

Interactive Inductive Learning: Application in Domain of Education

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Abstract – globalization presents an opportunity to obtain education from several education providers by using different study exchange programmes. This possibility, in turn, creates the need to compare available study courses in foreign institutions to courses on the curriculum of the institution which issues the degree. Manual course comparison is time consuming and requires involvement of highly skilled experts. Otherwise, the comparison may result in a superficial intuitive judgement and, consequently, course incompatibility problems. Interactive inductive learning supported by enterprise modelling is proposed as a supporting mechanism which can help to save the time an effort in study course comparison.

Keywords: inductive learning, enterprise modeling, compatibility, curriculum management

I. INTRODUCTION

Inductive learning is used for classification purposes in many different areas including the area of information systems design and development [1]-[4]. The use of machine learning methods helps to save human time and energy in information amalgamation, analysis, and organization. One of the typical difficulties in inductive learning is identification of relevant features (attributes) that describe the problem domain. It is also important to keep the classifier tuned to actual needs even if they change. Therefore, a model describing the problem domain is needed to extract features and provide insight into a potentially changing domain. In this paper we illustrate how an enterprise model can be related to inductive learning system in order to ensure (1) selection of appropriate set of classification features, (2) awareness of need to modify the set of features or build a new classifier. Enterprise modeling is one of the essential instruments that help to build useful information systems [5]. In this research enterprise modeling is performed using an enterprise model utilized in Enterprise Knowledge Development (EKD) methodology [6].

Globalization and student mobility have created the need to compare study programmes (curricula) and study courses in order to analyze their compatibility. On account of the large number of different educational institutions operating inside the global knowledge provision space, manual course comparison may become too time-consuming. Therefore, methods and tools are needed that may help to shorten the time by performing at least some operations automatically. In the field of inductive learning courses of study programmes may be viewed as knowledge classes. Taking into consideration that course contents of several study courses may overlap, interactive inductive learning is applied in order to benefit from human intervention in handling classification difficulties caused by conceptual overlapping of study courses.

TABLE I
USE OF TERMS OF EDUCATIONAL DOMAIN

Term	Explanation
Curricula, curriculum, study programme	Terms are used as synonyms to refer to a specific study programme and a set of study courses
Study course	A particular set of study topics included in a study programme under a particular title
Exchange programme	A study programme outside the home institution

The overlapping also suggests the use of multi-label classification instead of classical single-label classification. Multi-label classification allows the object to belong to multiple classes; in study course comparison context it means that one study course can be similar to several other courses. Application areas of interactive inductive course comparison system include student exchange, curriculum development, and alignment of different study programmes.

The aim of this work is (1) to illustrate usefulness of the enterprise modeling for creation of inductive learning system and (2) to outline a new approach for study course compatibility analysis support.

The paper is structured as follows. Section II briefly discusses the background concepts of enterprise modeling, interactive inductive learning, and multi-label classification. Section III illustrates the problem domain and shows how interactive inductive learning is used for study course comparison. Section IV is focused on the relationship between inductive learning and enterprise modeling. Section V gives an example of experimental results of the use of a proposed solution in real life course comparison and discusses the results of the experiments. Section VI sums up the paper presenting conclusions and points to the directions of further research.

II. BACKGROUND

The basic terms of educational domain used in this paper are described in Table I.

Today curriculum development, maintenance and management require continuous monitoring of knowledge provision space where different education providers offer a wide spectrum of knowledge acquisition opportunities. This is especially important in rapidly developing areas, e.g., information and communication technologies. Besides such issues as scientific developments, industrial needs, and students' background knowledge [7], curriculum developers also have to take into consideration knowledge offered by

other education providers. Therefore, appropriate models should be created to deeply understand the problem domain, to be able to ensure controlled student mobility and study program development. Enterprise modeling (see Section II.A) can be used as one of the ways how to create such models.

A. Enterprise modeling

One way of structuring the knowledge of an enterprise is to build its model. Enterprise modeling [5] deals with the process of understanding enterprise business and improving its performance through creation of enterprise models. It includes modeling of the relevant business domain (usually relatively stable), business processes (usually more changing), and information technology. Our approach employs the enterprise model used in EKD [6]. EKD is an integrated collection of methods, techniques, and tools that support process of analyzing, planning, designing, and changing business and defining requirements for information systems. EKD framework consists of Goals Model, Concepts Model, Business Rules Model, Business Process Model, Actors and Resources Model, and Technical Components and Requirements Model. Each of these models includes a number of components describing different aspects of the system. The components are related not only within a single model, but also with components of other models. Participants of modeling group with different knowledge and background discuss explicit relationships between elements belonging to different models. The model gives a possibility for participants to focus on the enterprise from different points of view related to their part of the business and see the impact of their decisions to the overall intentions and processes of the enterprise. Therefore, working with models benefits the organisation's culture and learning [6].

