An Ontology-based and Case-based Reasoning supported Workplace Learning Approach

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Abstract. The support of workplace learning is increasingly relevant as the change in every form determines today's working world in the industry and public administrations alike. Adapting quickly to a new job, a new task or a new team is a significant challenge that must be dealt with ever faster. Workplace learning differs significantly from school learning as it is aligned with business goals. Our approach supports workplace learning by suggesting historical cases and providing recommendations of experts and learning resources. We utilize users' workplace environment, we consider their learning preferences, provide them with useful prior lessons, and compare required and acquired competencies to issue the best-suited recommendations. Our research work follows a Design Science Research strategy and is part of the European funded project Learn PAd. The recommender system introduced here is evaluated in an iterative manner, first by comparing it to previously elicited user requirements and then through practical application in a test process conducted by the project application partner.

Keywords: Workplace Learning, Ontology Supported Learning, Personalized Learning, Recommender System, Case-based Reasoning, Public Administration, Ontology-based Case-based Reasoning

1 INTRODUCTION

Change is given and an employee's working environment, his/her tasks and duties changes quickly and ever often. According to the US Bureau of Labour Statistics [1], “the median number of years that wage and salary workers had been with their current employer was 4.6 years in January 2014”. Already in 2012, Forbes has reported that according to a survey ninety-one percent of Millennials (born between 1977-1997) expect to stay in a job even for less than three years [2]. However, not only 'job hobbing' requires (workplace) learning but also taking over new responsibilities within an organisation. In a survey conducted by Accenture [3] 91 percent of the respondents consider the most successful employees to be those who can adapt to the changing workplace. As pointed out by Tynjälä [4] workplace learning is different to school learning as it is mostly informal in nature, as - for example - usually no formal curriculum or prescribed outcomes exist, the emphasis is on work and experiences, it is often performed collaboratively, and no distinction is made between knowledge and skills. In our approach, we aim to formalize workplace learning by defining learning goals that are related to business goals, objectives, and strategies. Competencies required to reach the learning goals and hence, the business goals, are determined and described in the job profiles respectively role profiles. From this, an employee's competence profile is derived in which the level of acquired competencies is reported, for example in an objective agreement. Collaborative learning is supported by using a wiki as a learning platform.

For implementation, we use a model driven approach [5]. That is, we extended existing meta models, e.g. standard notations like Business Process Model and Notation (BPMN) [6] and Business Motivation Model (BMM) [7] or created new ones, based on standards (for example, the Competency Meta Model is deduced from the European Qualifications Framework (EQF) [8]) to model collaborative workplace learning centred on business processes and their context. We then transformed the models and relations between them into an ontological representation for machine execution. We also transformed these models and relations into wiki pages and links.

With this approach we can integrate workplace learning deeply into daily business, i.e. we consider a learner's context regarding tasks he/she has to perform in business processes combined with organizational knowledge about his/her position in the organisation and his/her working experience. Based on this context information, appropriate learning objects and learning material are determined and recommended to the learner according to his/her learning preferences.

Additionally, we complemented our approach with ontology-based case-based reasoning to identify and recommend the content of similar case from a case repository. The application domain is Public Administration (PA) as this sector must support extremely complex processes to provide services to citizens and companies. According to our business partner, today it needs up to two years of learning to become fully operational. These highly complex or knowledge-intensive processes demand the utilisation of an approach the do not require a prior generalisation of training data and previous acquisition of rules. Since such a rule acquisition task is difficult to manage for knowledge-intensive processes, we suggest in this paper the use of case-based reasoning, which requires a later manual or semi-automatic generalisation.

Workplaces in the industry and public administrations lack effective and not too expensive approaches that support workers in learning how to perform daily tasks at best. Unfortunately, no significant attention has been paid in the literature concerning integrated learning approaches in public administrations. Therefore, an ontology-based and case-based reasoning approach is needed that supports a collaborative workplace learning platform. This work is part of the European funded project Learn PAd (cf. http://www.learnpad.eu). The applied research method is Design Science

Research [9] complemented by the approach of Grüninger & Fox [10] for ontology design and evaluation. In Learn PAd a learning platform is created to support Public Administration (PA) with workplace learning. PA's can access the platform via a wiki interface (see Xwiki, http://www.xwiki.com/en/). The interface consists of two parts: left and right (see **Fig. 1**). The left part contains the properties of a process task as well as data input and output. The right part is what we call the recommendation panel where context-related and personalized recommendations are provided.

We assess our approach in an iterative process in the context of the overall Learn PAd project evaluation. A first evaluation was accomplished recently.

The paper at hand is structured as follows: In section two we give an overview of related work. Then we introduce an application scenario to illustrate our approach (section three). In section four we provide a specification of the recommender system, followed by a description of its implementation (section five). First iterations of evaluation are described in section six. We conclude in section seven.

Fig. 1. Recommender Interface

2 Literature Review

In our literature review we consider research on five aspects that are most relevant to our work: recommenders, competency frameworks, imparting knowledge, learning styles and ontology-based case-based reasoning.

2.1 Recommenders

There is today a broad agreement among researchers that e-learning content should adapt to the learner’s context and that learners should be guided through learning content based on such context. The recommendation of learning objects can be regarded as a special case of business-process oriented knowledge management. A wide array of recommenders have been proposed, all of which aim at recommending the next learning activity – very often interaction with a learning object – to a learner who is currently engaged with an e-learning system.

