Similarity of Business Process Models—A State-of-the-Art Analysis

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Business process models play an important role in today's enterprises, hence, model repositories may contain hundreds of models. These models are, for example, reused during process modeling activities or utilized to check the conformance of processes with legal regulations. With respect to the amount of models, such applications benefit from or even require detailed insights into the correspondences between process models or between process models' nodes. Therefore, various process similarity and matching measures have been proposed during the past few years. This article provides an overview of the state-of-the-art regarding business process model similarity measures and aims at analyzing which similarity measures exist, how they are characterized, and what kind of calculations are typically applied to determine similarity values. Finally, the analysis of 123 similarity measures results in the suggestions to conduct further comparative analyses of similarity measures, to investigate the integration of human input into similarity measurement, and to further analyze the requirements of similarity measurement usage scenarios as future research opportunities.

CCS Concepts: • **Applied computing → Business process modeling**; *Business process management*;

Additional Key Words and Phrases: Process model similarity, process model matching, process similarity measurement

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1 INTRODUCTION

Business process models are core artifacts of today's enterprises and play an important role in information systems research. Organizations need to handle hundreds or even thousands of

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process models within their model repositories, which serve as a knowledge base for business process management (see, e.g., the descriptions of enterprise model sets in Lau et al. (2011) and Song et al. (2011)). Managing these repositories requires effective and efficient methods for comprehensive process model analyses. This includes, for example, checking the conformance of process models with legal regulations or with reference models, enabling the reusability of process fragments for modeling purposes, and merging process models (for instance in the context of enterprise mergers and acquisitions) to name just a few application areas.

All these applications benefit from or even require detailed insights into the correspondences of process models and their contained nodes. That is, these applications benefit from or are facilitated by the knowledge of which particular process models have a high degree of similarity. For example, when a process modeler needs to design a new process variant, she/he could identify similar process models in a repository and possibly reuse these models, either entirely or partially (Koschmider et al. 2014). Regarding some application scenarios, measuring the similarity between particular models is even a basic requirement. Efficiently determining the conformance of process models with legal regulations is such an example. To check hundreds of models for large amounts of compliance rules manually would require an enormous effort resulting in high costs (Becker et al. 2016).

Against that background, many business process model matching algorithms and similarity measures have been developed in recent years. At the same time, many different objectives are addressed by the various approaches, so an overview on the state-of-the-art is helpful to researchers and practitioners confronted with calculating the similarity of process models. Furthermore, it is still unclear in which context which measures can be applied meaningfully and how the measures are characterized. Therefore, the article at hand aims at reviewing the current state of business process model similarity measures and addresses the following questions: (1) Which similarity measures do exist in the literature? (2) How can they be characterized and what are their limitations? (3) What are possible future research directions related to the similarity measurement of process models?

The article is organized as follows: In Section 2, relevant terms are introduced and explained in detail. Section 3 outlines related work distinguishing between theoretical conceptual and practical empirical overviews related to process model similarity. Afterwards, the research approach used in the article at hand and details on the literature identification procedure are described in Section 4. Subsequently, Section 5 presents classification criteria for process model similarity measures allowing the characterization of corresponding approaches. To provide further details on concrete measures, we describe common calculation techniques in more detail in Section 6. The developed morphological box forms the basis for the comparative analysis of the identified measures in Section 7. The results and limitations of the article are discussed in Section 8, including a description of possible future research directions. Finally, a conclusion is given in Section 9.

2 FUNDAMENTALS AND TERMINOLOGY

2.1 The Term "Business Process"

Referring to the Cambridge Dictionary,[1] the term "business process" can be described as a sequence of actions carried out in a business context for the creation of goods and services (Houy et al. 2015). In recent literature, it is distinguished between two dimensions: (1) whether a business process in the real world or in the model world is addressed, and (2) whether a business process instance, respectively, execution or a business process model is considered (Houy et al. 2015). The article at

[1] http://dictionary.cambridge.org.

hand primarily focuses on business process schemas describing the model world, whereby several options of representation exist. Generally, it is distinguished between informal, semi-formal, and formal representations (Desel and Juhás 2001). However, the models of interest in this article have semi-formal or formal characteristics and are typically represented as EPCs (Keller et al. 1992), BPMN diagrams (Object Management Group (OMG) 2011), or Petri Nets (Murata 1989).