While applied for different business analysis and systems development tasks, EKD modeling has not yet been used specifically for the identification of features for inductive learning based classifiers.

B. Interactive inductive learning

Induction is the process of converting particular facts into general regularities. An inductive learning system learns classification from training examples and uses induced rules to classify new instances. If the classifier is not complete, it may happen that none of the rules in the rule base can classify a new instance. Inductive learning systems with a low number of non-classifiable instances generally use a default rule for classifying new instances that none of the rules in the rule base can classify [8]. For a study course compatibility analysis it is expected that non-classifiable instances would not be rare, especially while rule base is incomplete. Therefore, an interactive inductive learning system is used. It (1) deals with non-classifiable instances by asking a human to decide on a classification and (2) improves its knowledge base with a rule derived from this experience [9].

Referring to the concept "interactive inductive learning", various ideas of user interaction in concept learning process are explored. Proposed systems and approaches are from different fields and suggest different levels of user interaction.

The following learning methods involving a human are distinguished [9]:

- Provision of classifier learning data, data selection for input [10]-[13].
- Extraction, processing, and selection of rules [11]-[12].
- New instance handling in classifier applying [9].
- Decision handling after the classification of new instances [14].

One should take a notice that most of references to interactive inductive learning are rather old. From this we can conclude that research area has experienced transformations. Only one above-mentioned method (new instance handling in classifier applying) is new and provides an appropriate model of interactivity for solving an inductive learning problem with classifying examples that do not fit any rules in the knowledge base. Therefore, interactive inductive learning system involves a human when it meets a new instance not consistent with the rule base. Such approach replaces the default rule that is usually applied in inductive learning when none of the rules in the rule base fits the instance. Classification by an expert can ensure not only correct classification of a particular study course; human-made decision can also be used to improve existing knowledge about courses, since the human-given advice can be saved and accepted as a new rule to be incorporated into existing rule base. This is done only if the human wants his decision to be saved for further use.

In the case of course classification one course can be similar to several other courses; therefore, assignment of more than one class is possible.

C. Multi-label classification

The majority of classification approaches do not consider creation of possibly useful rules with multiple class labels. A traditional classification algorithm tries to decide between the potential rules (if there is more than one corresponding rule) when classifying new instance and extracts only one class associated with the most obvious rule.

However, multi-label classification rules may often be useful in practice, since they bring up information that also has relevance; thus otherwise ignored rules may play a role in prediction and may be very useful to the decision maker [15]. The need for multi-label classification arises in such fields as bioinformatics, scene classification, and text categorization. Related works on multi-label classification application areas do not include curriculum management or education in general. Nevertheless, due to the conceptual overlapping of study courses, multi-label classification is appropriate here. It allows human refinement of classes [15].

Section III illustrates how inductive interactive learning can be used in the domain of education.

III. INTERACTIVE INDUCTIVE LEARNING FOR STUDY COURSE COMPARISON

This section illustrates how interactive inductive learning can be applied for learning outcomes based study course comparison which is mediated by standard competence framework.

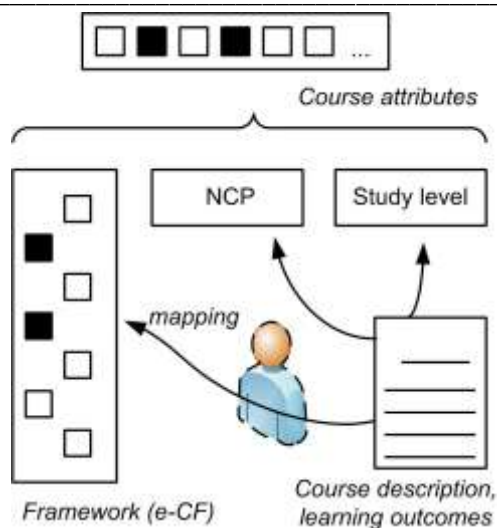


Fig. 1. Attribute extraction

A. Preparing for classification

While the courses of a study program may be viewed as knowledge classes where each course is relatively independent in terms of its title, running time, and other attributes, in terms of course contents, several study courses may overlap. To define the learning task for course comparison, the features describing the study courses must be chosen. Features have to be not only representative, but also available. The study course is an issue that does not naturally possess well defined attributes relevant for comparison of course contents.