Such recommendations can be based purely on a history of the learner activities within the same or previous sessions. Some approaches use content-based filtering; they recommended learning items that have a content similar to that of learning objects in the learner's current session [11, 12]. Others are based on collaborative filtering or association rule mining [12, 13], i.e. they recommend objects that other learners (with similar interests) used together with the objects from the current history. A survey of further approaches of this kind can be found in Sikka et al. [14].

Other researchers claim that – besides the current activities of the learner – additional information is needed to make useful recommendations:

- A profile of the learner including existing knowledge or skill levels, preferred learning style, and current learning goal to enable proper personalization of recommendations [15, 16].
- Meta information about the learning objects including required previous knowledge, content type and interactivity level to match them against the learner [15, 16].
- Information about the role of the learner and his/her position in the organization [15, 17, 18].
- Explicit information about the work context of the learner regarding a currently e.g. executed task or business process [15, 17, 18].

The approaches mentioned above all use ontologies to model the required information and rely on the computation of similarities between a learner's profile (and possibly work context) and the metadata provided with learning objects. Yu et al. [16] additionally use the dependencies between learning objects to create a "learning path" through all recommended learning objects.

Our approach is similar to the one in Schmidt & Winterhalter [15], which relies on semantic modelling as described in Abecker et al. [18]. We propose to model and use the same kind of information – i.e. we believe that all of the above-listed information is indeed necessary to make didactically useful recommendations. We take that approach further by concretising the meta models and ontologies required for modelling that information and by proposing concrete matching procedures.

2.2 Competency Frameworks

In order to develop an appropriate competency model we carefully studied frameworks related to competency, like the RDCEO (The Reusable Definition of Competency or Educational Objective), TRACE (TRAnsparent Competences in Europe), DeSeCo (The Definition and Selection of Competencies) [19], DIGCOMP (Developing and Understanding Digital Competence in Europe) [20], e-CF [21], Bloom's Taxonomy [22] and EQF (The European Qualifications Framework) [8].

Since our application partner in the Learn PAd project already uses the EQF framework, we decided to base the competency model on it. The European Qualifications Framework (EQF) is envisaged as a meta-framework that allows positioning and comparing qualifications. It consists of eight reference levels which are described regarding learning outcomes: knowledge, skills, and competences. For instance EQF level 4 for knowledge is "Factual and theoretical knowledge in broad contexts within a field of work or study"; for skill is "A range of cognitive and practical skills required to generate solutions to specific problems in a field of work or study"; and finally for competence is "Exercise self-management within the guidelines of work or study contexts that are usually predictable, but are subject to change; supervise the routine work of others, taking some responsibility for the evaluation and improvement of work or study activities" [8].

2.3 Imparting of Knowledge

One of the most important aspects imparting knowledge is the notion of a Zone of Proximal Development (ZPD), introduced by Vygotsky [23]. He defined the zone of proximal development (ZPD) as "the distance between the actual developmental level as determined by independent problem-solving and the level of potential development as determined through problem-solving under adult guidance or in collaboration with more capable peers" [23, p.86]. Vygotsky proofed that when a learner is in the ZPD for a particular task, he can achieve it if appropriate assistance is provided.

Another important aspect imparting knowledge is scaffolding. Scaffolding was coined by Wood et al. [24] whose conceptualization of scaffolding was consistent with Vygotsky's model of instruction and emphasizes the teacher's role as a more knowledgeable learner to help learners to solve problem-oriented tasks [25].

Quintana et al. stated, "the process by which a teacher or more knowledgeable peer provides assistance that enables learners to succeed in problems that would otherwise be too difficult" [26]. However, in workplace learning experts' involvement is not always feasible. As shown by Billett [27, p.53] one limitation of workplaces as learning environments is the "reluctance by experts to guide and provide close interactions with learners". Hence, other learning aids - i.e. learning material created with certain didactic considerations in mind, is to be recommended to support learners.

A rather young learning theory that also builds on the ZPD idea and that takes into account the role of technology for learning is the so-called connectivism [28]. Connectivism postulates that learning occurs when connections are made between nodes in a learner's network - where a node can be anything ranging from a piece of knowledge in the learner's mind to a digital artefact or another person. This implies that new knowledge must be connected to existing knowledge or experiences – which can be understood as a concretization of the ZPD and that such connection can be mediated by links in the digital environment.

2.4 Learning Styles

The theory of learning styles describes ways in which learning can be different between individuals and claims that hence different ways of supporting individual learning must be developed and adapted to a learner's individual preferences.

The Dunn & Dunn learning style model [29] describes several elements of learning styles: the environmental domain, the emotional domain, the sociological domain, the physiological domain and the psychological domain. People deal with information and ideas in different ways because of their preference. These learning styles influence the achievement of the learners. Using the right combination of learning preferences will help the learners to achieve their learning goals.

2.5 Case-based Reasoning

According to Leake [30], case-based reasoning (CBR) can be seen as "reasoning by remembering". It is a technology-independent methodology [31] for humans and information systems. CBR is "[...] the ways people use cases to solve problems and the ways [people] can make machines use them" [32, p.27].

