On the Transferability of Process-oriented Cases

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Abstract. This paper studies the feasibility of using transfer learning for process-oriented case-based reasoning. The work introduces a novel approach to transfer workflow cases from a loosely related source domain to a target domain. The idea is to develop a representation mapper based on workflow generalization, workflow abstraction, and structural analogy between the domain vocabularies. The approach is illustrated by a pair of sample domains in two sub-fields of customer relationship management that have similar process objectives but different tasks and data to fulfill them. An experiment with expert ratings of transferred cases is conducted to test the feasibility of the approach with promising results for workflow modeling support.

Keywords: Process-oriented case-based reasoning, transfer learning, CRM application

1 Introduction

Transfer learning (TL) addresses the "question of how the things that have been learned in one context can be re-used and adapted in related contexts" [14, p. 5]. TL has a long tradition in diverse research disciplines, ranging from psychology and education [32, 23] to cognitive science [8] and artificial intelligence (AI) [30, 22, 11, 14]. In the context of *case-based reasoning* (CBR), TL approaches use knowledge from a source domain "to enhance an agent's ability to learn to solve tasks from a target domain" [11, p. 54]. The *source domain* denotes the problem solving context in which knowledge is available at a mature level. The *target domain* is the problem solving context where the knowledge is sparse.

Process-oriented case-based reasoning (POCBR) is a recent research area of CBR that aims at applying and extending CBR methods for process and workflow management [16]. *Workflows* are "the automation of a business process, in whole or part, during which documents, information or tasks are passed from one participant to another for action, according to a set of procedural rules" [1]. The control flow of a workflow specifies the order of tasks to be executed. The data flow specifies the interaction of tasks with data items (documents or information). In POCBR a case is usually a workflow or process description expressing procedural experiential knowledge. There are many application domains for POCBR where procedural experiential knowledge is sparse. It requires time-consuming efforts to populate a case base for a POCBR system from scratch, also referred to as the cold-start problem. In certain cases, there is a related application domain where workflows are available at a mature level, either resulting from previous modeling activities, from process mining [17] or extracted from other information sources, such as Internet Communities [28]. The transfer of procedural knowledge provides an approach to solve the cold start problem of POCBR systems. In addition, it might strengthen mature process-oriented case bases by introducing a larger variety of cases to be reused.

TL has been successfully applied in several CBR application fields, such as games [2] or physics [12]. However, TL has not yet been studied in the context of POCBR and workflows. The aim of this paper is to investigate transferability of knowledge from a POCBR system in a source domain to a POCBR system in a target domain. In particular, we will propose a novel approach on TL for POCBR that claims that generalization and abstraction of workflows, as well as structural analogies between the vocabularies of the source and target domain support the transfer of process-oriented cases. We will use two related domains of customer relationship management (CRM) as a running sample to illustrate our approach and to test it in a lab experiment.

2 Related work

A large amount of work on TL in machine learning, especially for reinforcement learning, has been reported; see the 2009 survey [30] and the 2014 special issue of the German "KI" journal [14] for a review. A good overview on TL in data mining for classification, regression, and clustering is given by the 2010 survey of Pan & Yang [22]. The approaches from these research lines transfer a general concept that has been achieved by "eager learning" from training data. This means that a model has been learned from a data collection in a first phase to be used in a second phase. In contrast, there is a research line on *Case-based transfer learning* that is mainly addressing "lazy learning". CBR collects the examples in a case base [27, p. 280], learning from recording problem solving episodes. This means that the learning phase continues while the knowledge that has been learned so far is already in use. While TL has proven a significant benefit in several learning scenarios [30, 22, 14], it has not yet been studied in the context of POCBR.

A topic that has already been studied in case-based TL is the use of *models of analogy*. Sample analogy models that have been used for TL are structure-mapping engine [7, 12], graph isomorphism [15], cognitive modeling [25], or goal-driven analogical mapping [13].