Moreover, it is not always that education providers and trainers give detailed description of course contents [16]. However, learning outcomes usually are well described; therefore, they can be used as means for study course compatibility analysis. There are different ways how learning outcomes could be compared, e.g., manually, in group discussions, directly. In this paper indirect compatibility analysis is demonstrated, where course comparison or mapping is mediated by standard competence framework. Besides learning outcomes other accessible attributes can be involved in classification, namely, study level, number of credit points (NCP) for the course, a.o. Proposed innovative feature selection approach using EKD is discussed in more detail in Section V. It was introduced after evaluation of classification results achieved using only competences as domain features in previous experiments [16], which did not provide satisfactory results.

The European e-Competence Framework (e-CF) is chosen as a mediating competence framework. It is a European reference framework of ICT competences (see [17] for more details). The e-CF Framework is structured in four dimensions. These dimensions reflect different levels of business and human resource planning requirements. The target dimension in our approach is the second dimension which depicts e-Competences in general. E-CF has been chosen because it is one of the most popular frameworks and is oriented to learning outcomes that are important for course comparison.

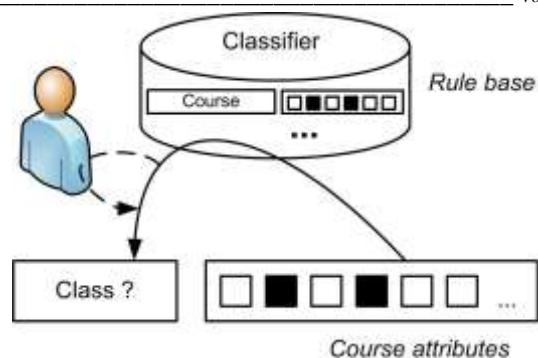


Fig. 2. Interactive inductive learning system for course comparison

B. Attribute extraction

The process of attribute extraction is carried out as follows (see Fig. 1). From available course descriptions human expert finds NCP and study level. From learning outcomes expert depicts correspondences to particular competences in the framework. Every study course thus obtains a vector of competences described in the framework. The value of a particular competence in the vector is *True* if the mapping from course description to this competence is made and *False* otherwise. Currently this task is executed manually, i.e., a human expert maps competences to the corresponding courses. This time-consuming work could be automated after available examples grow in number. From the point of view of automation, this is a text classification task where the section describing learning outcomes is the text to be classified in one or more classes (competences in the framework). Mappings done by the expert could serve as an example set which can be used to train the classifier. Automated text classification could help to extract learning outcomes from course descriptions easily. Adapting some automated classification method for this step is a subject of further research.

C. Classifier building and applying

The main stages of classifier forming and applying for study course comparison are as follows.

- 1) There are courses that are considered as standard (target courses); other courses are compared to them. Most likely they are courses from familiar study programs. Attributes for those courses are extracted (study level, list of e-CF competences corresponding to a particular course, number of credit points). For the target courses, expert's classification is the same as course name.
- 2) When all target courses are described and passed to the classifier, human expert should classify unfamiliar courses. Expert can decide that the unknown study course refers to more than one of target courses. The system receives course attributes and expert's classification and tries to find correspondences, and infer rules from provided examples.
- 3) When the classifier has seen enough human classified courses to make judgements itself, classification task of a new course (given as a set of attributes) can be passed to the system. If the classifier is able to find an appropriate rule in its rule base, decision on course

class (or classes) is made. If no rule can classify the course, a human is asked to classify it.

Such an approach leads to the development of study course comparison system that involves human decreasingly since it learns from human provided examples. The classifier will be taught to recognize only particular target courses; if other target courses are chosen and expert classification changes, the system should learn anew. This means that if the system is trained to make comparison against courses of one study program, it will not work correctly with other programs.

Fig. 2 shows summarized approach for course classification. In the beginning, the cycle starting with course descriptions and ending with classification of course is used to train the classifier and induce rules; afterwards the same cycle ensures semi-automatrical classification of new courses. In case the classifier cannot decide course membership, attributes of this course would be passed to a human expert to decide.

Section IV describes a real-life example of applying the interactive inductive learning approach to study course comparison.

IV. THE EXPERIMENTS

The aim of the experiments is to prove (1) that an inductive multi-label classification approach is suitable for study course comparison task and (2) that inductive learning accompanied with human expert performs even better. The rest of the section discusses tools used for classification, results with different attribute sets, demonstrates system application example and the rule base gained.

There is no wide range of tools providing classification for multi-label data. For this experiment *Mulan* is chosen [18]. *Mulan* is a Java library. It is built on top of *Weka* software [19]. *Weka* implements many learning algorithms and is popular among machine learning researchers and practitioners.

For the experiments small initial data set of 33 different courses with 16 class labels (target courses) was used as an example set. Each example is described with 34 attributes; 32 of them denote competences, one defines the number of credit points for the course and one describes the study level.