Thus, in this context, a business process model should not be understood as a model of a particular modeling language (as, e.g., EPC, BPMN, Petri Net) but as a model of a particular model class describing business processes. Hence, an abstract definition of a process model covering the wide range of existing modeling languages is needed as the foundation of this article. A corresponding definition especially requires an adequate generic representation of the graph structure and labeled nodes as these are essential parts used for similarity measurement.

Some formalizations of such a generic representation of business process models can be found in the literature, which generally address specific intentions. For example, Leopold (2013) and La Rosa et al. (2011) aim at consolidating several business process modeling notations with the intention of a best possible type equivalence. Due to the considered notations, the resulting formalizations differentiate a wide range of node types, which is not necessary to that extent in this article. In contrast to that, Dijkman et al. (2009) describes a business process model as a simple business process graph consisting of generic nodes and edges. Since connectors cannot be differentiated from other nodes, a consideration of the possible process behavior would not be possible. Polyvyanyy et al. (2012) differentiates activities and connectors as node types and includes the node labeling aspect as well. This formalization is enhanced by additional generic node types and serves as the basis for this article.

Definition 2.1 (Business Process Model). A business process model $M = (N, A, L, \lambda)$ is a directed graph consisting of three sets N, A, L and a function $\lambda : N \to L$ such that:

- $N = F \cup E \cup C$ is a finite non-empty set of nodes, with
- $F \subseteq N$: a finite non-empty set of activities (also called functions, transitions, tasks),
- $E \subset N$: a finite set of events,
- $C \subset N$: a finite set of connectors (also called gateways) as, for example, XOR, OR, AND.
- A is a finite set of directed arcs (also called edges) between two nodes $n_1, n_2 \in N$ defining the sequence flow.
- L is a finite set of textual labels.
- The function λ assigns to each node $n \in N$ a textual label $l \in L$.

Depending on the business process modeling notation, there may also exist additional nodes as, for example, organizational units, resources, and so on, which may again require additional arcs. As such additional node types only play a minor role for the examples presented in Section 6, it was decided to abstract from them. Note, however, that nodes of arbitrary other types might be relevant for and are used by particular business process model similarity measures.

2.2 Business Process Instances

As mentioned at the beginning of the previous subsection, one can distinguish between business process models and business process instances, which represent the execution of an actual process. Such an execution can either be observed (real world) or calculated, respectively, simulated (model world). One way to describe a business process instance is representing it as a trace (cf. de Medeiros et al. (2008)):

Definition 2.2 (Trace, Trace Length). A trace σ of a process model $M = (N, A, L, \lambda)$ is a sequence of activities $f \in F$. A trace denotes the order in which the activities are executed. It is written as

$\sigma =< f_1, \ldots, f_i, \ldots, f_n >$, whereby f_i may be equal to f_j with $i \neq j$, since it is possible that an activity occurs more than once in a trace. The length *len* of a trace σ is the number of instances of its activities.

2.3 Business Process Model Similarity

Business process model similarity measures try to quantify the similarity between business process models in general. However, the interpretation or the meaning of similarity is quite different. All existing similarity measures have in common that they use an abstract representation of business processes (e.g., a BPMN diagram, an EPC or a set of traces) as a foundation for quantifying the similarity between them. Thus, several dimensions of similarity have been studied in recent literature, for example, the graph structure and state space of a process model, the syntax and semantics of process model labels, the behavior of a process, or the similarity perceived by a human as well as combinations of them (see Section 5.2 for further details).

To quantify the similarity between two objects, in principle, there exist different possibly applicable scales: the nominal scale, the ordinal scale, the interval scale, and the ratio scale. The *nominal scale* solely allows a decision on equality (1) or inequality (0). In the context of business process model similarity it is, for example, used for label comparisons (string comparisons) in Akkiraju and Ivan (2010) and corresponds to the == operator of many programming languages. The *ordinal scale* describes the relationship between two objects based on a characteristic with several attributes that are in a specific order of precedence. It only plays a minor part in business process model similarity measurement until now as only one analyzed measure (Yan et al. 2010) uses such a scale. Possible attributes might be "no similarity," "weak similarity," "high similarity," and "equality."