As CBR can be viewed as a kind of analogical problem solving, existing approaches to adaptation in CBR can already be considered to perform a kind of transfer learning. Klenk et al. [11] call this approach "CBR as transfer learning method". It requires a certain amount of overlap between the source and the target domain such that certain pieces of knowledge (for example, cases or adaptation knowledge) learned or acquired in the source domain can be directly used in the target domain. In case of hierarchical case representations, such a transfer can also occur on a higher level of abstraction that is a proper common abstraction of both domains. In the context of POCBR, recently developed adaptation methods can be considered in this respect. In compositional adaptation, workflow are decomposed into meaningful sub-workflows called *workflow streams*, which immediately provide a means for case abstraction [3]. An abstract case is a structurally simplified workflow, using more abstract terms as descriptions of task and data items. During problem solving, abstract cases can be retrieved and reused by refining the occurring abstract items. This refinement step can then transfer an abstract case towards a specific case in the target domain. Also, adaptation by generalization and specialization can be used for transfer learning in POCBR [19]. A generalized workflow is structurally identical to the base workflow but the semantic descriptions of task and data items are generalized. If this generalization is performed to a level that covers the source and the target domain, the generalized cases from the source domain can be immediately be used in the target domain to solve problems by being appropriately specialized.

This approach to CBR as transfer learning is clearly limited to source and target domains in which there is a significant overlap between the domain ontologies. For transfer learning between two more distant domains, analogical mapping approaches are required that enable the alignment of the two ontologies and thereby support the mapping of abstract and generalized cases from the source to the target domain. This paper presents a first step towards the development of such a transfer learning method.

3 A typical example of a pair of POCBR domains

A usage scenario for TL on POCBR is modeling support to alleviate the cold-start problem when a company starts a new process repository and a set of workflows is to be created. The following running sample uses two typical business application areas for POCBR. Both areas are sub-fields of customer relationship management (CRM). We have chosen the domain of opportunity management as a sample target domain. Workflows for opportunity management, for example, comprise activities to identify and nurture sales opportunities. The related documents and data items interact with the company's CRM system [9]. Second, we have chosen churn[3] management as a sample source domain. Churn management is a domain that aims at predicting customers with a high probability for churn [31]. The domain shares some commonalities with opportunity management since in both domains customer data is analysed. Churn management involves tasks that are related to the identification of leads in opportunity

[3] The meaning of *churn*, according to the Cambridge English Dictionary, is: "If customers churn between different companies that provide a particular service, they change repeatedly from one to another."

management. A lead is a person that is likely to become a customer [9]. Sales persons aim at transforming leads into opportunities, i.e. to create new sales opportunities by nurturing leads with marketing activities [9]. Figure 1 depicts a typical churn management workflow [31] on churn analysis in Business Process Modeling Notation (BPMN) [4]. It starts with a task *"Measure cause variables"* which stands for a sub-workflow to measure different cause variables for churn from CRM data. The dotted box in the lower part of the figure contains the sub-workflow with the particular measuring tasks in parallel, such as for the customer complaint behavior and for the duration of the customer relationship. The resulting indices are further processed by a subsequent data mining task *"Logistic regression"*, which creates a model to divide customers into groups by their likelihood for churn. Churn management and opportunity management are a pair of typical domains for POCBR systems. We will study the transfer of knowledge from one POCBR system to another POCBR system illustrated by churn and opportunity management processes.

4 The transfer setting

The goal of our novel TL approach is to transfer parts of a case base CB_S from a source domain D_S to a target domain D_T in order to extend a sparsely populated case base CB_T to a richer case base CB'_T. The transfer setting is characterized by the transfer distance between D_S and D_T and by the means that are used to bridge the gap between the two domains.