Two problem transformation methods suggested in [20] were used, namely, *Label Powerset* and *Binary Relevance* with underlying popular *C4.5* algorithm implemented in *Weka* as *J48*. None of them showed significantly better performance than another.

A. Results

In the first experiment results with data set including course competences only and data set with all available attributes was compared. The produced decision trees were very similar, but the size of the tree was smaller for the classifier which used additional attributes. For further experiments the full attribute set was used.

When the classifier was trained with 31 instances from 33, the rule base shown in Table II was obtained. *C4.5* algorithm has extracted rules from training examples. These rules now form a rule base of the classifier and will be used to compare new study courses. Rules are formed as a conjunction of

significant competences present or absent for the target course. For example, the first rule in Table II says that if a course does not give competences *IS and Business Strategy Alignment*, *Systems Architecture*, *Technology Watching*, and *Forecast Development*, but gives a competence in *Technical Publication Development* then it refers to one target course *Research Methods for Business Informatics*. Other competences are not defined.

To test the classifier and show how interactivity can help to achieve better performance, two instances with the following attributes are passed to the classifier:

1) *number of credit points: 6; study level: master studies; Design and Development = true; Education and Training Provision = true; Relationship Management = true; all other competences = false; Class= KnowledgeManagementSystems.*

TABLE II
RULE BASE OF CLASSIFIER

N.	Rule
1	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 0 AND Forecast Development = 0 AND Technical Publication Development = 1 THEN CLASS = ResearchMethodsForBusinessInformatics
2	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 0 AND Forecast Development = 0 AND Technical Publication Development = 0 THEN CLASS = QualityRiskAndSecurityTechnologies
3	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 0 AND Forecast Development = 1 AND Channel Management = 0 THEN CLASS = Entrepreneurship
4	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 0 AND Forecast Development = 1 AND Channel Management = 1 THEN CLASS = BusinessAnalytics AND SystemsTheory AND PortfolioManagementTechnologies
5	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 1 THEN CLASS = KnowledgeManagementSystems AND e-BusinessSolutions
6	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 1 THEN CLASS = ServiceScienceManagementAndEngineering AND e-BusinessSolutions AND BusinessAnalytics
7	IF IS and Business Strategy Alignment = 1 AND Service Level Management = 0 AND Application Design = 0 AND Purchasing = 0 THEN CLASS = BusinessAnalytics
8	IF IS and Business Strategy Alignment = 1 AND Service Level Management = 0 AND Application Design = 0 AND Purchasing = 1 THEN CLASS = EnterpriseArchitectureAndRequirements Engineering AND BusinessAnalytics AND Entrepreneurship AND PortfolioManagementTechnologies AND BusinessLaw AND BusinessCommunicationSkills
9	IF IS and Business Strategy Alignment = 1 AND Service Level Management = 0 AND Application Design = 1 AND Specification Creation=0 THEN CLASS = EnterpriseArchitectureAndRequirementsEngineering AND EnterpriseInformationTechnology ArchitectureApplicationsAndIntegration AND BusinessProcessManagementAndEngineering
10	IF IS and Business Strategy Alignment = 1 AND Service Level Management = 0 AND Application Design = 1 AND Specification Creation=1 THEN CLASS = ArtificialIntelligenceInBusiness
11	IF IS and Business Strategy Alignment = 1 AND Service Level Management = 1 THEN CLASS = ServiceScienceManagementAndEngineering

TABLE III
IMPROVED RULE BASE OF CLASSIFIER

N.	Rule
1	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 0 AND Technical Publication Development = 0 AND Channel Management = 0 AND Forecast Development = 0 THEN CLASS = KnowledgeManagementSystems
2	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 0 AND Technical Publication Development = 0 AND Channel Management = 0 AND Forecast Development = 1 THEN CLASS = Entrepreneurship
3	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 0 AND Technical Publication Development = 0 AND Channel Management = 1 THEN CLASS = BusinessAnalytics AND SystemsTheory AND PortfolioManagementTechnologies
4	IF IS and Business Strategy Alignment = 0 AND Systems Architecture = 0 AND Technology Watching = 0 AND Technical Publication Development = 1 THEN CLASS = ResearchMethodsForBusinessInformatics

2) number of credit points: 6; study level: master studies; Design and Development = true; all other competences = false; Class = KnowledgeManagementSystems.

None of the rules in the rule base (Table II) satisfies preconditions of the instances; therefore, they cannot be classified. If the system asks a human to classify the first instance, after the classifier has recognized its failure to assign the class, the human would give the class *Knowledge Management Systems* to the particular instance, according to his own knowledge. System would treat the human classified instance as a new training example and reapply the rule induction procedure (more details about human decision incorporation can be found in [21]). After rebuilding the classifier, rules one to four are changed. New rules acquired by the classifier are represented in Table III. The rest of the rule base remains the same. Modification of the rule base ensures the classifier's improvement through system-human interaction.