With the use of CBR, one can utilise the experience (a lesson or case content) of previously situations by characterising the current situation and by using this characterisation to retrieve prior similar situations (former cases comprising of characterisation and content) from a case repository [33–35]. The retrieve phase is the first of the four major phases of the CBR cycle of Aamodt and Plaza [33], which comprises of the following four *Rs*:

1. *Retrieve* similar case(s) from the case repository.
2. *Reuse* the lesson from the retrieved case(s) as the suggested solution for the current situation.
3. *Revise* the current case after evaluating it in the current situation.
4. *Retain* the current case in the case repository.

In structural CBR, which is one of three major CBR approaches [36], the cases are described using a certain vocabulary or domain model [34]. However, such a model needs to be acquired ex-ante and can lead to an acquisition bottleneck. Several approaches, therefore, suggest the use of ontologies [37–39] or, more specific, the use of enterprise ontologies, which provide a CBR system with enterprise-specific knowledge [35, 40]. “The more knowledge is embedded into the system, the more effective [it] is expected to be” [41, p.54]. However, enterprise ontologies need to be created beforehand, and this can root in a knowledge bottleneck too. Therefore, several approaches [35, 40, 42–44] suggest the reuse of enterprise architecture descriptions when creating an enterprise ontology. Since architecture descriptions are descriptions of "[...] enterprise’s organisational structure, business processes, information systems, and infrastructure" [45, p.3], the architecture descriptions are a solid source of enterprise-specific models and vocabulary. CBR systems that are utilising an ontology-based knowledge container, called ontology-based case-based reasoning (OBCBR) systems, "[...] can take advantage of this domain knowledge and obtain more accurate results" [41, p.54]. Several approaches, such as jCOLIBRI [46], myCBR [47], COBRA [48] and ICEBERG [35] and other [49, 50] combine ontologies and CBR.

3 Application Scenario

The application scenario was developed based on a real case and as a result of several interviews and workshops conducted with representatives of our application partner in Italy, the Marche Region. The application scenario provides all information needed to instantiate all kinds of meta model relevant for workplace learning, i.e. process models, business motivation model, organisational model, document model and competency model. We also introduced two personas: Barnaby, a PA officer who joined the

Public Administration of Monti Azzurri not long ago; and Susan, an entrepreneur who requests a service from the PA.

Our illustration focusses on complex business process tasks that Barnaby performs and will show what Barnaby should learn and how our approach supports him.

The business process in question is called "Titolo Unico" and aims at providing permissions to activity requests of citizens, e.g. start a business, restructuring or extending a commercial location. Depending on the case, the related process can get rather complex. The most challenging tasks are as follows:

1. Assessing citizen's application form of an activity request. This includes the aspect of dealing with mistakes occurring in a form (e.g. declarations that are in contrast to each other or missing documents that require further material from the citizen, leading to time delays).
2. Involving appropriate organizational units (i.e. PA offices and/or private parties) for providing consensus on the activity request.
3. Arranging a service-conference meeting. This is a meeting held if the involved organizational units (a.k.a. third parties) do not reach a common agreement, or someone does not respond to the opinion request. It includes the behaviour of involved parties (e.g. did or did not attend the service conference and did or did not reply to a PA officer request within a given time).

Performing these activities while complying with related time constraints and taking right follow-up decisions is of crucial importance for successfully delivering the service. The two ingredients that enable the PA officer coping with such complexity are a comprehensive knowledge of the Italian law (i.e. national, regional, provincial and municipal norms and regulations) and deep work experience in the field. The latter applies mainly to the second activity on the above list, i.e. involving the appropriate organizational units. In fact, in this task the PA officer deals with various PAs that differ from the number of organizational units and the degree of specialization, i.e. PAs of the major cities (e.g. Rome or Florence) embeds many more organizational units and more ramified specializations than smaller cities (e.g. Ancona or Macerata). Additionally, in small realities (e.g. towns like Amandola, Sarnano and San Ginesio) a PA spans several municipalities, providing services together. Addressing the appropriate organisational units would be a mission impossible for an unexperienced PA officer. Conversely, a skilled PA officer knows the Italian law, the structure of the PA to be involved and the responsible officers in the related organisational units. Additionally, establishing a direct contact with responsible officers speeds up the execution of tasks (e.g. quicker responses to requests and less bureaucracy). Therefore, we consider this knowledge - although informal - highly relevant.

Finally, both accepted activity requests and reasons for the rejected ones help to improve the acceptance rate of next activity requests. Hence, this knowledge is also taken into account.

In the follow subsections we are going to introduce the three kinds of learning support Barnaby receives to overcome the described complexity, i.e. recommending experts, recommending learning resources and recommending historical cases.

3.1 Learning Support

In our application scenario, the entrepreneur Susan requests approval of building a chalet on the lake of Caccamo, which belongs to the municipality of Serrapetrona, which is in the province of Macerata, Italy. Susan uses the application form provided at the web-site of the PA, and we assume that she filled it out correctly.

By submitting the form, the business process at the PA of Monti Azzurri was started. The PA officer Barnaby took over the task to assess the form. Due to his little experience, Barnaby needs support to identify all the possible mistakes and/or missing documents. The LearnPAd system supports Barnaby using *historical cases*.

