* that has to be processed in the interactive classification system (see Section 3.2).
- Suggested approaches for updating the classifier (see Section 3.3).
- Classification system's structure, its modules and connections (see Section 3.4).

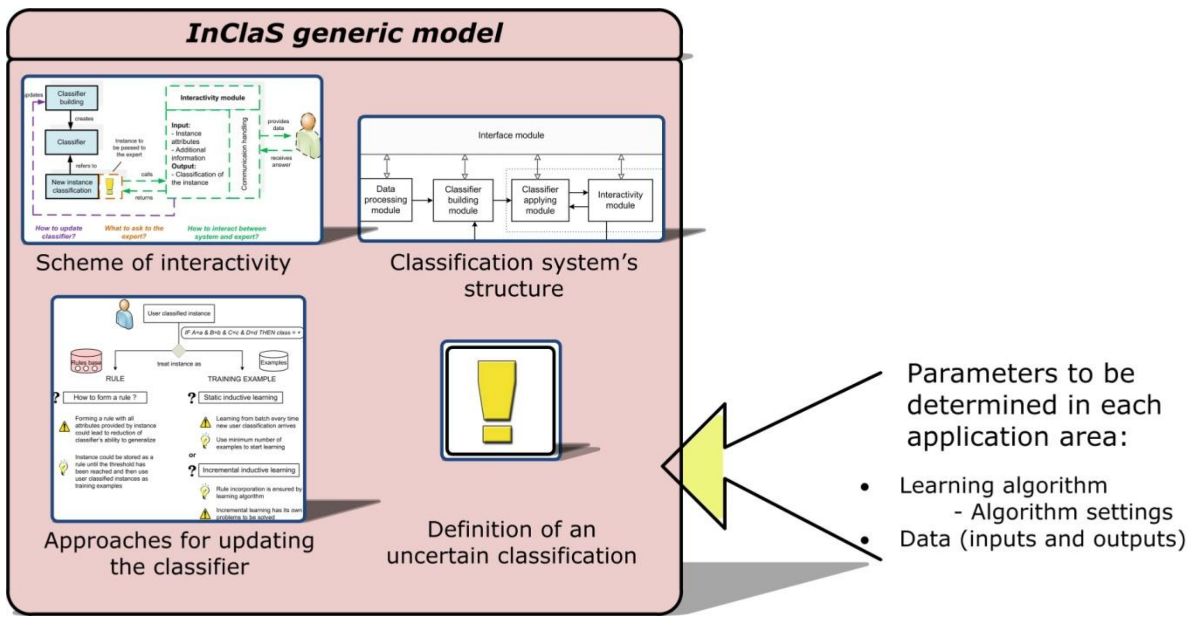

Figure 3.1. Base model of an interactive classification system

There are parameters identified which are to be determined in each InClaS application area (see Figure 3.1). The choice of a learning algorithm and its settings as well as descriptive attributes is to be made in all classification tasks, and the interactive approach makes no difference in this aspect. Development details of a classification system in a particular domain cannot be entirely predefined, however, they are supported with the thesis author's adapted five step procedure for designing intelligent systems by Bielawski and Lewand [47] which facilitates the work on classification system development.

3.1. General scheme of interactivity to be implemented

The aim of developing an interactive approach is not to enhance one certain learning algorithm. Instead, it is necessary to evolve an extension for those algorithms which lack a mechanism for dealing with unclassified or with low confidence classified instances. The proposed approach affects the way how the classifier is applied to new instances, not the way it learns and makes a predictive model (see Figure 3.2). The figure shows how the interactivity is implemented into the general model of the classification process.

Blocks with solid line are "standard" elements of a classification system. Blocks and arrows with interrupted lines are introduced to ensure interactivity with a human expert in order to assign class value(s) for uncertainly classified instances. This includes the following functions:

1. Capturing uncertain classifications in the classifier applying stage.
2. Forwarding these instances and additional information to the expert.
3. Receiving and processing the expert's decision.
4. Using expert-provided knowledge to update the classifier.

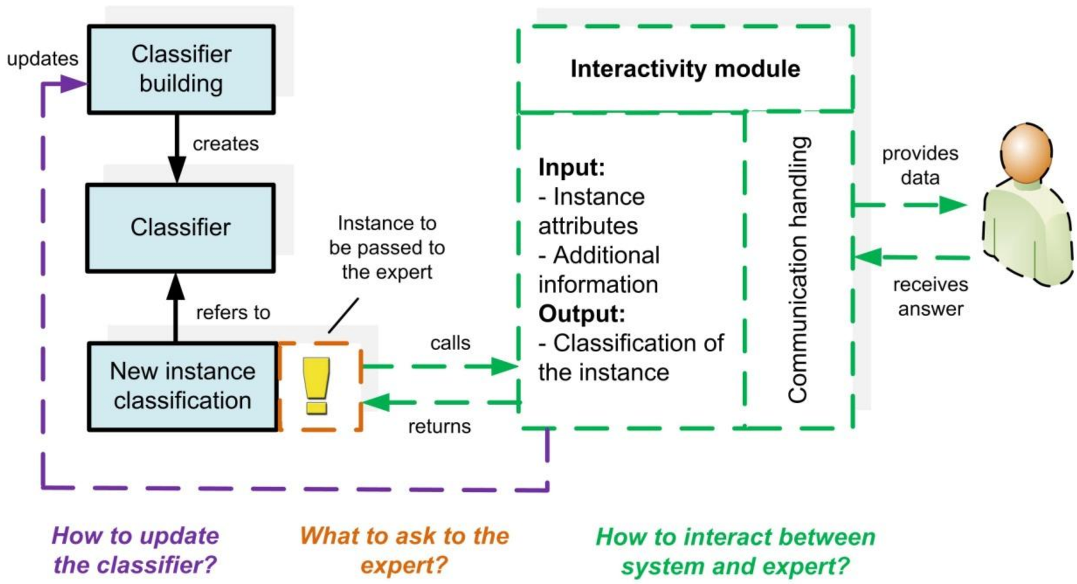

Figure 3.2. Inclusion of interactivity in the general classification model

The questions which arise from the classification system's extension with interactivity are resolved within the next subsections that concern other InClaS components.

3.2. Definition of an uncertain classification

To answer the question "What to ask to the expert?", it is important to define the characteristics of instances which are uncertain to the classifier and could benefit from the expert's perusal. Therefore, notion of terms used variously in machine learning literature – *unclassified instance, instance with low classification confidence* and *uncertain classification* – are clarified and their meanings in the context of thesis are defined.

Unclassified instance is an instance which was not covered by any rule (or a corresponding leaf in the decision tree) from the classifier's model in the classifier applying stage.

Taking into consideration the ***confidence which the classifier associates with the*** rule (or leaf) that is used to classify an instance, the classifier's decision can be marked as not confident enough. Confidence is based on example distribution in the training set which was used to build the classifier. For example, if the rule predicting class *A* covers 3 instances labelled as *A* and 2 instances labelled as *B*, then class distribution for an instance to be classified with this rule is 0.6 for class *A* and 0.4 for class *B*. Different learning methods apply distinct measures for calculating confidence. Traditionally, the confidence level 0.5 is the threshold for classifying an instance with this rule or not. However, other levels can be used to accomplish more confident decisions. An instance is said to be classified with low confidence if the confidence level for the class assigned by the classifier is below the selected threshold.

Uncertain classification includes both of above-mentioned aspects and is a term used to ascertain either unclassified or with low confidence classified instances.

Regarding multi-label classification more sophisticated uncertain classification definition is to be applied since more than one class can be assigned to an instance. This aspect as well as the method of achieving the most appropriate confidence levels for different data sets is outlined in next section along with InClaS particularization for multi-label classification tasks.

3.3. Suggested approaches for updating the classifier

To answer the question "How to update the classifier?" activities for accepting the expert's classification and updating the classifier in response to this decision are to be defined. The task of the interactive system is to accept the expert's decision and to update the classifier in response to this decision. Different classification approaches (e.g. static vs. incremental learning methods) with varied consequences can be used which are considered and depicted in Figure 3.3. The main considerations are either to treat the expert's classified instance as rule or use it as a training example. As a result, the author of the thesis proposes two approaches for expert-made decision incorporation into the classifier which maintain consistency of the classifier (e.g. its rule base) – *Threshold based static learning approach* and *Incremental learning approach*.