When the classifier receives the second instance, it is able to assign the right class to it, based on the rule one. It was not possible before the classifier got updated.

B. Discussion

Experiments proved the ability of the classifier to generalize from competences and to create rules describing regularities in them. The course level and the number of credit points so far did not play a significant role in classification, as the study courses did not differ much in these attributes. However, we cannot say that they are not important attributes; the classifier built without attributes *number of credit points* and *study level* was one rule longer (12 rules) than the classifier with these attributes (11 rules), therefore, ability to generalize depends also on these features.

The results of the experiment confirmed that human involvement in uncertain class assignment situations when the system tries to classify new courses itself helps not only to assign the right class labels to particular courses, but also improves the classifier, as the new training examples are very

important, especially while the training set is small. It has to be noted here that the rules are true for a particular data set; after providing other course examples they may change.

However, experiments marked out also several problems and shortcomings. Much more human-classified courses are needed for training to gain reliable predictions from the system. On the score of classifier accuracy, the available amount of data cannot bring significant results. The question of how many training examples are needed for the classifier to make its judgements trustworthy is of great importance. Persistent and invariable mapping from learning outcomes to e-CF competences turned out to be a vital factor in successful classifier building. Inaccurate learning data badly affects the classifier's ability to generalize.

V. RELATING EKD TO INTERACTIVE INDUCTIVE LEARNING

The previous section illustrated how interactive inductive learning helps to detect compatibility of study courses.