Recommending historical cases

The LearnPAd system applies the Case-Based-Reasoning approach to retrieve the most similar historical cases managed in all PAs. The specification of the approach will be described in the next section. Barnaby looks at the recommendation panel (see right-hand side of Fig. 1), which shows the case entitled *"Building a chalet in a beach area of Senigallia"* as the most similar case successfully managed from the PA Senigallia. Among other aspects, the retrieved case contains the "lesson learned" section from which Barnaby learns how to avoid potential missing documents and misinterpretation of law articles. Barnaby applies this useful information to accomplish the assessment of the current application form.

Next, based on the type of request specific actions are to be taken. In our case the type of request is "receptive tourism" and Barnaby knows this type always requires the authorization of the municipality according to the Italian law (norm 9 of 2006). However, Barnaby does not know the municipality of Serrapetrona and he is not sure of which organisational units should be involved. He needs an expert to advise him.

Recommending Experts

Barnaby enters the Learn PAd system, moves to the task "Identify Organisational Units" he has to perform and checks on the recommendation panel for help (see the right-hand side of **Fig. 1**). In the panel contact details of two experts – Sarah Brown and Laura Cruciani - are displayed. Sarah is a former PA officer of Monti Azzurri who now works for the municipality of Sarnano. The recommendation system still considers Sarah as an expert as she dealt with many cases concerning the municipality of Serrapetrona. Laura, is the boss of Barnaby, working for the PA of Monti Azzurri for many years.

Instead of searching internal phone books, asking around or applying the trial-and-error method Barnaby can contact one of the experts, who will suggest which organisational units to involve and to which law article it may refer. Additionally, the contact details of the personnel could also be provided to start establishing a not too formal business relationship.

Recommending Learning Resources

After Barnaby got advice which organisational units to involve, he sends requests to obtain the opinion on the case of the involved parties. Responses are expected within 30 days.

However, Barnaby receives answers in time from all but one of the parties. Now he needs help in how dealing with this situation. The Learn PAd system has a section in the recommendation panel that refers to learning objects and learning material (see **Fig. 1**). All models represented in the wiki are considered learning objects since the learner needs to get familiar not only with a process, its structure and tasks but also with the involved roles, organizational units, business documents, IT systems and so on. For differentiation we call dedicated technical books, tutorials, learning audio and video file and 'learning material'.

Thus, Barnaby checks on the learning material provided by the Learn PAd system. As recommendations in Learn PAd are context-sensitive and personalized the ZPD of a learner is considered. More in detail, Barnaby has an acquired competency EQF level of 3 in “Manage Specific Admin Procedure”. Learning material recommended in Learn PAd is also related to competencies it fosters.

In our example the book “Regulation of Titolo Unico” - is related to the same competence (“Manage Specific Admin Procedure”) but classified with level 4. The difference of 1 between the competency levels is considered conform to the ZPD of the learner. Since reading books falls within Barnaby’s preferences (preferences of PA officers are also made explicit in the model), in the book “Regulation of Titolo Unico”, Barnaby learns that if an organisational unit does respond, the “Silence and Consensus” procedure can be applied, i.e. it is assumed that the not responding partner approves the request of the entrepreneur. Since no further challenge comes to light, Barnaby finishes the assessment of the application and finally sends the approval to Susan for realizing her chalet on the lake of Caccamo.

4 Recommender System Specification

We learned from Vygotsky [23] and others that mentoring is very successful in supporting individual learning. However, particularly in workplace learning, experts might be too busy to provide the wishful support and spending their time with mentoring is simply too costly. Hence, an efficient solution is needed that provides a) alternatives, and b) guides to experts most capable of giving advice with respect to expert knowledge but also regarding the Zone of Proximal Development (ZPD) of the learner.

In our approach for recommending relevant information supporting the user in learning we consider three modes of learning: simulation (in a simulation environment a learner can simulate to perform a business process task), browsing (a user can view and navigate through wiki pages, represent his/her business environment like business process, tasks, organisational charts, related documents, etc.), and *execution* mode (using the wiki as a front end to perform a business service; often called learning by doing).

Furthermore, we differentiate between learning objects, learning material, experts and historical cases. As all Wiki articles correlate one-to-one to model elements, they are regarded as learning objects related to these model elements. Learning material is information dedicated to learning, for example (training) books, audio, and video files. Simulation and browsing are considered as interactive learning material.

Besides the characteristics of the wiki content (derived from the meta-model and the models), the recommender ontology also represents characteristics of the learning material as the EQF level of knowledge that is addressed. Furthermore, the ontology contains profiles of the learner, i.e. the workers in the PA, including his/her EQF specification, learning preferences and individual learning goals. With this holistic view on learners, their working environment, and organizational network it is possible to identify relevant learning objects, learning material and experts, appropriate for the ZPD of the learner and according to her learning style.

Most recommendations rely on rules. The left side of these rules (precondition) is defined regarding the learner's context - i.e. his/her required and acquired competencies (including levels) and learning style, as well as the context and application data of the currently executed business process. The right side of rules (consequence) contains the recommended material.

4.1 Basis for Recommendations

We start from the premise that in an organisation business goals and objectives are defined. They can be modelled in a Business Motivation Model BMM [7]. We extended the BMM meta model by introducing learning goals as new Course of Action. Learning goals can be related to business goals and strategies that support them. To achieve a learning goal certain competencies are needed. Note, that we use the term competency to summarize the three learning outcomes (knowledge, skill, competence) defined in EQF. Hence, learning goals defined in the BMM are related to the Competency Model in which competencies are described according to EQF including their levels (1-8).