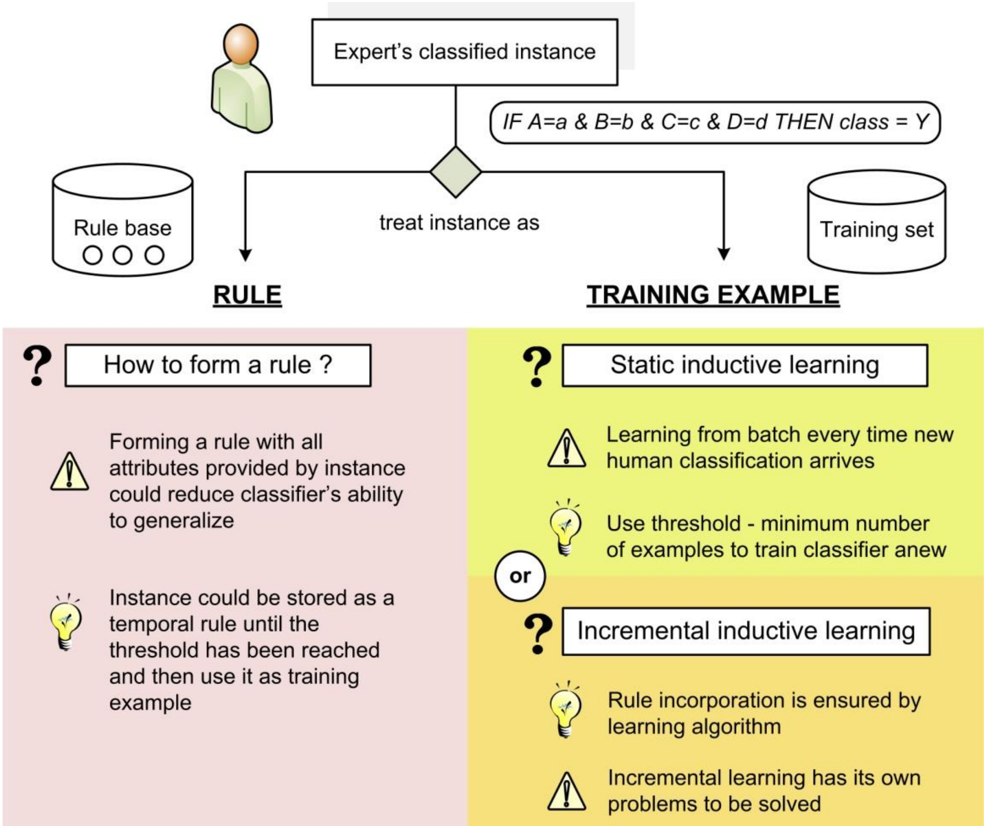

Figure 3.3. Considerations regarding expert classified instance incorporation

Threshold based static learning approach includes the following steps:

1. Set a threshold – positive number, representing the number of instances classified by the expert.
2. Store a human classified instance as a rule with all attributes and their values unless the threshold has been reached.
3. Use the static inductive learning method to rebuild the classifier and include expert classified instances into the training base.
4. Remove human classified instances used so far as rules from the rule base.
5. Replace the classifier with the new one.

Incremental learning approach includes the following steps:

1. Add expert classified instance directly to the incremental learning algorithm which by default allows extending the classifier as defined in this algorithm.

2. Use the updated classifier.

These approaches are described in more detail in [52].

3.4. Interactive classification system's structure

The system's structure holds part of the answer to the question "How to interact between the system and the expert?". A modular structure is chosen for the interactive classification system. Table 3.1 contains a detailed description of each module, explaining their functionality and connectivity with other modules. See also Figure 3.4.

Table 3.1

Modules of the interactive classification system

Data processing module
Provides exchange of data representation formats. - Ensures the user with a possibility to input learning data in different layouts and helps the user with data structuring. - Ensures the user with the possibility to view the learning data and classification rules in different representation formats. - Ensures data transformation for inner processes within and between modules. <u>Main connection with other modules:</u> - Interface module
Classifier building module
Produces a classifier for a given training data set. The classifier in its implementation internal structure is represented as an application-specific classification model. If-Then rules can be extracted from this format (if the representation form of the learning algorithm itself produces rules). The classifier building module is based on already implemented learning schemes (learning algorithms, validation methods etc.). <u>Main connection with other modules:</u> - Interface module
Classifier applying module
Applies the given classifier to the provided instances, finds classification and calculates statistics. This module is based on already implemented learning schemes which are extended with the ability to intercept instances that are not covered by any rule from the classifier. In this case the interactivity module is called. <u>Main connection with other modules:</u> - Interface module - Interactivity module
Interactivity module
Ensures communication handling with a system's user and expert. Closely tied to the classifier applying module. - Represents an uncertainly classified instance and additional information to the human expert as well as receives the answer. Additional information about the instance is, e.g., most similar rules. - Initiates classifier updates through updating the examples base after receiving the expert's response. - Ensures handling the expert's requests for classifier representation in form of rules. <u>Main connection with other modules:</u> - Interface module
Interface module
Ensures human-friendly communication between the system and its user/expert. - Represents data. - Transmits predefined user requests and inputs to other modules of the system. <u>Main connection with other modules:</u> - All system's modules

Figure 3.4 shows actions typically performed in the interactive classification system, without the inner process details within modules. The user can provide data for classifier training (*1a*), initiate classifier building (*2a*) and submit new instances to be classified (3a). If the classification can be made by rules in the *Classifier*, the user receives classification results as a response (*3c*). If there is an instance which cannot be certainly classified by the *Classifier applying module*, a request to the *Interactivity module* to handle the situation is sent (*3d*). The *Interactivity module* asks for an expert classification of the instance through interface (*3e*); this is the situation when a request for a response is being sent from the system to the user, not vice versa. After receiving the expert's feedback, the *Interactivity module* informs the user and updates the *Example base* with a new example that was built from the instance and the user-given classification to it (*3g*). Consequently, the *Classifier* can be updated. Techniques which an expert can use for decision making regarding instance classification are not considered in the scope of this work. The classification system accepts a single expert opinion.

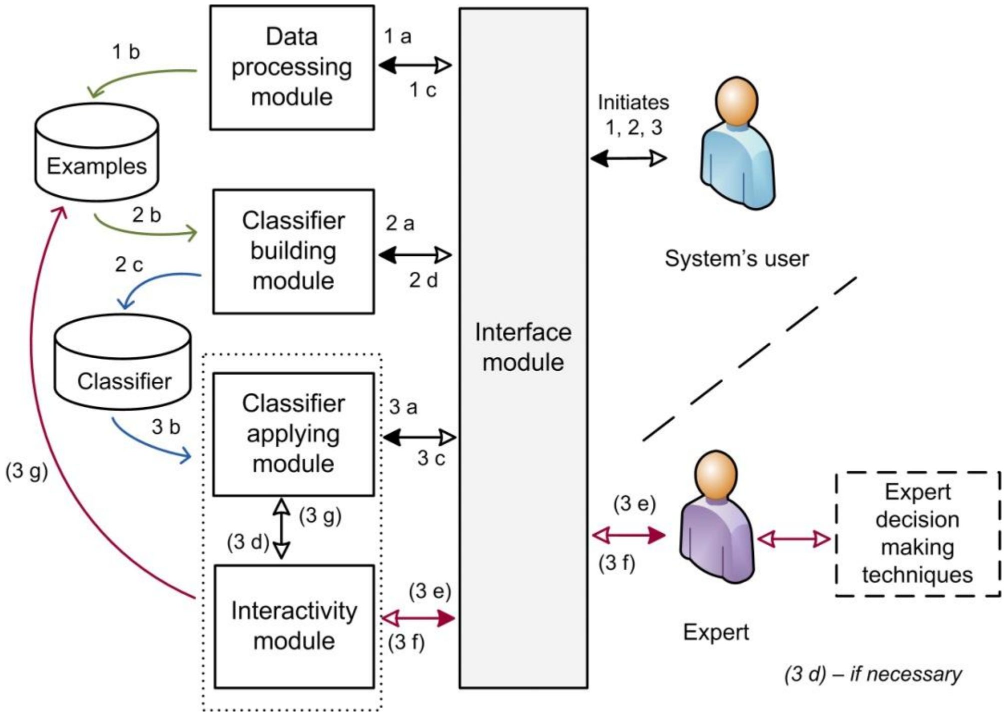

Figure 3.4. Modules and main processes within the interactive classification system

InClaS generic model provides general-purpose components to develop either a single-label or a multi-label classification system. Due to the scope of the thesis, InClaS is further developed to serve classification tasks with multi-label class membership. It is described in the next section.