The *transfer distance* can be delineated by the differences between the source and target problems [11]. Sample transfer distances consider the proportion of vocabulary that is shared across source and target or whether the transfer includes restructuring or composing of source knowledge (compare [11]). It has been stated in the literature [22] that the transfer distance may help to provide a measure for the transferability. Without providing a formal measure for the transfer distance yet, we make the assumption that both domains in our transfer setting are loosely related, i.e. D_S and D_T share little vocabulary to describe the process-oriented cases and the processes from both domains address slightly related objectives. We assume that ontologies O_S and O_T are available (or can be created) as vocabulary for both domains covering the workflow tasks and the data items of the workflows in CB_S and CB_T. In addition, we assume that the ontologies contain some concepts which both have in common, i.e. there is an overlap $O_S \cap O_T \neq \emptyset$. Please note that this includes concepts at a higher hierarchical level. For instance, the workflow task "*Behavioral scoring*" for leads in our running sample opportunity management is a "*Customer scoring*" task, as specified in the ontology. It provides a scoring of a lead who has shown interest based on patterns observed in interacting with the company, such as responding to an email, registering for a Webinar, or attending that Webinar. In churn management, there is a typical workflow task "*Customer complaint behavior analysis*" (compare the sample workflow in Figure 1) that is obviously different from "*Behavioral scoring*" for leads but has the super-concept "*Customer*

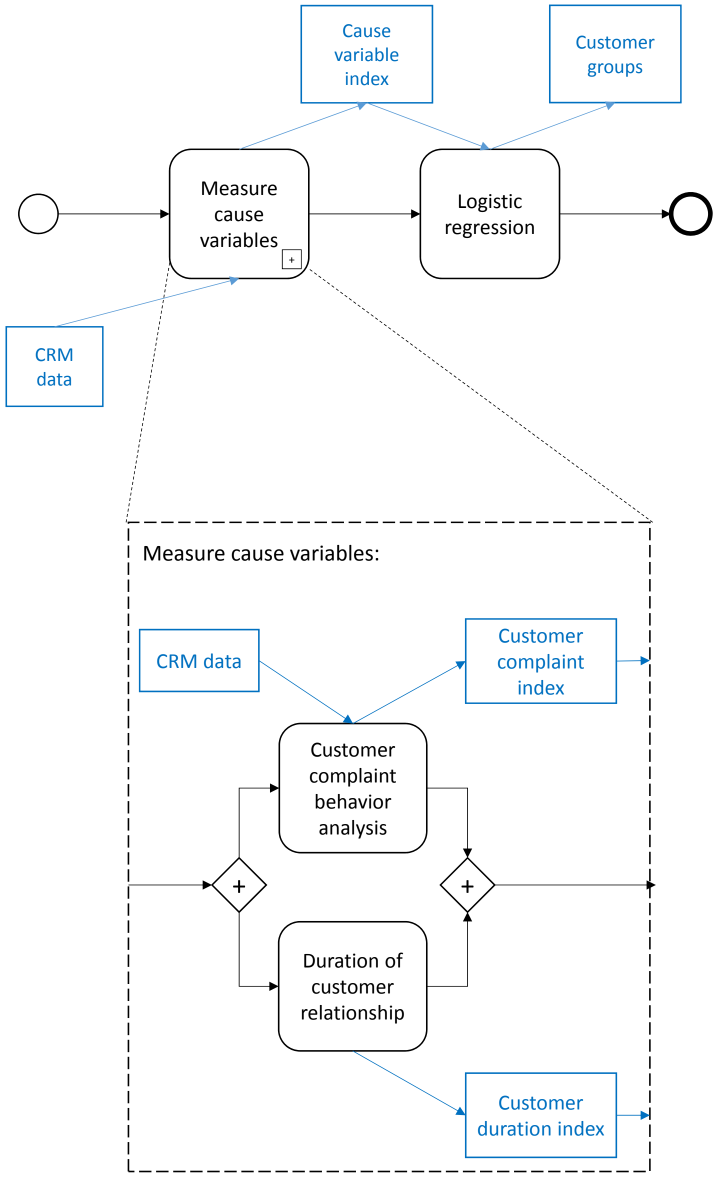

Fig. 1. Simplified sample workflow on churn analysis.

scoring" in the churn management ontology. This means that both ontologies share the common concept "*Customer scoring*". Further, we assume that there are workflows in CB_S and CB_T addressing corresponding goals or sub-goals, i.e. the process objectives are not identical but related. For instance, a churn management process might include the goal to measure the cause variables for churn (see also Figure 1) while an opportunity management process might address the corresponding goal to measure the impact factors on transforming a lead into an opportunity.