The *interval scale* allows for a metrical quantification of the distance between two process models. The existence of a point of origin with value 0 is typical for the interval scale, whereas an upper bound is not available. This is generally the case if the distance is used for similarity measurement as, for example, with a string edit distance (0 means that no operations are necessary for transformation while the upper bound depends on the string length). In contrast to that, the *ratio scale* quantifies the similarity between two process models within a lower and an upper bound. Therefore, the standardized interval [0 (no similarity); 1 (equality)] is usually used. Thus, the interval scale and the ratio scale provide the frame for the typical operationalization of business process model similarity in a metric space, whereby a metric is defined as follows (Zezula et al. 2006):

Definition 2.3 (Metric Space, Metric). $\mathcal{M} = (\mathcal{D}, d)$ is a pair of a domain of objects $\mathcal{D}$ and a (distance) function d. $\mathcal{M}$ is a metric space if the following properties of the function $d : \mathcal{D} \times \mathcal{D} \rightarrow \mathbb{R}$ (also called metric) hold:

$$
\begin{array}{ll}
\forall x, y \in \mathcal{D}, d(x,y) \geq 0, & \text{non-negativity,} \\
\forall x, y \in \mathcal{D}, d(x,y) = d(y,x), & \text{symmetry,} \\
\forall x, y \in \mathcal{D}, x = y \Leftrightarrow d(x,y) = 0, & \text{identity,} \\
\forall x, y, z \in \mathcal{D}, d(x,z) \leq d(x,y) + d(y,z), & \text{triangle inequality.}
\end{array}
$$

Thus, if D is a set of process models (the domain), the interval scale is used for measuring the distance $d : D \times D \rightarrow \mathbb{R}_0^+$ between two sets of process models, while the ratio scale is used for measuring their similarity $sim : D \times D \rightarrow [0, 1]$. Besides a direct calculation of a similarity value, distance measures are utilized (e.g., graph edit distance by Dijkman et al. (2009)). These can easily be transformed into a similarity measure in most cases. However, as shown in Kunze et al. (2011), many existing process model similarity measures do not fulfill the properties of a metric. Of 11 measures analyzed, only 3 met all metric properties. Thus, measures become a semi-metric in case the triangle inequality property is violated, a pseudo-metric in case the identity property is violated so $d(x, y) = 0$ for $x \neq y$, or a quasi-metric in case the symmetry property does not hold.

However, depending on the similarity measurement objective, there might be good reasons for violating particular properties. For example, if a similarity measure is used for searching process models containing specific process model fragments, it might be meaningful to violate the symmetry property. In this specific part-of search scenario, the search query would be a process model fragment. The similarity value should be 1 iff a process model contains the query fragment. On the contrary, when interchanging the query fragment and the process model containing the fragment, the resulting similarity value should be lower than 1. Hence, fulfilling the symmetry property is not desired in this search scenario.

2.4 Business Process Model Matching

Matching in general describes the procedure of taking two models as input, referred to as the source and target, and producing a number of matches between the elements of these two models as output based on a particular correspondence (Rahm and Bernstein 2001). Such matches represent a relation between the power set of the source nodes and the power set of the target nodes of the models involved in the matching. Thereby, the term *model* has a broad interpretation and can comprise database schemas (e.g., Evermann (2009)) as well as arbitrary other models.

The more specific term process model matching refers to the matching of single nodes, sets of nodes or node blocks of one process model to corresponding elements of another process model based on criteria like similarity, equality or analogy (Thaler et al. 2014). Such node matches serve as a foundation of most existing similarity measures for business process models as described in Becker and Laue (2012) and Weidlich et al. (2010) and also confirmed by our survey. Thus, node matching is a key concept in the context at hand. Thereby, it is generally distinguished between elementary and complex node matches, which are defined as follows:

Definition 2.4 (Elementary/Complex Node Match (Weidlich et al. 2010)). A match m is denoted by a tuple (N_1, N_2) of two sets of nodes. A match (N_1, N_2) is called elementary match, iff $|N_1| = |N_2| = 1$ and complex match, iff $|N_1| > 1 \vee |N_2| > 1$.

