Semantics-Based Business Process Model Similarity

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Abstract. Business process modeling has become an accepted means for designing and describing business operations. As a result, comparing and aligning business process models within and between organizations is increasingly important. However, due to differing use of modeling languages and domain languages for labeling models and their elements, model comparison is a non-trivial task. Presently, it is to be performed manually. For easing this workload, we present a novel approach for determining semantic similarity in an automated manner, directed at supporting business analysis through semantic reasoning.

Keywords: Business process modeling, model comparison, semantic similarity, semantic reasoning.

1 Introduction

Businesses all over the world are faced with the challenge of having to flexibly react to change and to dynamically work with varying business partners. Continuous shaping and reshaping of business processes and the supporting or even enabling IT is a critical success factor for a business's competitiveness [1, 2]. For establishing electronic business, the underlying processes, required information and subsequent IT-support need to be described precisely. Over the past decades, business process modeling has become an accepted means for designing and describing business operations in enterprises within and across company boundaries. Such models describe interrelated business objects and business activities in a specific sequence, expressed in a certain modeling language with elements labeled in natural language. Thereby, major tasks in working with models are the analysis of these descriptions for the purpose of quality and compliance checking and detecting commonalities with models of different origin [3, 4]. This involves checking models with regard to the modeling languages and, most importantly, the domain language used for labeling the model elements. If the choice of words of the labels representing the business semantics is not dominated by rules, models are semantically heterogeneous, not only concerning their modeling language, but more importantly, concerning their domain language. This makes their comparison or integration a non-trivial task [5, 6].

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As a result, differing types of models and dissimilarly applied business terminology prevent direct automated business process interactions without prior manual preparation efforts for resolving discrepancies. Typically, these challenges arise in all kinds of e-business integration projects, such as enterprise architecture, data and process integration scenarios [7]. Especially at the time of mergers and acquisitions and setting-up business collaborations where the models to be integrated originate from different independent sources, semantic analysis requires extensive intellectual efforts and time [8]. Therefore, in practice the problem presently to be tackled is the task of having to analyze hundreds of business process models manually. Models need to be compared regarding the intended meaning of their elements and their structure, whereas structural analysis cannot be performed until successful alignment of the domain language [9]. For easing this workload, automated support is deemed desirable by way of enabling (semi-)automatic alignment of process models concerning their semantic similarity. For supporting the analysis of models with regard to the intended meaning of language concepts present, the idea of applying semantic technologies in business process modeling has been suggested [10]. Semantic annotation of business process models has been proposed to allow for analyzing and comparing models [11, 6, 12]. As a complement to these efforts, we here present our method of analyzing and reasoning over business process models based on the domain facts contained.

We report on our research and continue with presenting a typical application scenario encountered, followed by a description of our method based on Semantic Web technologies and show its application. We conclude with an evaluation and discussion of our proposition together with a view onto related work and future research directions.

2 Motivating Example Application Scenario

To demonstrate our method, we show a typical application scenario for business process model integration. The motivating example is a situation occurring within enterprises at the time of outsourcing. It is a case of a travel agency implant where a company decided to hand over the booking of travel related services to an agency belonging to an independent business partner but installed on the premises. Fig. 1 shows two example models, an Event-Based Process Chain (EPC) called “Travel Reservation” (adapted from [13]) and an UML Activity Diagram called “Travel Booking” (adapted from [14]). The models describe a similar business operation, namely the booking of travel services, in different modeling languages and using different domain expressions as model element labels. As often encountered in real-world situations, the models contain errors and mismatches. Upon comparison, differences in the domain language usage can be detected, e.g., “Request airline reservation” corresponds to “flight reservation” and “vehicle reservation” corresponds to “car reservation”. Before resolving these differences, an analysis of the flow of activities depicted cannot be done.