We investigate ontology alignment as a means to bridge the transfer distance between POCBR domains. The idea is to develop a *representation mapper* [13] that aligns O_S and O_T via an analogical mapping. The resulting mapping f is used to transfer selected items from CB_S to populate CB'_T. The representation mapper creates the analogical mapping based on generalization, abstraction, and structural analogy. *Generalization of a workflow* is a transformation into an isomorph workflow based on an ontology of data items and workflow tasks [19]. The representation mapper uses the super-concepts in the ontology O_S for workflow tasks and data items where a direct alignment to a concept in O_T is not feasible. Thus, a concept $x \in O_S$ can be aligned via generalization to the closest ancestor $\hat{x} \in O_S$ that is part of the mapping, i.e. $f(\hat{x}) \in O_T$.

Further, we observed that a pair of workflows with similar goals can comprise quite different tasks organized in various control flow and data flow structures. In such cases generalization of particular workflow elements such as tasks or data items would result in an alignment of concepts only at a very high hierarchical level of the ontology. Abstraction is used as a means to analogize workflow fragments. Polyvyanyy defines *abstraction of a workflow* as "a function that ... hides process details and brings the model to a higher abstraction level." [24]. An *abstraction rule* aggregates a fragment of a workflow into a single task [24]. Abstraction rules comprise elementary abstractions that have been introduced for BPM abstraction [24], such as sequential abstraction, block abstraction, or elimination. Under the assumption that the workflows follow a Single-Entry, Single-Exit (SESE) model [26] [4] an abstraction rule can be specified for each workflow stream [18]. A workflow stream denotes a set of SESE regions of a workflow that are required to achieve a sub-goal [18], such as measuring the cause variables for churn. We introduce the notion of an *abstracted workflow task* for a workflow task that subsumes a workflow stream at a higher level of abstraction. The abstracted workflow task aggregates the control flow as well as the data flow of the workflow stream. For example, the sub-workflow "*Measure cause variables*" in Figure 1 is represented by the abstracted workflow task "*Measure cause variables*". The abstracted task aggregates the control flow by an AND block abstraction. The input data item of the abstracted task is "*CRM data*" while the output data is "*Cause variable index*" which is an aggregation of "*Customer complaint index*" and "*Customer duration index*". O_S and O_T are enriched by the abstract workflow tasks for all workflow streams that can

[4] SESE regions of a workflow are either a single workflow task or a larger fragment enclosed by corresponding split and join connectors [26].

be identified. The representation mapper uses the abstracted workflow tasks to align O_S and O_T at a higher level of abstraction. Thus, a workflow stream can be aligned via abstraction to the closest ancestor $\hat{x}_a \in O_S$ of its abstracted workflow task $x_a \in O_S$ that is part of the mapping, i.e. $f(\hat{x}_a) \in O_T$.

In addition to the mapping of concepts that are common to both ontologies, we seek *structural analogies* in the ontologies to identify further mapping candidates. Gentner [8] defines analogy as an alignment process between two structured representations. As a starting point, we have chosen to analyse ancestor-descendant structures in the ontologies based on results of research on ontology alignment [21]. Ancestors of similar descendants, based on lexical similarity, become mapping candidates. In case a pair has a similar ancestor and a similar descendant with intermediate items in the target ontology the analogy detection method inserts intermediate items into the source ontology to alleviate the mapping of siblings of the descendant from the source ontology [5]. During the semi-automatic process of ontology engineering, it is decided which candidates become part of the actual mapping.

5 The transfer process

The transfer process aims to brigde the gap between the domains. It comprises two phases namely build time and transfer time.

The *build time* is the phase where transfer knowledge is created. The result of the build time is the representation mapper as described in Section 4. The phase includes two steps namely to enrich the ontologies and to create the analogical mapping. First, the existing case bases CB_S and CB_T are analysed to derive abstraction rules and to enrich the ontology with abstract workflow tasks as described above. At the moment, we identify workflow streams and the according abstract workflow tasks in a manual engineering process. More generally, abstraction tasks could be learned (compare recent work on learning adaptation operators [20]). Next, the analogical mapping is constructed following the ontology alignment methods decribed in Section 4.