We further assume that competency profiles are set-up for organisational units or roles to specify a set of competencies *required* by this entity. We also maintain competency profiles of employees which contain the acquired set of competencies. The difference between the required competencies, of a role and the acquired competencies of a person who has this role, determines the individual learning goal.

In addition, we can model specific competencies needed for example to perform certain tasks and hence, related to an extended process model. In this manner we can identify the knowledge gap, a learner has, the learning goals he/she is supposed to meet and his/her learning preference that is also captured in the learner's competency profile.

We finally assume that while a knowledge worker is handling a certain case (i.e. an instance of a business process), we have information about the task-related and case-related context. This comprises information about the current task the user is working on and decisions that have been taken in previous tasks. In addition, it implies that we have knowledge about the case and the application data that define it – in the case of the Titolo Unico process introduced in Section 2.5, this refers to the filled-in forms that the applicants submit to the SUAP office and on which Barnaby needs to decide.

Depending on the learning mode, recommendations differ in range. The more is known about the learner's working context, the better (filtered) the recommendations. Thus, most valuable recommendations can be provided in the execution mode. Here the recommender system knows exactly what task a learner is about to perform, what tasks are already done, what decisions have been taken during the business process so far and what application data is relevant. In best case within the simulation, such context information can be 'faked', i.e. instead of real data fictional data is used but the same kind of recommendations can be provided. A less accurate recommendation can be made within the browsing mode as the learner is free to navigate within one or more processes. Hence, no information is available about former actions and application data.

In the following, we are going to introduce three examples of how recommendations are determined with respect to experts, learning material and historical cases.

4.2 Recommending Experts

The difficulty in recommending experts lies in identifying the appropriate expert. Obviously, the choice of an expert depends on the work situation - and hence the knowledge required - as well as on the level of knowledge of the learner and possibly existing relationships between the learner and the expert. We consider three ways to determine experts:

1. line managers from the same organisation the learner belongs to
2. colleagues having (had) the same role as the learner but having executed the very task several times
3. persons having the same role as the learner but belonging to another PA

In the following the recommendation of an experienced colleague is described in detail. As mentioned above for building the recommender we follow the approach of Grüninger & Fox [10] for ontology design and evaluation.

Thus, in the following the informal competency question (CQ) is provided first, followed then by its transformation into an SPARQL query.

Informal competency question

Given a user logged into the Learn PAd system and the role this user has in a task and some constraints regarding task (e.g. the task a performer is about to execute) and work experience (e.g. a performer’s work experience), what internal experts can be recommended?

- *rationale*: the answer is used to recommend experts from the same organisation that executed the tasks most often.
- *decomposition*: the name of the user, the user is an actor, an actor has a role in the task, the role is assigned to more than one performer, the performer has task log.

Formal competency question (SPARQL query)

```
SELECT  ?experiencedPerformerName ?email WHERE
 { { SELECT  ?experiencedPerformer (COUNT(?executedTaskInstance) AS ?count)
     WHERE
     { ?taskInstance rdf:type bpmn:Task .
       ?executedTaskInstance rdf:type ?taskInstance .
       ?executedTaskInstance emo:activityIsPerformedByPerformer ?experiencedPerformer .
       ?currentPerformer emo:performerHasEmailAddress "barnaby.barnes@fhnw.ch"
       FILTER ( ?currentPerformer != ?experiencedPerformer )
     }
     GROUP BY ?experiencedPerformer
 }
  ?experiencedPerformer rdfs:label ?experiencedPerformerName .
  ?experiencedPerformer emo:performerRepresentsPerson ?experiencedPerformerBusinessActor
  OPTIONAL
  { ?experiencedPerformerBusinessActor foaf:mbox ?email}
 } ORDER BY DESC(?count) LIMIT 1
```

The result of the query is a colleague of the performer, working in the same organisation, having the same role and great work experience in the tasks the performer is about to execute. In the recommendation panel, the name and contact details are provided.

4.3 Recommending Learning Material

For recommending appropriate learning materials, the zone of proximal development of a learner must be considered. That is, the level of competency that the learning material fosters should be reasonably higher than the learner’s current level of this competency (cf. application scenario described above). Furthermore, the learning material should support the learner's preferred style as, for example, the learning material that matches his/her preferred learning style is listed on top of the list and the link to it is presented in bold characters. It is also possible to completely filter out learning material that doesn’t meet a learner’s learning style.

Informal competency question

Given a user logged into the Learn PAd system and her learning style and some constraints regarding competencies (e.g. acquired and required, i.e. fostered competencies and their level), what information material is recommended?

- *rationale*: the answer is used to provide learning material (i.e. links to documents, video files, simulation) that are relevant to the learner, i.e. fosters one or more competencies she has to improve and the level of the fostered competency is exactly one level higher than the level of the acquired competency.
- *decomposition*: the name of the user, the user is an actor, an actor has a profile, the profile contains acquired competencies and their level and the user’s learning style, learning the material, learning material fosters one or more competency at a certain level suitable for a certain learning style.