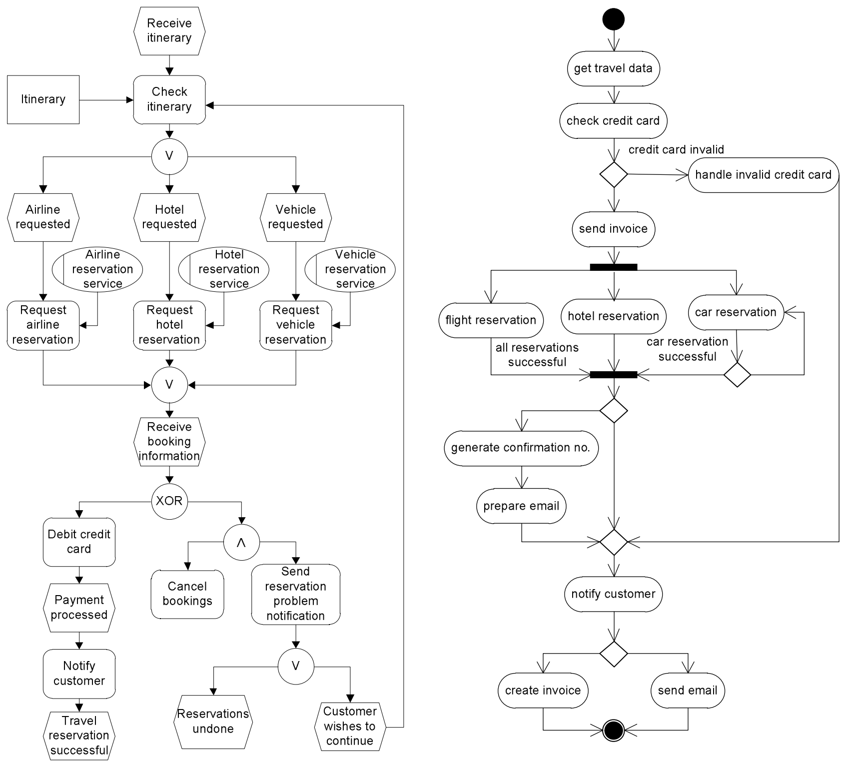

Fig. 1. Two Example Business Process Models from the Travel Domain

In order to be able to reason over the models, they need to be analyzed and compared. On this basis, questions can be answered. The key question we focus on in this paper is the measure of *similarity* between two models. Thereby, similarity means the semantic correspondence of two models with respect to the business domain.

3 Business Process Model Similarity

There are numerous definitions of business process model in the literature [3, 15–17]. For our purposes, it is sufficient to postulate the following requirements for a business process model (or simply "model" if the context is clear): (a) it has a name; (b) it is defined in a business process modeling language, e.g., BPMN, EPC, or UML activity model; (c) it consists of labeled nodes and arcs that are optionally commented.
For comparing such models, we distinguish different dimensions of model similarity:

- *Syntactic similarity*: taking into account the types of modeling languages and language elements,
- *Semantic similarity*: taking into account the meaning of model and element labels and comments,
- *Structural similarity*: taking into account the model graph structure.

Syntactic and semantic similarity can both be applied to models as a whole as well as to individual model elements, e.g., nodes. We express the *measure of similarity* between two models as a numeric value between and including *0* and *1*. The measure *1* denotes identity of two models, a smaller measure indicates a lower degree of similarity. This notion of similarity conforms to the notion of similarity measures according to [18].

3.1 Total Model Similarity (TMS)

Total Model Similarity (TMS) measures the degree of similarity between two models. It is a composite metric based on various individual similarity metrics, as shown in Fig. 2.

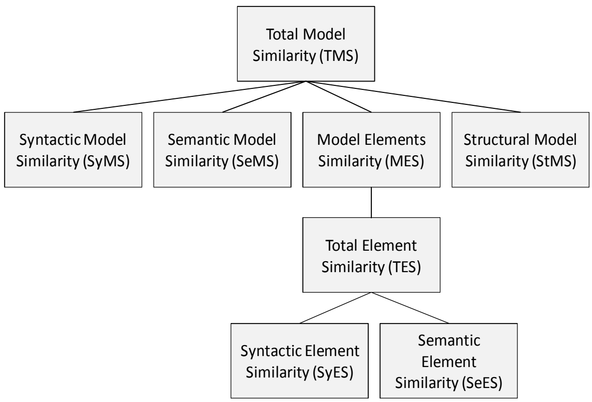

Fig. 2. Total Model Similarity (TMS)

TMS is computed as the weighted sum of individual similarity measures as shown in Eq. 1.

$$TMS(m_1, m_2) = \frac{\sum_{i=1}^{n} s_i\,(m_1, m_2) \cdot w_i}{\sum_{i=1}^{n} w_i} \qquad (1)$$

where

- m_1, m_2 : models to be compared,
- s_i : individual similarity measure, i.e., *SyMS, SeMS, MES, StMS,*
- w_i : weight of individual similarity measure as a numerical value > 0,
- n : number of similarity measures, here *4 (SyMS, SeMS, MES, StMS)*.

For *TMS* and all similarity metrics specified in this section, a value *threshold* is defined with a statically assigned value, e.g., *0.5*. Each similarity measure $s < threshold$ is, per definition, set to *0*. For reasons of readability, the threshold handling is not expressed in every equation explicitly.