The *transfer time* is the phase where the transfer knowledge is applied to the workflows from the source domain. We operationalize the transfer knowledge into a set of abstraction and generalization operators OPS, which transform workflows still within the source domain. The transfer process for a workflow W_0 is a search for operators o_1, o_2, ..., o_n to form a transformation path $W_0 \Rightarrow^{o_1} W_1 \Rightarrow^{o_2} ... \Rightarrow^{o_n} W_f$ with the goal that the resulting workflow W_f uses only vocabulary that is aligned to the target domain. Next, W_f is translated directly into a workflow W'_f in the target domain by replacing each activity and data object following the representation mapper. Please note that multiple transformation paths may exist for a workflow and that the translated workflows are likely to be on a high conceptual level. At the moment, we conduct a complete search for all transformation paths. This implies that there is a potential to create redundant cases which are structurally distinct. The phenomenon has been discussed in the literature on workflows, referred to as "workflow paraphrases"

[28] or "variability" [10]. It occurs frequently in repositories of workflows that have been designed by human modeling experts. In our sample target domain, we consider it an advantage to achieve a variety of solutions. It could be useful to create additional opportunities by executing multiple workflows for the same problem.

6 Evaluation

We have conducted a preliminary experiment on initially five sample workflows with the aim to test the feasibility of our approach. We have chosen churn management as a source domain D_S and the loosely related domain opportunity management as D_T. The experiment includes ratings from a CRM expert of the eleven workflows in the target case base CB'_T that have been created by transferring the sample workflows from the source domain.

The experimental data includes two small case bases CB_S with three workflow samples on churn management and CB_T with two workflow samples on opportunity management. The workflow samples have been modeled in BPMN [4] following textual descriptions on typical churn and opportunity management processes. We retrieved the textual descriptions for CB_S from SAP help [5]. The opportunity management samples originate from a book on Salesforce [29] and from a tutorial on lead management [6].

The experiment comprises the two phases build time and transfer time. During build time, two ontologies O_S with finally 48 concepts and O_T with finally 47 concepts have been engineered. O_S includes four abstracted workflow tasks that have been derived directly from the workflow samples via their sub-workflows. O_S has been enriched by three additional abstracted workflow tasks for workflow streams that have been identified in the workflow samples by the ontology engineers. The names for the latter tasks are taken from a reference process model on churn management from the literature [31]. Analog, O_T has been enriched by one additional abstract workflow task following the nomenclature of a reference process model on opportunity management from the literature [9]. Table 1 lists the results of constructing the representation mapper for the workflow tasks. Only *"Customer profiling"* (line 4) is an abstracted task. The other tasks are generalized concepts in both domains. The mapping participants of data items are depicted in Table 2.

During transfer time, the three churn management workflows have been transformed using the representation mapper. We fully expanded the search space with the result that each source workflow achieved two target workflows. The first workflow resulted from preferring abstraction over generalization operators, the second vice versa.

We simulated the use of the transferred workflows for modeling support as follows. We have chosen manually a workflow stream from the target domain to refine every abstracted task. Since the size of our experimental data is quite

[5] http://help.sap.com, last visit May 14, 2016
[6] https://rdatascientist.wordpress.com/2015/08/15/, last visit May 14, 2016

Table 1. Workflow tasks that are part of the mapping.

	Churn task in O_S	Lead task in O_T	Type of structural analogy
1	Analysis	Analysis	Direct overlap
2	Marketing action	Marketing action	Direct overlap
3	Data mining task	Data mining task	Direct overlap
4	Customer profiling	Customer profiling	Direct overlap
5	Customer scoring	Customer scoring	Inserted as intermediate concept
6	Preparatory analysis	Transform data	Via similar descendant

Table 2. Data items that are part of the mapping.