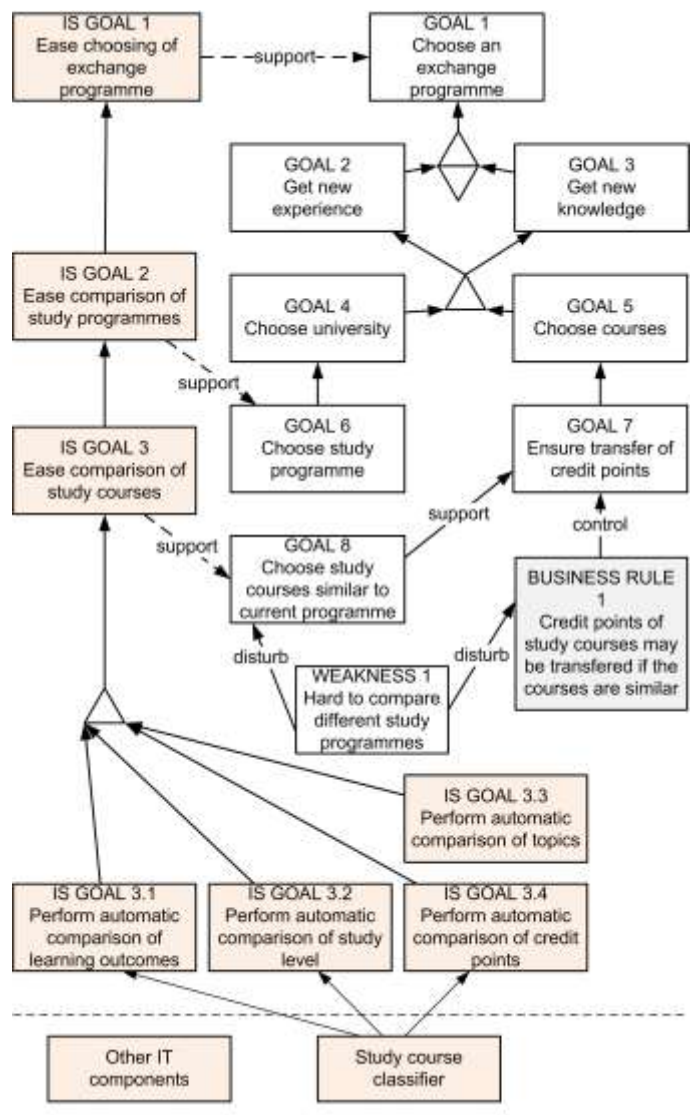


Fig. 3. Technological component model supporting goals

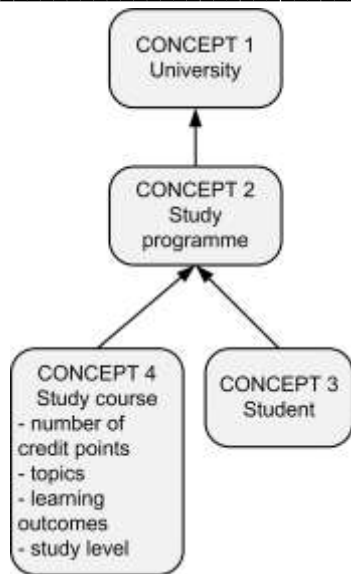


Fig. 4. Concept model

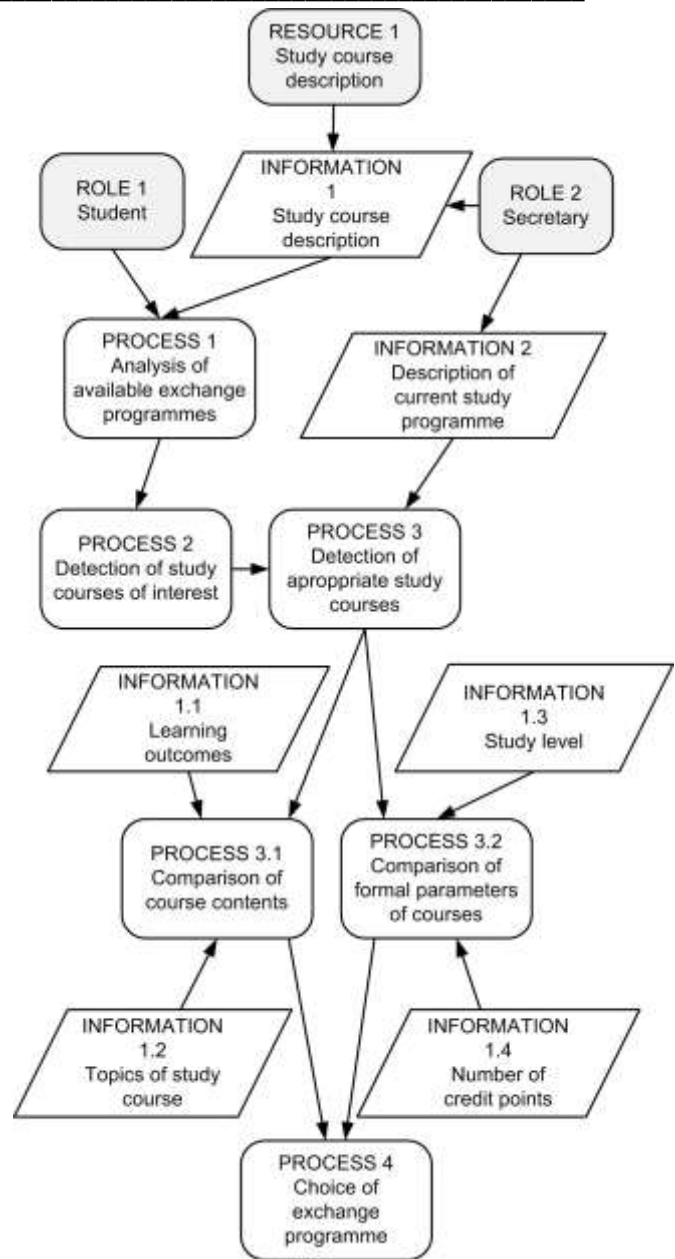


Fig. 6. Process model (simplified fragment)