The weights of individual similarity measures can be statically assigned, e.g., w_{SyMS}=0.9; w_{SeMS}=1.1; w_{MES}=3; w_{StMS}=1. It is obvious that $0 \leq TMS(m_1, m_2) \leq 1$ if $0 \leq s_i\,(m_1, m_2) \leq 1$ for all similarity metrics s_i.

3.2 Syntactic Similarity Metrics (SyMS, SyES)

Syntactic Model Similarity (SyMS) and *Syntactic Element Similarity (SyES)* compare the types of modeling languages and language elements based on their meta-models. For example, an EPC is more similar to a UML activity model than to a UML class model. This is because EPC and UML activity models are both expressed in business process modeling languages, whereas UML class models are expressed in a structure modeling language. Analogously, on the element level, an EPC function is more similar to a UML activity than to a UML class. We have implemented a simple similarity metric, namely *Static Similarity Measures*. Similarity measures between model types and model element types are statically assigned, e.g., *SyMS(EPC, UML activity diagram)=0.8* and *SyES(EPC function, UML activity)=0.8*. Currently we are experimenting with a more complex and flexible similarity metrics, which we call *Meta-Model Reasoning*. In this metric, syntactic similarity measures are determined according to distance measures of model element types in the meta-model.

3.3 Semantic Similarity Metrics (SeMS, SeEs)

Semantic Model Similarity (SeMS) and *Semantic Element Similarity (SeEs)* compare the meaning of models and model elements, based on their labels and comments. It is a common characteristic of labels in business process models to consist of multiple terms each carrying a semantic meaning but together not forming a grammatically complete sentence. For example, a model named “Travel reservation” is more similar to a model named “Travel booking” than to a model named “Purchasing”. This is because “reservation” is a synonym of “booking”. Analogously, a model element named “request airline reservation” is more similar to an element named “flight reservation” than to an element named “hotel reservation” since “airline” and “flight” are related terms. We have implemented various versions of semantic similarity metrics with increasing complexity and accuracy. Thereby, we are presently concentrating on models with labels in the same natural language.

String-Based Matching

In the simplest form, the number of identical terms in the model labels (for *SeMS*), respectively element labels (for *SeEs*) is set in relation to the total number of terms, e.g., *SeMS(“Travel Reservation”,“Travel Booking”)=0.5*. More sophisticated string-based similarity measures compare characters and their positions in words (e.g., Jaro metric [19]) or the similarity of words in expressions (e.g., Jaccard Metric [20]) [21].

Synonym Matching

More complex, but also more accurate metrics include domain-specific knowledge by incorporating a general-language thesaurus like WordNet [22] extendable with further domain-specific thesauri as needed. By rating synonym terms with a pre-defined measure, *SeMS* would return, for example, *SeMS(“Reservation”,”Booking”)=0.9*.

Language-Aware Semantic Matching

The most sophisticated semantic similarity matching procedure we applied is based on a heuristic approach as described in [23]. It combines exact matching, synonym matching and string-based proximity matching for multi-term phrases. Thereby, different ontology matching and linguistic methods are used. For aggregating the results, parameters can be set for weighting the strength of synonyms, stop-words matched and the proximity. In addition, for computing the aggregated result, the term order can be considered, e.g. *SeMS("Travel Reservation", "Travel Booking")=0.95.*

3.4 Structural Model Similarity (StMS)

The way nodes of a model are connected by arcs, e.g., as loops, can be described as *model structure*. For example, a business process model with three loops is structurally more similar to one with four loops than one with none. We show exemplary one metric for *Structural Model Similarity (StMS)* that measures the difference in the number of loops between the models normalized to the total number of loops, as shown in Eq. 2.

$$StMS(m_1, m_2) = \begin{cases} 1 & , l(m_1) = l(m_2) = 0 \\ 1 - \dfrac{|l(m_1) - l(m_2)|}{l(m_1) + l(m_2)} & , otherwise \end{cases} \tag{2}$$

where

- m_1, m_2 : models to be compared,
- $l(m)$: number of loops in model m.

It is obvious that $StMS(m_1, m_2) = 1$ for identical models and $0 \leq StMS(m_1, m_2) \leq 1$ for all models m_1, m_2 .

3.5 Total Element Similarity (TES) and Model Elements Similarity (MES)

Total Element Similarity (TES) is measured as the weighted sum of measures resulting from individual similarity metrics. Since this is analogous to Total Model Similarity (TMS) as described in Sect 3.1, we do not show the formula here.