4. INCLAS MODEL FOR MULTI-LABEL CLASSIFICATION

To deal with multi-label classification, InClaS model has been extended with the following additional and specified components (see Figure 4.1):

- Algorithm for detecting uncertain classification (see Section 4.1).
- Method for determining the most appropriate confidence level (see Section 4.2).
- Architecture of a classification system – system's design steps and structure (see Section 4.3).

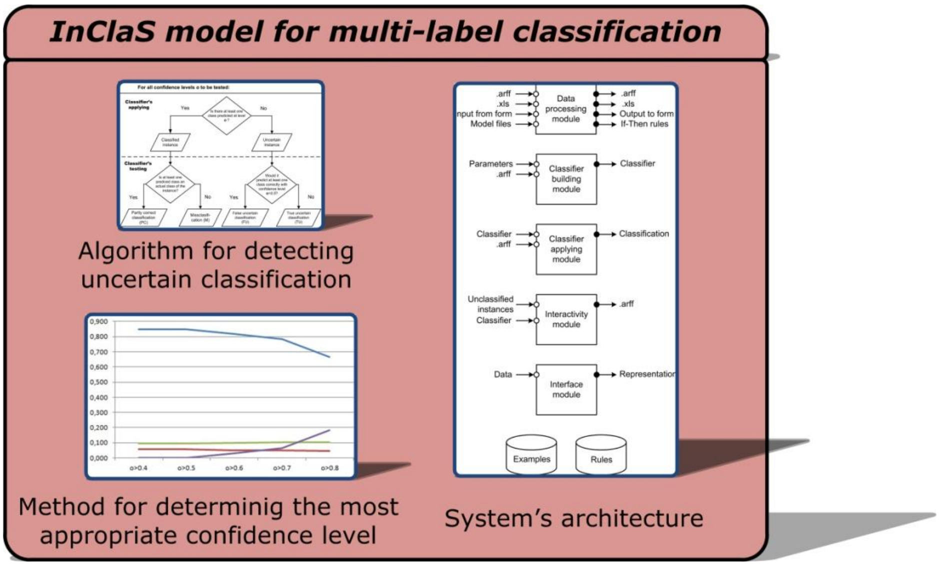

Figure 4.1. InClaS extension for multi-label classification

4.1. Algorithm for detecting uncertain classification

Before defining an algorithm for detecting uncertainly classified instances, the notion of uncertain classification in multi-label classification tasks and additional measures of interactive multi-label classification are to be defined. Multi-label class membership requires an extended definition of uncertain classification and unclassified instance since each object can belong to an unknown number of classes which makes the classification task more complicated. One of widely used approaches for multi-label classification is binary relevance [54] – splitting the initial problem into several single-label classification tasks. Therefore, the classification of a new instance comes from a combination of *n* single-label classifiers where each classifier predicts classification for just one of all *n* classes. If none of the classifiers predicts positive class, instance is defined as unclassified (thus also assigning uncertain classification mark). Table 4.1 demonstrates an example with four class labels. Using binary relevance approach for transforming this multi-label task into four separate binary classification tasks, each classifier predicts a membership only to class A, B, C or D separately, showing also their confidences. Depending on the threshold set, resulting classification gives one or two class labels as output. In both cases the instance is classified since at least one class is predicted by binary classifiers with chosen confidence level.

Table 4.1

Classification results with two different confidence levels

	Classes			
	A	B	C	D
Actual class labels	**1**	**0**	**1**	**0**
Confidence of each binary classifier	**0.4**	**0.1**	**0.6**	**0.5**
Response from the resulting classifier (at confidence threshold 0.5)	**0**	**0**	**1**	**1**
Response from the resulting classifier (at confidence threshold 0.6)	**0**	**0**	**1**	**0**

To consider usefulness of user involvement in classification process and impact to number of misclassified instances, as well as expert's workload, the thesis author introduces several simple measures to be detected and evaluated:

- *Partly correct or completely correctly classified instance (PC)* – at least one of predicted classes is the actual class of an instance, $Y_i \cap Z_i \neq \emptyset$, where
  Y_i – actual label set of instance *i*, Z_i – predicted labels set of instance *i*.
- *Misclassified instance (M)* – none of predicted classes is the actual class of an instance, $Y_i \cap Z_i = \emptyset$.
- *True uncertain classification (TU)* – the classifier would misclassify an instance (*M*) (that is, with the confidence level 0.5 none of actual classes would be predicted).
- *False uncertain classification (FU)* – the classifier would classify instance partly or completely correctly (*PC*) (that is, with the confidence level 0.5 at least one of actual classes would be predicted).

Certainly, it is desirable to strive for a classifier which maximizes the number of *PC* instances; however, if achieving high number if PC instances is hindered due to incompleteness of the classifier, the classification system should at least be aware of its "lack of knowledge" and be able to detect uncertain classifications.

Metrics for expert's workload assessment:

- $W_{inexpedient}$ – how many correctly classified instances an expert should review to classify one misclassified ($W_{inexpedient} = \frac{FU}{TU}$).
- W_{total} – how many instances an expert should review in total ($W_{total} = FU + TU$).

An algorithm for detecting uncertain classification in multi-label domains which defines that an instance is uncertainly classified if at the chosen (or default) confidence level none of actual classes of instance is predicted, is given in Figure 4.2.