Since definition 2.4 does neither specify necessary nor sufficient criteria for a match, it is not a definition in the strong sense but a formalization. Nevertheless, it covers the formal border of a match. Moreover, the instantiation of a match is considered as a decision problem, which can be well-structured but also ill-structured (Thaler et al. 2014). This leads to the fact that no unique correct match between particular nodes exists, since ill-structured decision problems have no solution and well-structured decision problems have several solutions (Thaler et al. 2014).

However, there are various approaches trying to approximately derive adequate correspondences, respectively matches, between nodes of models. A common technique is the consideration of (normalized) edit distances (Dijkman et al. 2011) like the Levenshtein distance (Levenshtein 1966). Other approaches described in Antunes et al. (2015) and Cayoglu et al. (2014) additionally apply techniques from the area of Natural Language Processing (NLP), thereby taking into account, for example, semantic information of node labels concerning synonyms, homonyms, antonyms, and so forth.

To conclude the fundamentals on process model similarity, Figure 1 shows the procedure of similarity calculation, which is essentially a three-step procedure, including a model phase, a matching phase, and a similarity phase. The *model phase* corresponds to choosing models, which should be compared with respect to their similarity. Afterwards, two different variants of similarity calculation can be found in the literature. The first one is based on matches between process model elements (arrows marked with *a* in Figure 1), while the second variant does not require any matches

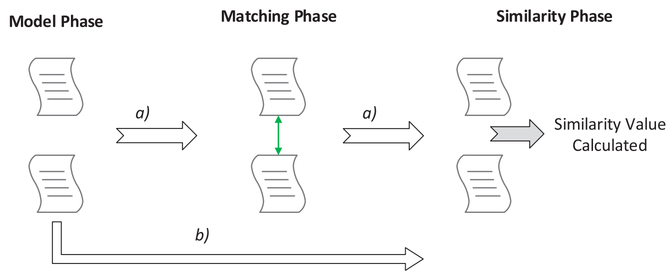

Fig. 1. Procedure for similarity calculation.

to calculate a similarity score (arrow marked with *b* in Figure 1). The first variant results in two separate steps for similarity calculation: First, matches need to be determined in the *matching phase* before, second, a similarity value can be calculated in the *similarity phase*. Regarding the second variant, corresponding approaches directly "jump" from the model phase to the similarity phase without requiring a matching phase. During the similarity phase a similarity value is calculated, which is typically quantified in the interval $[0, 1]$ (see also Section 2.3).

Hence, some similarity measurement techniques require a matching of nodes before the actual calculation of a similarity value. Examples for such similarity calculation approaches are, for example, the Graph-Edit Distance based approach of Dijkman et al. (2009) or the techniques based on Causal Footprints (van Dongen et al. 2008) and Behavioral Profiles (Weidlich et al. 2010). Further details on these techniques can be found in Section 6. Thereby, corresponding publications usually not only describe how to calculate a similarity score, but also provide details on how to determine matches. If this should not be the case (e.g., some publications only state that a matching is required), then one of the recently proposed techniques in Cayoglu et al. (2014) and Antunes et al. (2015) could be used.

Yet, other approaches do not require a matching between process models. These refer to other means of similarity calculation like clustering of process models based on the values of process model metrics (Melcher and Seese 2008), usage of techniques from information retrieval based on the labels in process models (Schoknecht et al. 2016), or the amount of shared business rules associated with models (Rinderle-Ma and Kabicher-Fuchs 2016).

3 RELATED WORK

Currently, two other comprehensive literature surveys on process model similarity have been published (Becker and Laue 2012; Niesen and Houy 2015). Besides these, a few other articles give an overview of published similarity measures as well as matching techniques. One highlights open questions regarding similarity measurement (Dijkman et al. 2013) and another four compare different approaches in evaluation settings (Thaler et al. 2016; Antunes et al. 2015; Cayoglu et al. 2014; Dijkman et al. 2011).