Model Elements Similarity (MES) measures how similar all elements of two models are. It sums up the *TES* measures of all element pairs e_i, e_j, i.e., the Cartesian product $m_1 \times m_2$, normalized to the mean number of elements, taking into account a trim factor. See Eq. 3.

$$MES(m_1, m_2) = \min\left(\frac{\sum_{e_i \epsilon m_1, e_j \epsilon m_2} TES(e_i, e_j)}{t_{MES} \cdot (|m_1| + |m_2|)/2}, 1\right) \tag{3}$$

where

- m_1, m_2 : models to be compared,
- $e_i \epsilon\ m$: labeled elements in model *m,*
- $|m|$: number of labeled elements in model m,
- t_{MES} : trim factor for MES; $0 < t_{MES} \leq 1$.

We only consider labeled elements to allow for their semantic comparison. The trim factor t_{MES} may statically be assigned as a constant. It allows aligning MES to the constraints of the model analysis. For example, if 25% correspondence between model elements is regarded sufficient then t_{MES} should be set to *0.25*. $MES(m_1,m_2)=1$ if every element $e_i \epsilon m_1$ has exactly one element $e_j \epsilon m_2$ with $TES(e_i,e_j)=1$, assuming $t_{MES}=1$. The normalized sum could be greater than 1 if, additionally, elements $e_i \epsilon m_1$ have other elements $e_j' \epsilon m_2$ with $ES(e_{i,} e'_j) > 0$ and / or $t_{MES} < 1$. The use of the minimum function ensures that, in those cases, MES is bound to 1. It is obvious that $MES(m_1, m_2) \geq 0$ for all models m_1,m_2 if for all $e_{i,} e_j$, $TES(e_{i,} e_j) \geq 0$.

4 Evaluation

We have implemented the similarity metrics for business process models by using Allegro Common Lisp, AllegroGraph, and AllegroProlog by Franz Inc. and the Semantic Web concept framework as described in [24]. The semantic similarity metrics for model names and element names were imported from the LaSMat system as described in [23]. We have conducted a first empirical validation of the approach presented and its implementation. The results indicate the feasibility of our method and are used as the initial base for proceeding. To avoid biased business process modeling, we have chosen six models from literature, as shown in Table 1.

Table 1. Business process models for evaluation

#	Id	Name	Type	Ref.
1.	TRVR	travel reservation	EPC	[13]
2.	TRVB	Travel_Booking	UML Activity Model	[14]
3.	SALS	sales process	EPC	[25]
4.	STOR	standard order handling	EPC	[26]
5.	PROP	procurement-process	EPC	[27]
6.	PROC	procurementprocess	EPC	[27]

The models contain a total of 204 nodes and 229 edges and cover different business domains, namely travel, sales, and procurement. The expected matching pairs are shown in Table 2.

Table 2. Expected matching pairs of business process models

Domain	Similar Models
Travel	(1.) TRVR - (2.) TRVB
Sales	(3.) SALS - (4.) STOR
Procurement	(5.) PROP - (6.) PROP

For determining the expected matching pairs, independent domain experts have been chosen to rate the similarity between the business process models, taking into account their domain knowledge.

For the evaluation, the similarity parameters were set as shown in Table 3.

Table 3. Similarity parameters for business process model evaluation

Formula	Constants
TMS	$w_{SyMS}=0.9$; $w_{SeMS}=1.1$; $w_{MES}=3$; $w_{StMS}=1$
TES	$w_{SyEs}=0.9$; $w_{SeEs}=1.1$
MES	$t_{MES}=0.25$
General	*threshold=0.5*

The rationale for the parameters settings is as follows. Semantic similarity ($w_{SyMS}=w_{SeEs}=1.1$) is rated higher than syntactic similarity ($w_{SyMS}=w_{SyEs}=0.9$). This, and a *threshold* value of *0.5* leads to the desired effect that elements that are syntactically identical (e.g., two EPC functions, *SyES=1*) but semantically non-similar (e.g., "cancel bookings" and "notify customer", *SeES=0*) are rated as being non-similar (*TES=0*). Total element similarity ($w_{MES}=3$) is rated equally to all similarities on the model level ($w_{SyMS}+w_{SeMS}+w_{StMS}=3$). 25% of matching elements is considered enough for model elements similarity ($t_{MES}=0.25$). The result of the systematic measurement of TMS for all pairs of process models is shown in Table 4.