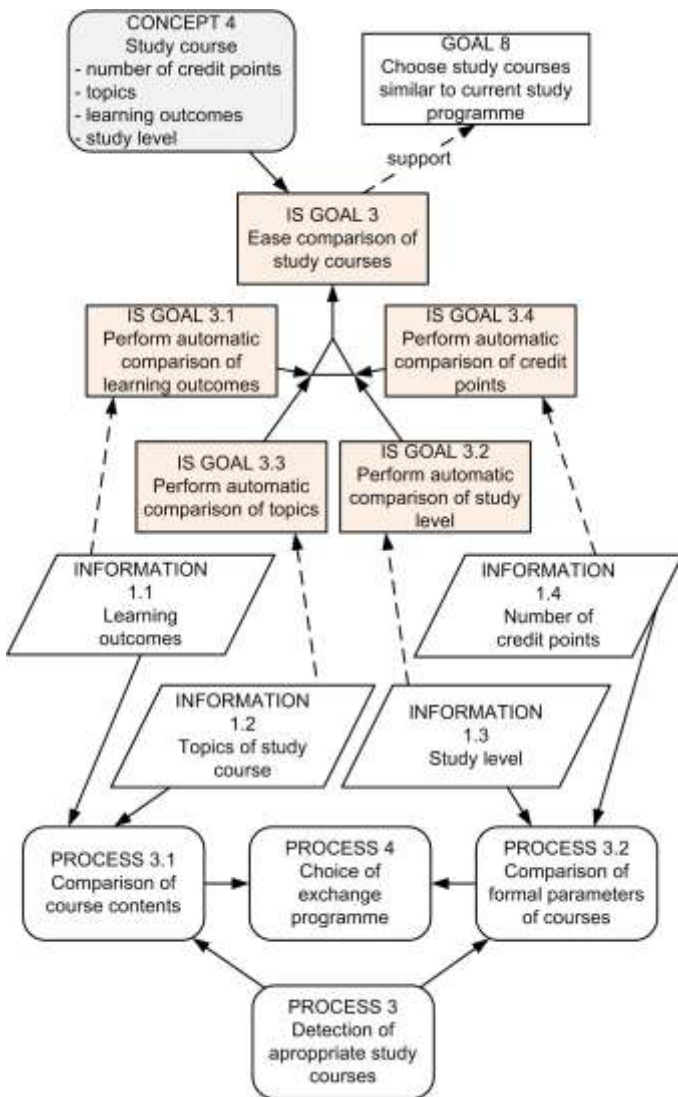


Fig. 5. Origins of IS Goals

Application of EKD [6] helps to detect different classification possibilities and to decide which of them to perform manually and for which to implement supporting interactive inductive learning system. EKD is based on the enterprise model that is a system of several sub-models such as Goals Model, Concepts Model, Requirements and Technological Component Model, Rules Model, Process Model, and Actors Model.

The relationship between the enterprise model and interactive inductive learning is illustrated for the student mobility management case where the student has to choose an appropriate exchange program. Fig. 3 depicts an excerpt from Goals Model and Requirements and Technological Component Model which supports goals depicted in the Goals Model. The approach described in Section III corresponds to IS Goals 3.1, 3.2, and 3.4. However, the enterprise model

points to additional comparison opportunity – IS Goal 3.3. This goal is hard to reach because of limited access to study topics in most of the study course descriptions. Therefore, study topics are not used as attributes in the proposed course comparison system. In case study topics are available, they can be used as additional information for manual comparison. The goals are related to the part of the Concepts Model which is reflected in Fig. 4, i.e., Concept 3. Concept 4 summarizes course attributes available in a particular situation. Course description attributes may change depending on educational institution, thus bringing in new changes in goals in the models. Some course attributes can be compared automatically, e.g., course level and number of credit points; learning outcomes have to be mapped to the competence framework for being compared automatically, but study topics are left outside the classifier. The choice of attributes is essential to resulting classifier as it was described in Section IV B.

Origins of IS Goals are represented in a more detailed way in Fig. 5 (information sets 1.1; 1.2; 1.3; and 1.4). These information sets are used in Process Model, part of which is represented in Fig. 6. Thus, the enterprise model shows that study course compatibility can be assessed on the basis of comparison of learning outcomes and comparison of other features of study courses. These features might be added to the classifier or assessed separately. IS goals in Fig. 3 show that for a given enterprise of student mobility management, comparison could be done at the level of study programmes or curricula as well. A new classifier could be built for this purpose; it would include the course comparison approach discussed in this paper as its sub-component. It can be seen that requirements for interactive inductive learning may come from any model utilized in EKD.

VI. CONCLUSIONS AND FUTURE WORK

The paper illustrated how the use of the enterprise model can support interactive inductive learning in the domain of education. It outlined a new approach to study course compatibility identification using interactive inductive learning.

One of the purposes of designing the system is saving time needed for student mobility management. To ensure that the system is appropriate for the domain of its use, the EKD methodology was applied to model problem domain and extract features of study courses that are relevant for their comparison. The experiments with the interactive inductive learning in the domain of education let to conclude the following:

- 1) The proposed classifier can help to identify study courses that most probably correspond to particular competences in the competence framework for which the algorithm is trained to relate study courses to competences. Analysis of the results of application of the algorithm to study courses of several study programs helps to see their competence coverage similarity and thus decide upon compatibility of the courses.

- 2) The spectrum of attributes included in the classifier impacts its performance.
- 3) Representation of educational domain by EKD models can help to identify and select attributes that are to be included in the classifier.
- 4) Inductive multi-label classification approach is suitable for study course comparison task.
- 5) Inductive learning accompanied with human expert performs even better than without it (see Section IV A.).

Development of the interactive inductive learning service model and its relationships to EKD models is a subject for further research. The method illustrated in this paper is an initial attempt to use interactive inductive learning in curriculum management. There are several issues to be considered in order to obtain even better results in classification and improve usability of the classifier. It might be possible to provide software tools for mapping. We also aim at incorporating different mapping approaches such as hierarchical mapping and mapping using different types of class inclusion relationships.