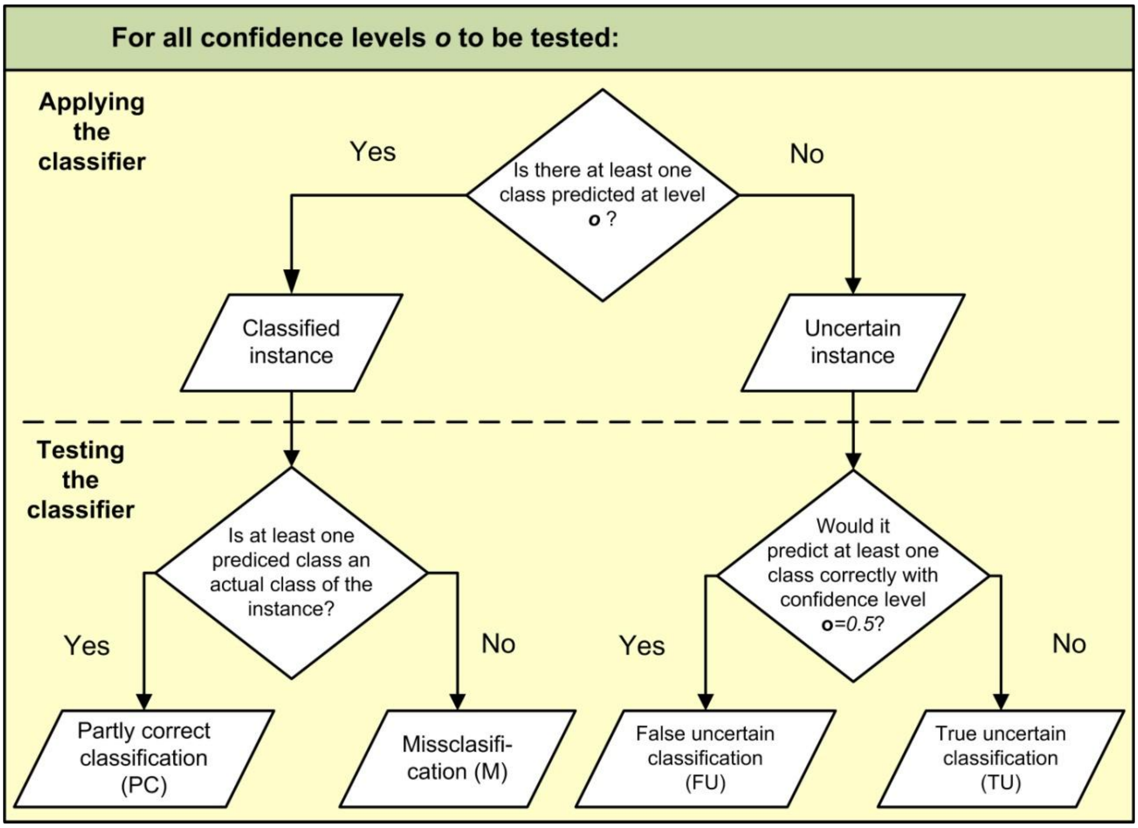

Figure 4.2. Algorithm for detecting uncertain classification in multi-label domains

4.2. Method for determining the most appropriate confidence level

The impact of the threshold which is chosen to separate confident classifications from not confident was already examined in the example from Table 4.1. It is assumed that a higher confidence level brings less misclassified instances, although it increases the number of uncertain classifications (instances below this confidence level) which in the interactive approach are passed to the expert. Therefore, the compromise should be achieved between the expert's workload and the number of misclassified instances left in the classification results. Different domains have various specifics regarding the confidence level. The author of thesis developed a method for determining the most appropriate confidence level for each data set. For indicators of the area to be searched through two measures are introduced – **a**verage **c**onfidence for classes which are **a**ctual classes on an instance (*ACA*) and **a**verage **c**onfidence for classes which are **n**ot actual classes on an instance (*ACN*).

The goal of the method is to determine the most appropriate confidence level where number of misclassified instances (*M*) is minimal taking into consideration given constraints regarding the expert's workload (r_1 and r_2): $M \rightarrow min$, $W_{total} \leq r_1$; $W_{inexpedient} \leq r_2$.

Method for manual determination of the most appropriate confidence level

1. Choosing a learning method for classifier building; training and testing the classifier, determining *M, PC, FU, TU,* W_{total} and $W_{inexpedient}$ at the default confidence threshold 0.5. If W_{total} is unacceptably high, choose a different learning method since W_{total} will only increase by increasing the confidence threshold.
2. If W_{total} is acceptable, *for* the confidence interval to be searched through *do*: increase the confidence threshold and measure *M, PC, FU, TU,* W_{total} and $W_{inexpedient}$. Various step sizes for level increasing can be used, e.g. 0.1.
3. Represent and analyze the results regarding *M, PC, FU, TU,* W_{total} and $W_{inexpedient}$.

   When evaluating different confidence levels, consider these factors:
   - If *M* has not increased since previous step, increase the confidence threshold.
   - If *M* is the same at several confidence levels, prefer level with lower W_{total} .
   - There are possible several equivalent confidence levels which hold the same parameters.

Also an automatic method has been developed which takes input parameters W_{total} and/or $W_{inexpedient}$ and outputs a confidence level at which *M* is minimal considering the given input.

Note that estimations are based on data distribution in the training set and can be inexact to the data which the classifier will meet in the future when classifying new instances.

4.3. Architecture of an interactive multi-label classification system

Design of an interactive inductive learning based classification system for a multi-label classification task is guided by a five step procedure for designing intelligent systems by Bielawski and Lewand [47]. Design decisions for a university study course comparison task are explained resulting in a more detailed system's structure which defines particular inputs and outputs of the modules. This component of the InClaS model is detailed in the author's publications [8, 55-57].

The developed InClaS generic model and its extension for multi-label classification provides a sufficient theoretical and methodical ground for implementing an interactive classification system as a software prototype.

5. INCLAS PROTOTYPE

A prototype has been implemented in order to bring the InClaS model into life and test it. This section describes the functionality of the prototype, paying attention to embodiment of InClaS model components into software. The main features of the prototype are provided.

- Within the prototype already implemented classification algorithms and methods are used; basic learning algorithms are called from *Weka* software [3], multi-label classification methods which make use of them are implemented in *Mulan* [4] library. A prototype in the exploitation mode currently uses 11 static learning algorithms or method-algorithm combinations from *Weka* and *Mulan*, applying default settings.
- To implement an interactivity scheme, the classifier's application stage has been improved with the ability to trace the confidence of classification and intercept uncertain classifications. Classification results are presented to the user (expert) which can apprise classes assigned with different confidences and make his classification if no classification is given with the confidence 0.5 or more.
- For classifier updating after the expert's classification of an uncertainly classified instance, *Threshold based static learning approach* with threshold = 1 is used. Consequently, the classifier is updated each time a new instance arrives. In practice, if the expert classifies more than one instance at a time, all these instances are used to update the classifier.
- Data input and output through graphical user interface (GUI) is provided.
- An algorithm for detecting uncertain classifications has been fully implemented into the classifier applying module. During new instance classification, confidences are achieved which are further used in decision making.
- The classification system extracts and saves the rules held in the classifier (in a text file) in a human-readable form.
- In the experimental mode a prototype has no complete graphical user interface, however, it provides wider testing capabilities, including 20 classification algorithms (which could be extended more) and evaluation measurements: several traditional multi-label metrics and the author's proposed *M, PC, FU, TU, ACA, ACN*.
- A method for determination of the most appropriate confidence level is to be applied manually, based on measurements provided by the classification system.

To emphasize the novelty of development differences and improvements in comparison to *Weka* tool and *Mulan* library are summarized. From this aspect the main InClaS contributions are (1) the developed GUI for *Mulan* library (developers of *Mulan* do not provide GUI), (2) the ability for a system's user to examine the classifier rule base conveniently (if a particular learning algorithm produces rules), and (3) GUI for ensuring interactivity. Thus all together the InClaS prototype provides a unique environment for multi-label classification in a more user-friendly way than it was possible before as well as novel interactivity facilities between the classification system and its user. Figure 5.1 shows an example of a user interface of an interactive classifications system's prototype while Figure 5.2 depicts an example of classification rules obtained with the system.