Formal competency question (SPARQL query)

```
SELECT  ?learningMaterialTitle ?learningMaterialType ?learningMaterialURI WHERE
 { { SELECT  ?nextCompetencyLevelNumber ?aquiredCompetencyLabel ?learningStyle
     WHERE
     { ?competencyProfile emo:competencyProfileIsAquiredByPerformer ?performer .
       ?competencyProfile cmm:competencyProfileContainsCompetencySet ?aquiredCompetencySet .
       ?aquiredCompetency cmm:competencyBelongsToCompetencySet ?aquiredCompetencySet .
       ?aquiredCompetency cmm:competencyHasLevel ?competencyLevelNumber .
       ?aquiredCompetency rdfs:label ?aquiredCompetencyLabel
       BIND(( ?competencyLevelNumber + 1 ) AS ?nextCompetencyLevelNumber)
        ?competencyProfile lpd:competencyProfilePrefersLearningStyle ?learningStyle
       }
   }
   ?nextCompetency cmm:competencyHasLevel ?nextCompetencyLevelNumber .
   ?nextCompetency rdfs:label ?aquiredCompetencyLabel .
   ?nextCompetency lpd:proposedLearningDocument ?learningDocument .
   ?learningDocument elements:documentHasType ?documentType .
   ?learningStyle lpd:learningStyleBelongsToDocumentType ?documentType .
   ?learningDocument emo:documentRepresentsdocument ?foafDocument .
   ?foafDocument elements:documentHasTitle ?learningMaterialTitle .
   ?foafDocument eo:documentHasStorage ?documentNode
   OPTIONAL
   { ?documentNode lpd:xwikiPageRepresentsNode ?learningMaterialURI}
   OPTIONAL
   { NOT EXISTS
     { ?documentNode lpd:xwikiPageRepresentsNode ?learningMaterialURI .
       ?foafDocument elements:documentHasSource ?learningMaterialURI
     }
   }

 }
```

After giving two detailed examples of how we build recommendations we describe the technical implementation of our approach.

4.4 Recommending historical cases

As already mentioned, the LearnPad system platform retrieves similar historical cases by implementing the CBR approach. As we saw in chapter 2.5, this approach draws upon existing research, in particular on the approach by Martin et al. [51]. The adopted CBR approach makes use of ontology for case retrieval and similarity determination, i.e. OBCBR (see the second part of chapter 2.5). Our already existing LearnPAd ontology was extended with concepts representing characterisation of cases. For space reasons, we show a limited number of both case characterisation concepts in Table 1 and case content elements in Table 2.

Table 1. Case Characterisation

Concepts	**Descriptions**
Applicant	A person who submitted the application.
Application type	Application type can relate to new productive systems (i.e. realization, (de)localization) or modification of existing ones (i.e. restructuring, transformation, reconversion, expansion, or quitting an activity).
ATECO	ATECO is an Italian standard classification of economic activities issued by the National Institute of Statistics (ISTAT) –

	http://www.istat.it/it/archivio/17888 available in Italian only)
Zone	A zone can span one or more cities, provinces and regions, e.g. the National Park of Monti Sibillini located across the two regions Marche and Umbria, encompassing several provinces and cities.
…	…

Table 2. Case Content

Content Element	**Content Manifestation**
Case Folder	Documents created, used and/or updated throughout the Titolo Unico process
	Reports/notes about decisions, i.e. accepted or rejected application and explanation
	Descriptions of a lesson learned, i.e. missing documents and misinterpretation of law articles.
	…

While case characterizations are metadata that describe cases, case content relates to information used to process a case, e.g. documents or links to external information sources. Table 2 provides the content element and its manifestation, i.e. the case folder as a pool containing information produced during case execution.

Extending the LearnPAd ontology with the case characterization concepts allows inferring similar cases. This reflects the first phase of the CBR cycle in which a query case is compared to historical cases (see Fig. 2) [35].

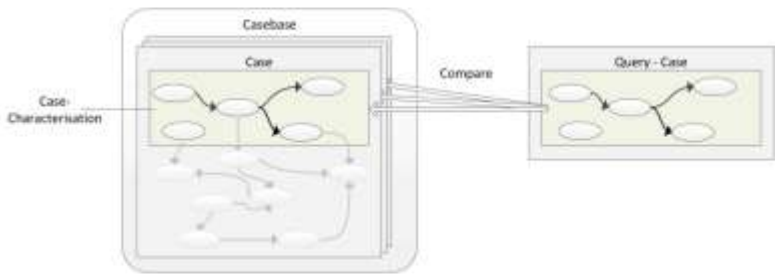


Fig. 2. Comparison of a query case with historical cases [35]

Similarity Model

To retrieve similar cases, similarity measures were applied. We consider two types of measures: global similarity measures, which are defined on the level of cases, and local similarity measures, which are defined on the level of attributes. The global similarity measure provides a way to aggregate all the local similarity values into one value. For our application scenario, case characterizations are mostly simple attribute-value pairs – hence, the global similarity measure can be a simple weighted average of local similarities. However, for other scenarios where case characterizations are more complex, more sophisticated functions can be used [52].