We will continue to improve interactive inductive learning system by considering the use of other inductive learning algorithms and tools. Further experiments will be performed involving a larger learning base and several inductive learning algorithms for comparison. The relationship between rules included in the inductive learning algorithm and rules in the enterprise model's Rules Model are to be investigated.

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and pattern recognition.



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Ilze Birzniece, Mārīte Kirikova. Interaktīva induktīvā apmācība: pielietojums izglītības jomā

Pieaugošais informācijas apjoms pasaulē ir veicinājis tādu automatisku datu apstrādes tehniku attīstību, kas spēj atvieglot cilvēka rutīnas darbu, apstrādājot lielus datu apjomus. Mašīnāpmācībā 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. Lai uzlabotu induktīvās apmācības sniegtos rezultātus, ir iespējams iesaistīt cilvēku to objektu klasificēšanā, kurus induktīvās apmācības izveidotais klasifikators nespēj klasificēt pats. Globalizācija sniedz iespēju iegūt izglītību vairākās izglītības iestādēs, tai pat laikā iegūstot grādu vienā mācību iestādē. Šis iespējas savukārt rada vajadzību salīdzināt pieejamās ārzemju studiju programmas ar tās mācību iestādes programmu, kur izsniedz izglītību apstipriņojo grādu. Tas ir nepieciešams, lai pārliecinātos, ka studijas ārpus pamatmācību iestādes atbilst izvēlētajai studiju programmai un iegūstamajam grādam. Katrs studiju priekšmets ir atšķirīgs no citiem pēc nosaukuma, apjoma un citiem parametriem. Tomēr satura ziņā daļa priekšmetu var pārklāties. Lai risinātu priekšmetu salīdzināšanas problēmu, tiek piedāvāts izmantot interaktīvu induktīvās apmācības sistēmu. Netiešajā studiju priekšmetu salīdzināšanā par raksturīgajām iezīmēm izvēlētas iegūstamās kompetences, studiju līmenis un priekšmeta apjoms kredītpunktos. Šie parametri kā būtiskākie studiju priekšmetus raksturojošie lielumi iegūti ar uzņēmuma zināšanu attīstīšanas metodi (Enterprise Knowledge Development — EKD). Mācību priekšmetos iegūstamās kompetences tiek attēlotas Eiropas e-kompetenču ietvarā (e-CF), veicot priekšmeta apraksta un sasniedzamo mācību rezultātu sasaisti ar ietvaru. Sākotnējie eksperimenti parāda, ka ar interaktīvas induktīvās apmācības palīdzību iegūtais klasifikators spēj likumu veidā vispārināt studiju priekšmetiem raksturīgākās kompetences un klasificēt jaunus studiju priekšmetus atbilstoši apgūtajam standartam.

Илзе Бирзни́це, Мари́те Кири́кова. Интерактивное индуктивное обучение: применение в сфере образования

Увеличивающийся объём информации в мире способствовал развитию автоматических техник обработки данных, которые способны облегчить рутинную работу человека по обработке больших объёмов данных. В машинном обучении используется широкий набор методов, однако преимущества методов индуктивного обучения проявляются в системах, где человек должен понимать ход принятия решения, а также впоследствии обрабатывать полученный результат. Чтобы улучшить результаты индуктивного обучения, можно привлечь человека для классификации тех объектов, которые созданный в ходе индуктивного обучения классификатор не может классифицировать самостоятельно. Глобализация даёт возможность обучаться в нескольких учебных заведениях одновременно, получая степень в основном учебном заведении. Эти возможности, в свою очередь, приводят к необходимости сравнить имеющиеся зарубежные программы обучения с программой того учебного заведения, которое выдаёт подтверждающую образование степень. Это необходимо, чтобы убедиться в том, что учёба вне основного учебного заведения соответствует выбранной программе обучения и получаемой степени. Каждый учебный предмет отличается от других по названию, объёму и другим параметрам. Однако в части содержания некоторые из предметов могут перекрываться. Чтобы решить проблему сравнения предметов, предлагается использовать интерактивную систему индуктивного обучения. Для косвенного сравнения предметов в качестве наиболее характерных признаков выбраны получаемые компетенции, уровень обучения и объём предмета в кредитных пунктах. Эти параметры как величины, наиболее характеризующие учебные предметы, получены с помощью метода развития знаний предприятия (EKD). Получаемые в рамках учебных предметов компетенции представлены в соответствии с Европейской квалификационной рамкой ИКТ-компетенций (e-CF), связывая описание предмета и получаемых результатов обучения с рамкой компетенций. Предварительные эксперименты показывают, что полученный с помощью интерактивного индуктивного обучения классификатор может в виде правил обобщить наиболее характерные для учебных предметов компетенции и классифицировать новые учебные предметы в соответствии с освоенным стандартом.