	Churn data in O_S	Lead data in O_T	Type of structural analogy
1	Analysis result	Analysis result	Direct overlap
2	CRM data	CRM data	Direct overlap
3	Customer list	Customer list	Direct overlap
4	Customer groups	Customer groups	Direct overlap
5	Classification result	Classification result	Inserted as intermediate concept

limited this has led to five further target workflows. Figure 2 illustrates a sample workflow that results from transferring a churn management workflow with preference on abstraction operators. The workflow describes a three-step analysis of customer data in order to create new sales opportunities. It starts with the task *"Customer scoring"* that analyses the CRM data to filter out promising customers. *"Customer profiling"* is the task to acquire additional data on the customers. Finally, *"Customer segmentation"* is performed to identify the most promising customers. The abstracted task *"Customer profiling"* has been replaced by a workflow stream from CB_T, including the specialization from *"Customer list"* in the main workflow to *"Lead list"* in the sub-workflow. The modeler would probably propagate the same specialization to the main workflow, change some further data items and fill the black box for the abstracted task *"Customer segmentation"*, which has not be refined so far because the input data item of the candidate workflow stream from CB_T does not match the input of the abstracted workflow task.

The eleven newly created target workflows from CB'_T have been rated by an expert with a Likert scale for the estimated usefulness for the purpose of modeling support. The range is from a score of 1 for "unusable" to 5 for "extremely helpful". The results are shown in Table 3. Workflow S3 from the source domain results only in 3 target workflows since workflow 13 from the target domain does not contain any abstracted workflow task. Workflow 4 has a relatively low score because the order of tasks is not appropriate. The expert felt irritated with workflow 6 which contains two parallel tasks that apply a neural network to the same input data. This duplicate is a result of the sparse target ontology, which contains only one classification task namely neural networks. The results do not show a clear preference for the level of abstraction or for the preferred operators.