Regarding local similarity, applied functions depend on the attribute type. For string attributes (i.e. free text to be entered by the user), we adopted string similarity measures such as the *Levenshtein* string edit distance (which is the minimal number of edit operations when transforming one string to another) or SOFTFIDF*JaroWinkler* similarity [53]. The latter works well with names or text fields that consist of several words, which might be syntactically arranged in different ways without impacting semantic similarity. For categorical attributes where possible values are taken from the predefined list, but not structured in a particular way, we used a simple equality (corresponding to a similarity of 1) or inequality (similarity 0) of attribute values. Our application scenario addressed two additional relevant attribute types - *Categorical attributes with taxonomic value range* and *Categorical attributes which can take more than one value.*

- *Categorical attributes with taxonomic value range:* those attribute values structured hierarchically, e.g. via a taxonomy like in a tree structure. Among the existing approaches that define local similarity measures, we followed the reasoning of Bergmann [34]. Bergmann proposed to manually assign a similarity value to each inner node of the tree-based on expert experience. This approach overcomes the disadvantage of commonly adopted path length methods where nodes in deeper tree branches are more dissimilar to other branches. In Bergmann approach, the similarity of two leaf nodes is the value that is assigned to the lowest common parent node of the two leaves – or 1 if the values are equal. As an example, let's consider the taxonomic structure of the attribute "Application Type" and its value range, represented in Fig. 3. The rationale is that e.g. the introduction of a new business – even if it is not the same sub-type – is more similar to another new business than to a modification of an existing business. Hence, we defined:
  - sim(Localization, Realization) = 0.8 > 0 = sim(Localization, Restructuring).

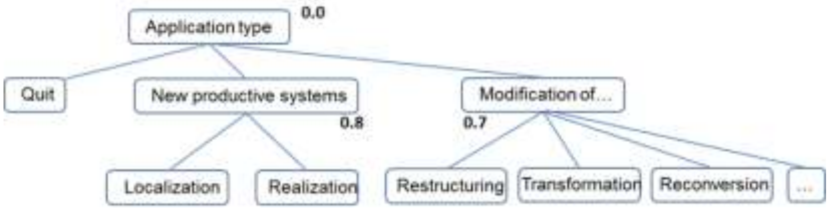


Fig. 3. Taxonomy with similarity values assigned to inner nodes

Categorical attributes which can take more than one value: there exists a *1:n* relationship between a case and the attribute, i.e. the case can be associated with more than one value of the attribute. We rely on our research [52], which is inspired by retrieval functions in information retrieval. The main idea is that a historical case should not be "punished" for having attribute values that are not shared with the new case (which we call the "query case"). As long as the values of the historical case match values of the query case, its additional values are neglected. For example, consider the two historical cases C1 and C2 and its attribute “zone”. Value for “zone” in C1 is “beach area”, and in C2 “Beach area” and “national park”. If a civil servant wants to find cases that are similar to a new business which is located in a “beach area” (Q1), we argue that both C1 and C2 should be equally similar to Q1 because both share the value of the zone attribute (“beach area”). However, in case a civil servant wants to find cases in which a new business is located in a “beach area” and in a “national park” (Q2), only C2 should be provided as it covers more relevant aspects than C1.

The property of asymmetry of similarity is useful especially in cases where initial case characterisations (queries) are incomplete. In our application domain, the PA officer enters attribute values while performing the process. At the beginning of the process, only a few attribute values might be available whereas in the end all might be entered. Hence, asymmetry is useful for that domain, but not ensured by most similarity measures that are traditionally used in CBR.

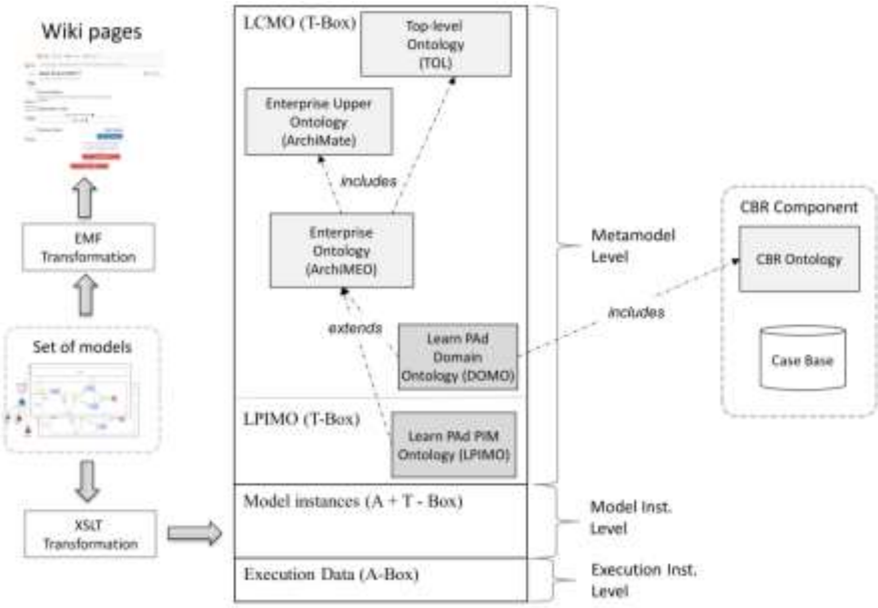
5 Recommender System Implementation

The recommender system is an integrated part of the Learn PAd system platform and incorporates mainly the modelling environments, the transformation component, the learning platform’s Wiki frontend and the ontology recommender component, which includes a CBR component.

The core of the recommender system is the ontology and recommender (OR) component. The platform independent meta-models and the conceptual meta-models are represented in OWL [54] and loaded at runtime by the OR component. The component is written in Java and uses the open source library Jena [55] which provides an API to work with ontologies.