Table 4. Results for *TMS(m1, m2)*

TMS (m1, m2)	TRVR	TRVB	SALS	STOR	PROP	PROC
TRVR	**1.00**	**0.84**	0	0	0	0
TRVB	**0.84**	**1.00**	*0.79*	0	0	0
SALS	0	*0.79*	**1.00**	**0.55**	0	0
STOR	0	0	**0.55**	**1.00**	0	0
PROP	0	0	0	0	**1.00**	**0.83**
PROC	0	0	0	0	**0.83**	**1.00**

Expected similarities (hits) are typeset in bold, non-expected similarities (false positives) are typeset in italics. For assessing the results, we use *Precision (P), Recall (R)* and *F-Measure (F)*, which are commonly applied measures from Information Retrieval. *P* describes the correctness, *R* describes the completeness and *F* is their weighted harmonic mean. The resulting measures are *P=0.86; R=1.0; F=0.92*. These are satisfying results.

The false positive measure *TMS(TRVB, SALS)=0.79* is due to a high *MES* measure. When analyzing the individual *TES* measures, one finds values like *TES("Article reserved", "hotel reservation")=0.5*. This is, in fact, correct (true positive), since a travel booking is a kind of sales activity whereby a hotel accommodation is being sold.

On the other hand, the value *TES("Posting", "send invoice")=0.75* is incorrect (false positive) since *"Posting"* refers to posting of sold goods and not to posting the invoice.

5 Related Work

Reasoning over business process models is an active field of research. In [28], the use of rules is explored for supporting process design and for reasoning about process alternatives when redesigning processes. In [29, 30], ontologies are used for querying and reasoning over business process models in order to support process redesign. The key criterion is the determination of process similarity. In contrast to our approach, a prior developed description of the organization and its processes and process components is required as background information. Aspects of the potentially heterogeneously used domain language used and inter-model relations are not explored. Due to the aim of these research works, metrics for determining the degree of similarity between models have not been addressed.

Some efforts in determining the similarity of process models are concentrating on the aspect of the model languages' semantics for migrating or transforming from one modeling language to another [31–33]. Others are focusing on matching through meta models [34]. These approaches offer methods for analyzing models with respect to their modeling languages, thus leaving out the question of heterogeneously used business language for labeling the model elements.

As a solution for preventing semantic differences concerning the domain language, using agreed-upon sets of terms for creating labels for model elements has been suggested [6, 35]. Such a set may be a business or domain model on the conceptual [35] or business level [36], a domain specific language [5, 37], a domain ontology [38-40], or an enterprise ontology [41, 42]. These approaches assume their prior existence before modeling or a separate top-down development of such domain models. Present suggestions at comparing process models follow this notion by assuming the existence of a separately top-down developed domain ontology for providing mutual understanding of the element's meaning [4, 43]. Works in the field of semantic business process management via model matching over the domain language often rely on such a pre-defined business terminology [12, 44, 45]. However, since the focus is on the alignment of models, metrics for assessing the degree of similarity are not developed in the scope of these works.

Metrics for measuring the similarity of business process models have been developed, concentrating on business process models of a certain type, e.g. EPC [46] or BPMN [47]. Research in the field of consistency regarding model syntax using meta model rules have been done, for example, for determining the soundness of process models [15]. Analysis for semantic consistency concerning the domain language presently focuses on the validation of consistency in the area of Business/IT-Alignment for analyzing appropriate transformation of business process models into executable models [48-50]. In this, differing use of the domain language among process models is not explored.

To our knowledge, the development of measures for process model similarity regardless of the modeling language chosen has not yet been explored. Furthermore, so far, no propositions have been made regarding metrics for determining the similarity of process models considering both the modeling language and domain language. In this, our approach of measuring semantic similarity as shown could complement the existing efforts in model analysis.

6 Conclusion and Outlook

In this paper, we have presented a novel approach for measuring similarity of business process models. The similarity metric encompasses syntactic similarity, structural similarity, and semantic similarity. Different business process modeling languages like EPC or UML Activity modeling are supported. Semantic similarity takes into account the business domain language. We have implemented the approach and applied it to business process models from literature. Our first evaluation results have shown that the method developed allows for computing similarity close to experts' opinion. The benefit lies in leveraging automated computing power in supporting users in determining semantic similarity between arbitrary models.

Future work will include further refinement of our method, especially improving the text mining mechanisms for semantic similarity, allowing for more natural languages than English, analyzing element comments in addition to labels, adding more sophisticated structural similarity metrics, and handling hierarchical business process models. As a long-term goal, our research will focus on applying our methods onto issues surrounding conformance checking of business process models, i.e., measuring the conformance of company-specific business process models to standard reference models.

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