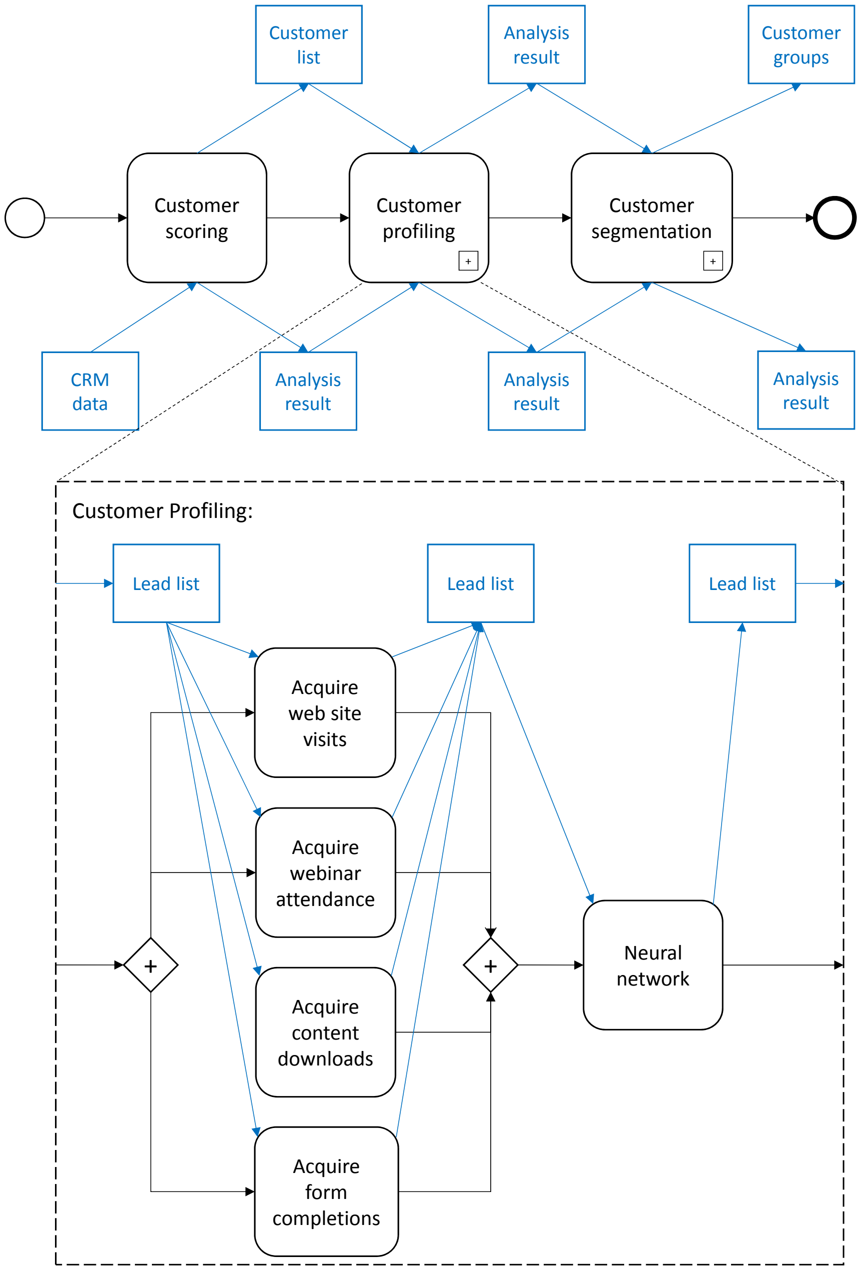

Fig. 2. Workflow on opportunity management as a sample transfer result.

However, the illustrating samples have been rated quite high, which provides a first hint for the general feasibility of the approach.

Table 3. Score for the target workflows resulting from the expert rating.

No in CB'_T	No in CB_S	Preferred operators	Level of abstraction	Score
3	S1	Abstraction	Unaltered	4.5
4	S1	Abstraction	Refined	3
5	S1	Generalization	Unaltered	3.5
6	S1	Generalization	Refined	3
7	S2	Abstraction	Unaltered	4
8	S2	Abstraction	Refined	4
9	S2	Generalization	Unaltered	5
10	S2	Generalization	Refined	5
11	S3	Abstraction	Unaltered	4
12	S3	Abstraction	Refined	4.5
13	S3	Generalization	Unaltered	4

7 Discussion and conclusion

We have introduced a novel approach to transfer learning for process-oriented case-based reasoning and demonstrated its feasibility with a first lab experiment. Ontology alignment has been adopted to bridge the transfer distance between loosely related domains by a representation mapper. In particular, generalization and abstraction have been proposed to align workflow fragments in cases where a direct alignment is not feasible. Structural analogies in the vocabulary have been investigated in order to provide further transfer knowledge to be used by the representation mapper. The implementation is ongoing. The work is a first step towards an extension of the POCBR methods investigated in the research community so far.

Obviously, there are many open issues that might stipulate further research. The representation mapper requires improvement and a formative evaluation with a larger experimental base. The role of standard ontologies could be investigated as well as more sophisticated structure mapping approaches than our straight-forward analogical mapping. It is an intriguing open research issue which further methods of ontology alignment and beyond are promising to enrich the ontologies by useful transfer knowledge, such as mappings using further lexical and structural features [21] or machine learning approaches [6]. More sophisticated mapping methods will be investigated in our future work. A mapper could hypothesize correspondences between source and target concepts, for example, by using the ontologies O_S and O_T as previously described to match names, input and output data items for abstracted workflows tasks, or structural properties such as the same number of input and output data items. For each hypothesis, a mapping strength value could be determined. Specific matching rules [8, 7] could be defined, for example, the rule that one source ontology concept must always be mapped to the same target ontology concept. Finally, the global mapping could be constructed such that it is consistent and maximizes an evaluation score that considers frequency numbers and the mapping strengths.

The subsequent step of our future work is to consider the *run time*, i.e. the phase where the transferred workflows in CB'_T are used. For modeling support, a workflow W'_f can be directly suggested to a user. Alternatively, a sequence of generalization and abstraction operators o'_1, o'_2, ..., o'_m in the target domain can be searched to be applied "inversely" as specialization and refinement operators to W'_f. Currently, the latter is not yet implemented. A first idea is to employ methods of compositional adaptation using workflow streams [18].

A further interesting direction of research is to address the transfer of adaptation knowledge, such as process-oriented adaptation cases or workflow streams.

In addition, the impact of the transfer distance can be studied, for instance by varying the distance of workflow objectives or vocabulary. As a first step, such investigations require to develop a formal measure for the transfer distance between two domains. Encouraged by our preliminary results, we believe that TL for POCBR is a challenging new field with a reasonable chance of success and with a high impact for practical issues in business process management.

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