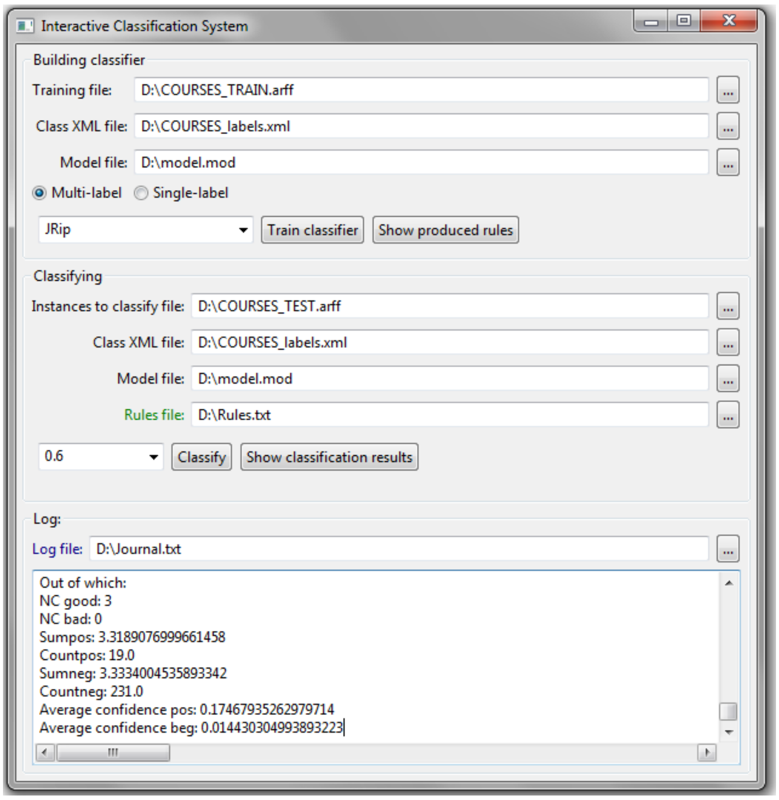

Figure 5.1. Classifier's testing results output in the InClaS prototype's GUI

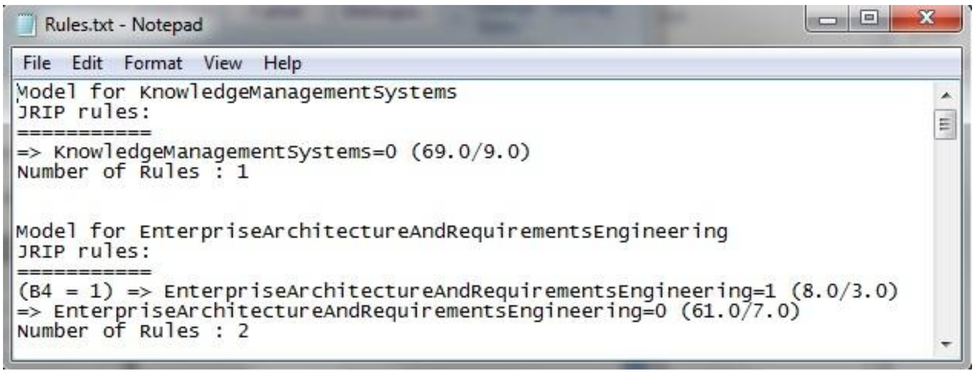

Figure 5.2. Classification rules from experiments in a study course comparison domain

6. EVALUATION OF INCLAS MODEL

This section describes the experimental plan and main results in practical evaluation of the InClaS model and its prototype. To solve the problem which is addressed in the thesis, from machine learning viewpoint, it is necessary to satisfy the following features: (1) understanding decision making steps is important for the classifier's user and the expert, (2) the available initial learning base is small, (3) initial data is semi-structured or unstructured, (4) the domain defines many classes with equal frequency, and (5) each object can have a multi-label class membership. The developed InClaS model takes these features into consideration. Domains used for InClaS approbation are the university study course comparison and diagnostics in medicine. Part of experimental results are published in [58]. The aim of experiments is to examine the utility of the InClaS model, usability of the system's prototype as well as verify the theses (T1, T2, and T3) stated in the introduction.

The following aspects are to be evaluated in order to assess an InClaS utility:

- *Comparison of number of misclassified instances,* applying the standard non-interactive approach and the proposed interactive approach (relates to T1).
- Apprise of a *method for determining the most appropriate confidence level* (relates to T2).

Regarding usefulness of the proposed solution in education area:

- Verification of the statement made that this problem domain is not appropriate for traditional automatic machine learning solutions, whereas *inductive learning methods based interactive multi-label classification system for supporting study course comparison* can provide acceptable solution (relates to T3).
- Evaluation of a direct (using attributes achieved directly from full course descriptions) and indirect (using mediated attributes from course descriptions) study course comparison.

6.1. Experiments in higher education

Figure 6.1 shows several ways for comparing study courses. In manual approach only human-expert effort is used in detecting course correspondence. In computerized approaches expert knowledge investment is used for creating an automatic or interactive classification system. The figure shows two kinds of attribute extraction for a formal domain description which were also discussed in Section 1.3. Resulting data set can be processed within traditional automatic or the proposed interactive classification system. Therefore, the computerized approach defines 4 combinations (later on – stages): (1) word vectors with automatic classification, (2) mediated attributes with automatic classification, (3) word vectors with InClaS, and (4) mediated attributes with InClaS.

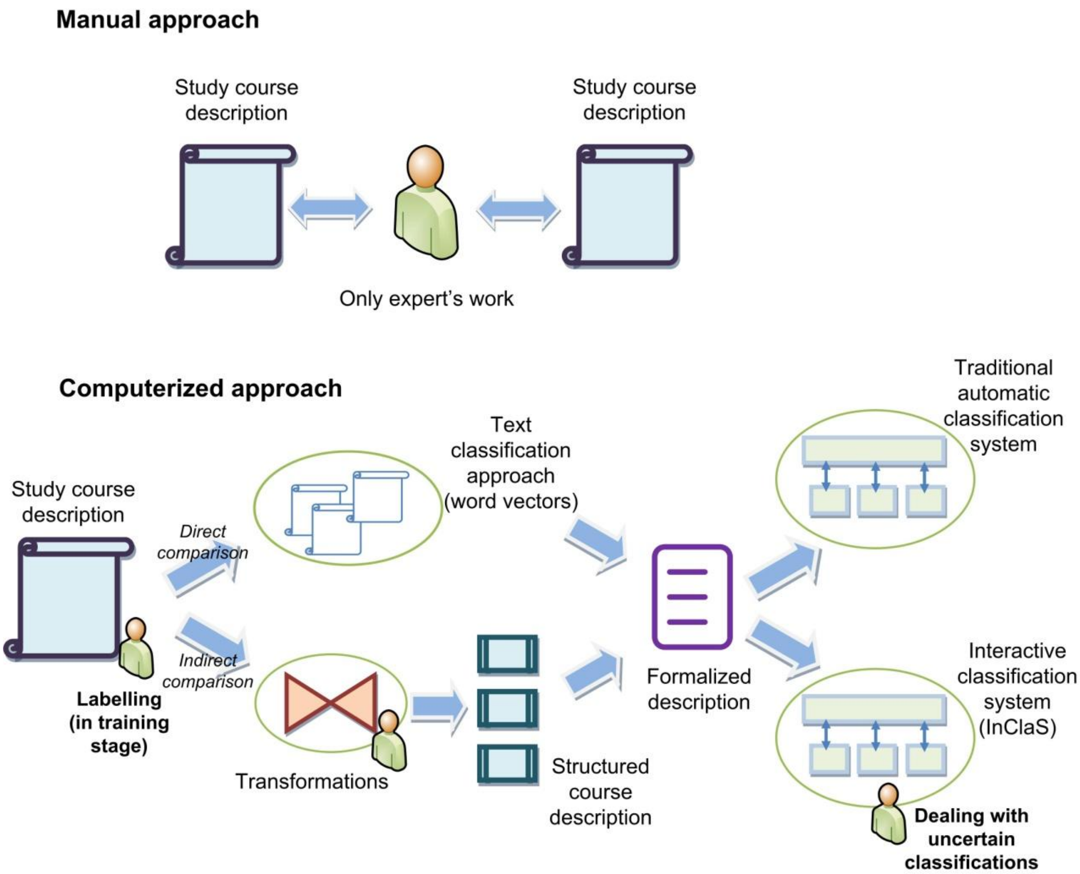

Figure 6.1. Manual and computerized study course comparison

The formal data set representation from the machine learning viewpoint is given in Table 6.1 and Table 6.2. Figure 6.2. demonstrates an example of formalizing course attributes and detected classes (two in this example) in both comparison cases for one course from *Vienna University of Technology*. This is done in order to prepare an appropriate input data format – formalized attributes and classes – for classification algorithms.

Table 6.1

Attributes and classes in indirect (competency based) study course comparison

Attributes a	**Attribute values** v_a	**Data type**	$n = 38$
Number of credit points (ECTS)	[3; 6; 9; 15]	Nominal	
Study level	[Bachelor – 1; Master – 2]	Nominal	
Competency A1 from e-CF	[0; 1]	Nominal	36 attributes
Competency A2 from e-CF	[0; 1]	Nominal	
..	..	..	
Competency E9 from e-CF	[0; 1]	Nominal	
Classes L			$j = 25$
Business Analytics	[0; 1]	Nominal	25 class labels
Knowledge Management Systems	[0; 1]	Nominal	
..	..	..	