A new set of models published via the modelling environment is exported in a proprietary XML format. These exported models are transformed in a generic way into Wiki page representations based on the Eclipse Modelling Framework (EMF) [56]. The transformation into the ontology instances is using XSLT [57] templates and an XSLT Engine. This approach enables a straightforward transformation directly into the specific target model and format of the ontology. The models are transformed into RDFS [58] conform classes and are formatted in the Turtle format for a convenient work with text -based version control systems. In a second step, a more generic meta-meta model-based transformation is evaluated. After the transformation into the ontology, an inferencing step is applied to run SPIN [59] rules and infer relations to corresponding conceptual model classes and eventually already existing instance. Examples of such existing instances might be an organisation's employee directory received from a human resource system. The combination of the platform independent and conceptual models, as well as the transformed model objects, build the upper two levels in our OR component knowledge base shown in Fig. 4.

Valuable recommendation rules require context information besides the information from the enterprise models. Application data and logging information from process executions can provide such information. This extended information is made available for reasoning together with the ontology and model instances. However, here, we face the problem of the missing support of multilayer ontologies by the ontology description standards, like OWL. If we add execution data to our ontology, we have an instance of an instance problem, i.e. the execution data represents one layer, the process, and other model instance the next higher layer and our PIMM/LCMM meta-models the highest layer. Fanesi et al. [60, 61] propose an approach with RDFS-FA respectively OWL-FA to overcome that problem and still keep it decidable by reasoners. Executed processes and tasks in our example are added as instances of the



process instances. This allows applying a counting rule which suggests a performer as an expert if the performer has executed the task most often.

Fig. 4. Ontology Levels and Transformations

Another set of learning recommendations relies on a case base with historical cases. The integrated CBR component allows retrieving historical cases of the public administration stored in the case base. The case base and the similarity calculations are all based on ontologies. The cases are stored as instances of the case ontology, and the case characterizations are defined by applied annotations from the CBR ontology.

6 Evaluation

Before proposing the design of our recommender, we compiled requirements based on literature (see Section 2) and the results of a questionnaire that was filled in by 52 civil servants. In this section, we present a summary of how our recommender design satisfies these requirements. This is followed by a summary of results from a qualitative evaluation. The results presented here cover only the recommendations of experts and learning materials – recommendations of historical cases are more complex to evaluate and will be validated as part of the final validation of the entire Learn PAd approach.

6.1 Requirements met

Regarding the interplay of the recommender with the platform that handles the execution of the business process and the necessary context awareness, the following requirements were satisfied:

- Questionnaire respondents had stated that, while receiving recommendations on a particular task, these recommendations should be detailed, but at the same time, they would like to keep an overview of the whole process. This is satisfied by presenting a process overview in the main window of the prototype and displaying recommendations within a sidebar.
- Civil servants emphasized that they often not know where the information contained in existing or new (learning) material should be applied. The recommender helps them in this because recommendations are context-specific (i.e. they get the recommendation where they need it). Context-sensitive recommendations are enabled by rules whose conditions are matched to the learner's current work context

Furthermore, requirements regarding the competence-awareness of the recommender are satisfied as follows:

- The choice to use EQF for the definition of learners' competence levels resulted in the adoption of an EQF-based meta-model for modelling learner profiles
- Based on the definition of the zone of proximal development (ZPD) in Vygotsky [23], we formulated the requirement that the recommender should recommend learning objects aiming to teach the learner competencies at a level just above her current level. This is satisfied by describing learning objects with intended outcomes regarding EQF competency levels and making sure that this level is just above the learner's current EQF competence level for each recommended learning object.

Another category of satisfied requirements concerned the adaptation of recommendations to the learner's learning style:

- Since questionnaire participants expressed the desire to get recommendations for a diverse range of content types, the recommender is able to suggest not only documents or multimedia learning objects but also experts (see below) and historical cases.
- Based on the concepts proposed by connectionist learning [28] which imply the need to make connections with a learner's existing knowledge, the recommender creates such connections e.g. by proposing historical cases.

Finally, requirements regarding expert guidance are satisfied as follows:

- Since questionnaire participants stated the need to have quick access to recommended experts, the recommendations include contact information
- Based on the notion of ZPD [23] and scaffolding learning [24], we ensured that recommended experts have a more advanced level of knowledge than the learner by making rules dependent on experts' EQF competence levels.

6.2 Qualitative Evaluation

The qualitative evaluation consisted of a workshop where civil servants interacted with a prototype of the Learn PAd collaborative platform, which included – among other functionalities – the features of the recommender. The interaction was performed along the application scenario described in Section 2.5, and the corresponding application data and learner context were known to the system. The recommender was integrated into the prototype in the form of a sidebar where context-dependent suggestions were displayed. Most of the participants' feedback revolved around aspects of the recommender that were not yet implemented in the prototype. Thus, participants commented that there should be:

- a registration form where a user's competencies can be assessed and then stored in a profile
- more recommendations of multimedia content
- recommendations also on the level of the whole process.

We consider this feedback as a confirmation that these features will be perceived as useful when implemented later.

7 Conclusion & future work

With our approach, we could show how workplace learning can be improved by providing context-sensitive and personalized recommendations for learning in a collaborative environment. In the future, we plan to work on key performance indicators for learning goals to assess learning progress. We intend to develop a cockpit to identify for example goals that are not satisfied and the reasons that cause this effect.

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