Table 6.2

Attributes and classes in direct (word vector based) study course comparison

Attributes *a* (words in course descriptions)	**Attribute values** v_a	**Data type**	$n = 1884$
attrib	[0; 1]	Nominal	*1884* attributes
compliance	[0; 1]	Nominal	
..	..	..	
model-driven	[0; 1]	Nominal	
..	..	..	
Classes *L*			$j = 25$
Business Analytics	[0; 1]	Nominal	25 class labels
Knowledge Management Systems	[0; 1]	Nominal	
..			

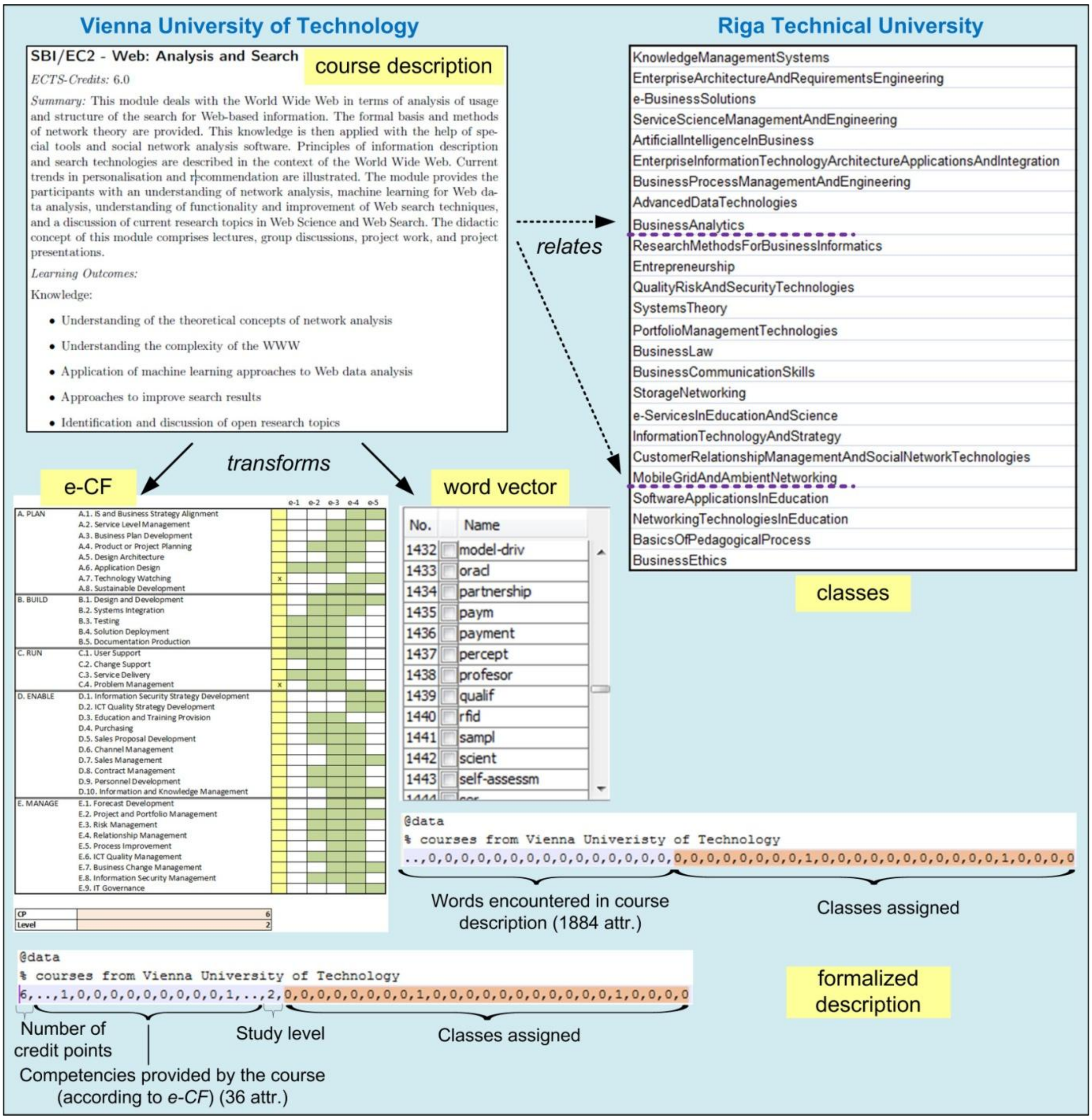

Figure 6.2. Data preprocessing in the educational domain

Experimental settings are described in Table 6.3.

Table 6.3

Experimental settings for study course comparison

	Stage 1	Stage 2	Stage 3	Stage 4
Input data set	Full study course descriptions (extracting word vectors in preprocessing)	Competencies of study course, number of credit points, study level	Full study course descriptions (extracting word vectors in preprocessing)	Competencies of study course, number of credit points, study level
Classification approach	Automatic classification	Automatic classification	Interactive classification (InClaS model)	Interactive classification (InClaS model)
Classification algorithms (methods)	20 classification algorithm-method combinations (from *Weka* and *Mulan*)	20 classification algorithm-method combinations (from *Weka* and *Mulan*)	4 best methods from Stage 1	4 best methods from Stage 2
Evaluation measures	Hamming loss, Micro-average precision, Micro-average recall, One-error, Coverage	Hamming loss, Micro-average precision, Micro-average recall, One-error, Coverage	*M, PC, FU, TU*	*M, PC, FU, TU*

The full data set consists of 79 instances from different European universities providing Business Informatics related curricula, namely, 25 instances from RTU, 6 instances from *University of Rostock*, 31 from *Vienna University of Technology* and 17 from *University of Vienna*. In a reduced set, the labels with less than 4 examples are removed. Label density of a data set is the average number of labels of the examples divided by number of labels. Label cardinality of a data set is the average number of labels of the examples in this set. Distinct labelsets present the number of different label combinations within a data set. Parameters of data sets are given in Table 6.4.

Table 6.4

Study course data set

	No. of attributes	No. of instances	No. of classes	Label density	Label cardinality	Distinct labelsets
Full data set (word vectors)	1884	131 (79)	25	0.0620	1.6203	52
Full data set (competencies)	38	79	25	0.0620	1.6203	52
Reduced data set (competencies)	38	64	12	0.1341	1.6094	36

Main experimental results

Table 6.5 shows 3 times repeated random sub-sampling validation results (stage 3) of four methods which achieved the best results by means of Hamming loss, Micro-average precision, Micro-average recall, One-error, Coverage in stage 1. *BR* stands for the Binary Relevance method. Classification measures hold the following correlations:

PC +Misclassified(without interactivity)=1(all classifications in an automatic manner).
PC+TU+FU+Misclassified(with interactivity)=1(all classifications in an interactive manner).
Misclassified (without interactivity)=TU + FU + Misclassified (with interactivity).

Table 6.5

Interactive approach for direct study course comparison (word vectors)

	Partly correct (*PC*)	**True uncertain classification (*TU*)**	**False uncertain classification (*FU*)**	**Misclassified (with interactivity)**	**Misclassified (without interactivity)**
RAkEL(J48)	0.267	0.333	0.000	0.400	0.733
BR(AdaBoost)	0.100	0.400	0.000	0.500	0.900
BR(Bagging)	0.067	0.600	0.000	0.333	0.933
BR(JRip)	0.267	0.367	0.000	0.366	0.733

Results in Table 6.5 should be interpreted as follows. Using the automatic classification where only partly or completely correct classifications (blue part of the table) and misclassifications (red part of the table) exist, 27% of instances would be *PC* (in case of *RAkEL* method) and 73% – misclassified. If the interactive approach is used, the number of *PC* remains the same; however, 33% of instances from previously misclassified are marked as uncertain to the classifier and given to the expert, reducing the number of misclassified instances to 40%. Results in Table 6.5 show that without applying interactivity the number of misclassified instances is much higher for all methods. Note the assumption that the expert makes correct classifications to the instances passed to him. To all appearances, the given data set does not provide a complete concept description as it was assumed when considering domain features.

Table 6.6 represents results of stage 4 experiments.

Table 6.6

Interactive approach for indirect study course comparison (competencies)

	Partly correct (*PC*)	**True uncertain classification (*TU*)**	**False uncertain classification (*FU*)**	**Misclassified (with interactivity)**	**Misclassified (without interactivity)**
BR(NB)	0.234	0.633	0.000	0.133	0.766
BR(Bagging)	0.167	0.733	0.000	0.100	0.833
BR(AdaBoost)	0.267	0.433	0.000	0.300	0.733
BR(JRip)	0.267	0.367	0.000	0.366	0.733

Alike stage 3 results, the ability of the InClaS classification system to track uncertain classifications allows to decrease the number of misclassified instances, although results vary much between the methods used. Graphical representation of *JRip* results in Figure 6.3 emphasizes the impact of the interactive approach even more. Without interactivity (Figure 6.3 part A), all instances in the red column of the table would be misclassified reaching only

27% of *PC*. Such classification results do not encourage the use of the automatic classification in this problem domain. In turn, the interactive approach (Figure 6.3 part B) with the ability to handle uncertain classification makes it possible to save half of misclassified instances and assign to them correct classifications after the expert's review. Thus, 37% of instances are misclassified, which, obviously, is not a great result, but is much more promising than 73% with the automatic classification.

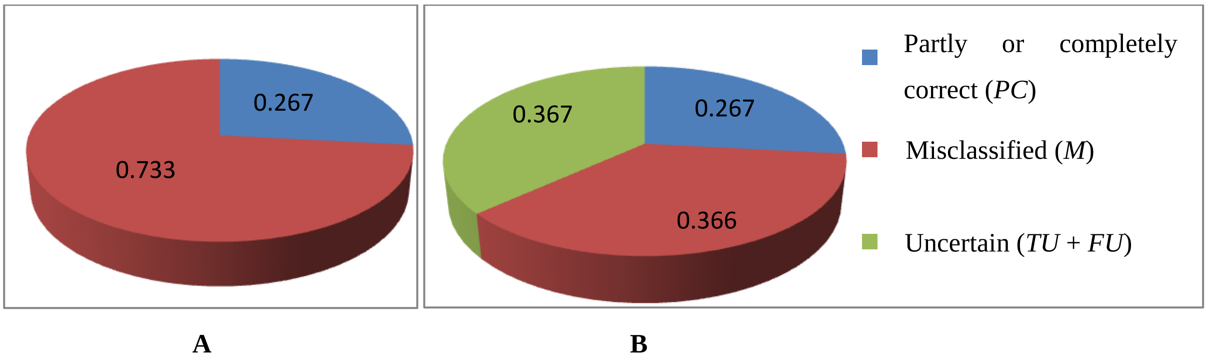

Figure 6.3. Test results of *JRip* algorithm in course comparison task with automatic (A) and interactive (B) classification

To consider the situation when the number of training examples regarding each class has increased, experiments with the reduced data set are carried out. The results lead to conclusion that interactive classification system improves its results and less frequently disturbs the expert when the training set grows in time. Therefore it is useful to spend expert's time more in the initial period of classifier's usage in order to obtain better classification results later. Figure 6.4 shows the difference between results in the data set with reduced number of classes where each class is described with slightly higher number of examples (part A) and the full data set which includes many underrepresented classes (part B). In reduced data set *PC* reach 50% of instances leaving 17% of instances for expert's decision and also decreasing the number of misclassified instances. All these parameters are improved in comparison to the initial data set.

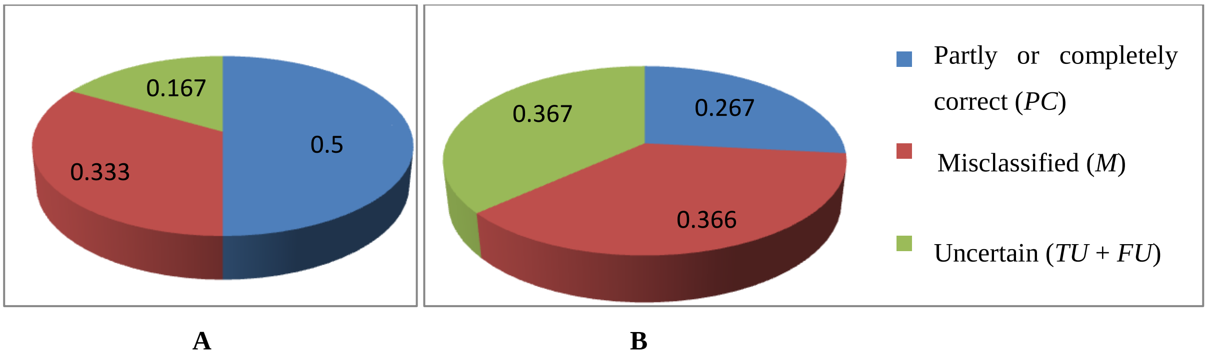

Figure 6.4. Test results of *JRip* algorithm in course comparison task with reduced (A) and full (B) data set

Experimental results also deny assumption that the indirect course comparison provides better classification results than the direct comparison. That is, structured and meaningful information extraction from course descriptions produce attributes which do not surpass full course description usage to make word vector based attributes by means of number of misclassified instances and (partly) correct classifications. Both approaches can be used, however, the indirect comparison currently requires much more expert's work in attribute extraction phase since competencies are not accessible directly in course descriptions. If course descriptions are standardized, it makes the situation more convenient for such approach. As a disadvantage of word vector usage to define attributes its low semantic meaning should be mentioned. It does not provide useful knowledge to the expert as it only describes occurrences of different words in descriptions wherever in the text they appear – either preconditions or learning outcomes. Therefore, the knowledge about underlying communalities of the course content can be mined if meaningful attributes are used, like competencies which the study course provides.

6.2. Experiments for determining the most appropriate confidence level

Method for determining the most appropriate confidence level is applied to the study course indirect comparison full data set. The following example shows the method's usage. Several restrictions are set; in case *A*, the total number of instances which the expert admits to classify is defined, in case *B*, the usefulness of the expert's work is defined while case *C* does not set workload restrictions but requires the best state for minimizing the number of misclassified instances. The confidence level is denoted as **o**. The search area is set to (0.1; 0.8) with the step size 0.1.

A) $W_{total} \leq 5$ (out of 10 examples to be classified)

B) $W_{inexpedient} \leq 0.5$

C) Best state ($M \rightarrow min$)

Table 6.7 and Figure 6.5 show results after 3-fold crossvalidation. *M, PC, FU, TU,* W_{total} and $W_{inexpedient}$ are relative to the test set size.

Table 6.7

Measurements for the most appropriate confidence level detection

	o=0.1	o=0.2	o=0.3	o=0.4	o=0.5	o=0.6	o=0.7	o=0.8
PC	0.267	0.267	0.267	0.267	0.267	0.267	0.200	0.000
M	0.733	0.366	0.366	0.366	0.366	0.366	0.266	0.133
TU	0.000	0.367	0.367	0.367	0.367	0.367	0.467	0.600
FU	0.000	0.000	0.000	0.000	0.000	0.000	0.067	0.267
$W_{inexpedient}$	-	0.000	0.000	0.000	0.000	0.000	0.250	0.526
W_{total}	0.000	3.667	3.667	3.667	3.667	3.667	5.333	8.667

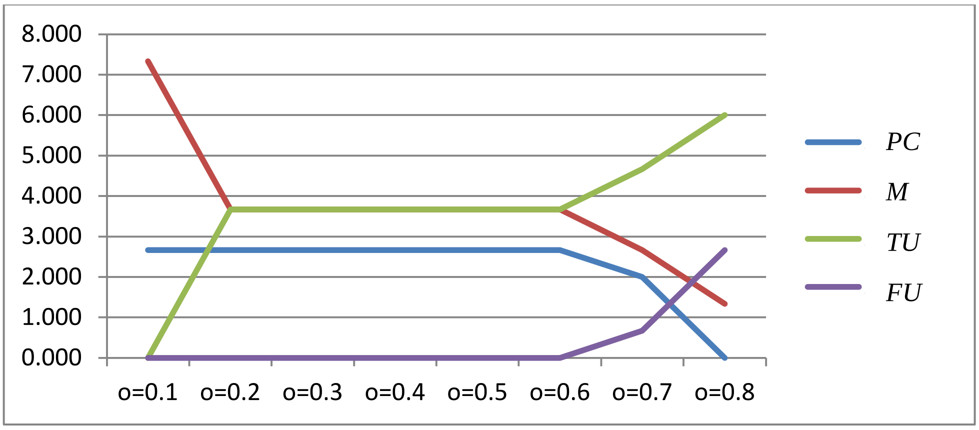

Figure 6.5. Graphical representation of parameters (X axis – confidence, Y axis – number of examples)

Considering restrictions the most appropriate confidence levels are as follows:

A) $W_{total} \leq 5$ (out of 10 examples to be classified): o=0.6. The search area can be expanded between level 0.6 and 0.7 using smaller steps.

B) $W_{inexpedient} \leq 0.5$: o=0.7. The search area can be expanded between level 0.7 and 0.8 using smaller steps. Graphical representation shows that the states from o=0.2 to o=0.6 are equivalent.

C) Best state ($M \rightarrow min$): o=0.8

6.3. Experiments in medical diagnostics

In addition to the main application domain, the interactive approach is evaluated also on textual medical data which describes patient condition, therapy applied and diagnose (or several diagnosis) by means of *ICD-9-CM* codes. Data is published during *Computational Medicine Center's 2007 Medical Natural Language Processing Challenge* [59]. The main feature which differentiates this data set from educational domain is its training set size – it is not characterized as small. However it does not decrease *feasibility* to InClaS usage (since the constraints of expert availability and expert interpretable problem domain hold), only decrease its *necessity*, as the automatic classification works acceptably in this domain. Data set parameters are given in Table 6.8.

Table 6.8

Medical data set

	No. of attributes	No. of instances	No. of classes	Label density	Label cardinality	Distinct labelsets
Data set	1449	978	45	0.028	1.245	94

Division into learning and testing set is kept as originally provided [59]. Experiments were carried out with different classification methods from which the best results were achieved by Binary Relevance method with *JRip* algorithm. Results using the default confidence level 0.5 are shown in Figure 6.6.

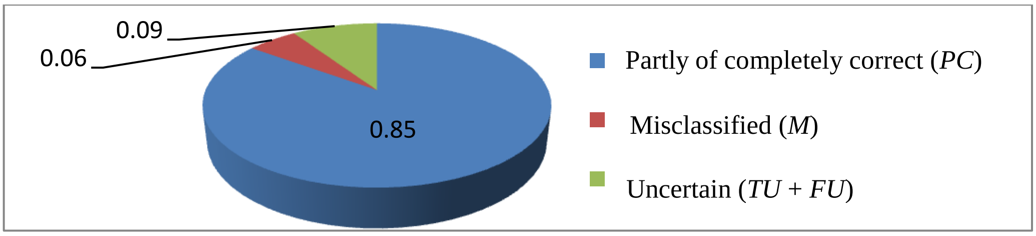

Figure 6.6. Results of Binary Relevance (*JRip*) in medical domain

As depicted in Figure 6.6., the number of *PC* instances is much higher than in the study course data set reaching 85%. This is most likely due to a sufficient training set. However, even there interactivity could improve classification results by marking 9% of all instances which are classified uncertainly and would be misclassified with the automatic classification approach. Note that the aim of experiments in this domain was not to find the best classifier (the author does not claim that 85% is the highest possible *PC* number) but to prove that the interactive approach can improve classification results in comparison to the automatic classifier.

After experimenting with data sets in higher education and medicine, the utility of proposed InClaS model is approved. The number of misclassified instances can be reduced if the interactive classification system is applied. The best improvements can be reached in the domains where the initial classifier is weak like it is in educational data set which provides an incomplete training set and unsatisfactory classification results if the automatic classification is applied.

MAIN RESULTS AND CONCLUSIONS

The doctoral thesis provides an InClaS model which defines algorithms, methods and other components which allow to develop an interactive classification system for decreasing misclassified instances in domains where a human-expert is available. Evaluation of the model has been carried out in educational and medical domains which proved the ability to decrease the number of misclassified instances if uncertain classifications are detected and passed to the expert's review. Improvements are especially significant in the domains where the initial classifier is weak and without applying the interactive approach the classifier produces much more wrong decisions than correct ones like in the study course comparison task. Therefore, one can conclude that the goal of the thesis – *to develop the model of semi-automatic classification system which allows interactivity with an expert at the classifier's applying stage if the classifier meets an object which it cannot classify or is not confident of the classification made* – has been reached and **recommendations of InClaS application** can be drawn.

The use of the interactive classification system is *feasible* in areas where:

- Human-expert is available that can classify individual instances.
- Problem domain is defined by the attributes which are comprehensible for the expert – not too overwhelming in amount and available in a human interpretable form.

The interactive classification approach is *more appropriate* than the automatic classification in areas where at least one of the following statements holds:

- It is essential to receive a correct classification for as much instances as possible, and it is acceptable to invest the expert's work and time to achieve it.
- It is hard to extract or define domain features resulting in attributes which do not describe the underlying concept completely.
- Only a small initial learning set is available and it is suspected not being representable.

Theoretical results of the thesis

Development of the thesis has given theoretical results which can be grouped as follows:

- The developed Interactive Inductive Learning based Classification System's (InClaS) model which amalgamates components necessary for creating an interactive classification system:

- Defined general scheme of interactivity to be implemented into the classification system.
- Developed general architecture of the interactive classification system – functional modules of a classification system, their properties and connections between them defining *Data processing*, *Classifier building*, *Classifier applying*, *Interactivity* and *Interface module*.
- Elaborated two advisable approaches for incorporation of an expert-classified instance into an existing classifier – *Threshold based static learning approach* and *Incremental learning approach*.

- The developed extension of the InClaS model which amalgamates components required for creating an interactive multi-label classification system:
  - Defined algorithm for detecting an uncertain classification in multi-label classification tasks.
  - Developed method for determining the most appropriate confidence level of the classifier's decision at which an instance is considered to be uncertainly classified and is redirected to the expert.
  - Defined measures for interactive multi-label classification evaluation – *average confidence for classes which are or are not actual classes of an instance* (*ACA* and *ACN*), $W_{inexpedient}$ – how many correctly classified instances an expert should review to classify one misclassified, W_{total} – how many instances an expert should review in total, notion of *Partly correct or completely correctly classified instance (PC)*, *Misclassified instance (M)*, *True uncertain classification (TU)*, *False uncertain classification (FU)*.
  - Adapted five step procedure for designing intelligent systems [47], which facilitates the analytical work in implementing an interactive classification system for a particular application area.
  - Developed interactive classification system's design by means of modules, their inputs and outputs.
- Summaries of original studies concerning related works:
  - State-of-the-art in computer supported educational document comparison.
  - Classification of inductive learning algorithms.
  - Comparison of current interactive classification approaches regarding dealing with unclassified instances.
  - Summary and comparison of classification systems' architectures.

Practical results of the thesis

Development of the thesis has revealed the following practical results:

- Developed a prototype of an interactive multi-label classification system which is adjusted for study course comparison task.
- Developed an application for syntactical data transformation between single-label and multi-label representation formats (*.arff* files), which is practically applicable for multi-purpose tasks.
- Detected course correspondences between *Business Informatics* master study programme in *Riga Technical University* and courses of several corresponding study programmes in Europe.

Future works

The theoretical and practical results of the thesis provide opportunities for further research. Some of future investigation directions are as follows.

- Define a more sophisticated than currently used (*is corresponding* or *is not corresponding*) similarity measures for a study course comparison, e.g. by applying weights that denote the degree of course correspondence.
- Extend InClaS application opportunities to domains with large attribute sets by developing a user-friendly solution for presenting a big amount of attributes and their values.
- Define a more complex *partly correct* classification measure.
- Consider other supervised and semi-supervised machine learning approaches for the comparative analysis of university study courses, e.g., co-training and case-based reasoning.

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