Becker and Laue (2012) provide a detailed overview of the exact calculations used by process model similarity measures and compare them in relation to eight desired properties of a similarity measure. In contrast, the survey at hand gives a broader overview of the similarity measures through the inclusion of different other aspects like the validation status of similarity measures or the availability of implementations. That is, besides the incorporation of a greater number of similarity measures, this article provides a different point of view on the current status of process model similarity measures. These aspects are also not considered in the survey conducted by Niesen and Houy (2015). The authors restrict their investigation to NLP techniques used in process model similarity measures. Besides, the amount of analyzed publications is significantly higher than in Niesen and Houy (2015) (123 vs. 84 investigated publications).

The survey of Dijkman et al. (2013) describes categories of problems related to the measurement of process model similarity. This article does not provide a structured classification of different approaches through a literature survey, but describes process model similarity research from a theoretical, conceptional point of view. The authors focus on various aspects important for similarity measurement. These include, for example, challenges arising during similarity calculation as well as notions of similarity, an application scenario for process model similarity, and future research directions.

Furthermore, the evaluations described in Cayoglu et al. (2014), Antunes et al. (2015), Dijkman et al. (2011), and Thaler et al. (2016) can be regarded as a sort of survey as at least a few process model similarity or matching measures are summarized and compared to each other. Hence, these articles constitute practical, empirical works. The first one presents results of the process model matching contest at the BPM Workshops 2013 (Cayoglu et al. 2014). During this contest, seven matching approaches were compared regarding their performance of finding similar activities in two process model data sets. Thus, this contest focused on the matching task (see Section 2.4), leaving aside the final similarity calculation. The second publication (Antunes et al. 2015) refers to the contest's second edition,[2] providing new data sets modeled in various languages and comparing twelve process model matching approaches. Therefore, these contests provided an opportunity to comparatively assess existing process model matching approaches without considering the similarity of process models. The third article presents a comparison of three similarity measures for process model retrieval, which are evaluated with one data set (Dijkman et al. 2011). Finally, the fourth publication compares eight similarity measures regarding run time and correlation of their similarity values (Thaler et al. 2016). In contrast to these works, this article provides a structured literature review focusing on process model similarity measurement. The result is a structured classification of corresponding approaches, while practical, empirical aspects are not regarded.

To conclude, the following structured literature analysis presents results that are complementary to the results described in Becker and Laue (2012) and Niesen and Houy (2015), by analyzing further aspects of process model similarity research and by broadening the scope of analysis. The other five articles differ in their research focus as they are either theoretical, conceptional or practical, empirical works.

4 RESEARCH APPROACH

This article aims at elaborating the state of the art of business process similarity measures and is based on a structured literature review as research approach. We applied the literature search procedure described by Webster and Watson (2002). Thus, a structured literature search was conducted, whereby, in a first step, Springer Link, ACM, IEEE, Ebsco Host, ISI Web of Knowledge, and Google Scholar served as databases for scientific literature. As a second step, a backward search was conducted. Generally, a full text search was executed wherever possible. In all other cases, the search was limited to title, abstract and keywords. The literature search was conducted in April 2016, while no further limitations were applied. Additionally, further publications the authors became aware of were included.

The following query strings, which incorporate typical terms and synonyms related to process model similarity utilized in the literature, were used to identify the relevant publications: "process model" AND "matching," "process matching," "process model" AND "similarity," "process similarity," "process model" AND "duplicate," "process model" AND "equivalence," "identical

[2] https://ai.wu.ac.at/emisa2015/contest.php.

Table 1. Number of Literature Search Results

Search term	Springer	ACM	IEEE	Ebsco	ISI	Google Scholar
"process model" AND "matching"	19,627	698	8,324	3,817	202	51,600
"process matching"	1,046	62	338	298	24	3,410
"process model" AND "similarity"	11,914	442	3,292	7,316	145	42,800
"process similarity"	515	49	211	186	43	1,920
"process model" AND "duplicate"	2,882	145	1,067	604	7	10,400
"process model" AND "equivalence"	3,994	179	1,228	1,388	38	16,500
"identical process models"	7	1	2	0	0	17
"distance" AND "process models"	15,441	483	2,595	3,393	62	43,700
"dissimilarity" AND "process models"	682	13	89	263	1	1,780
"process model" AND "clustering"	10,156	309	3,847	1,581	71	23,100
"process correspondence"	227	4	22	524	5	1,640
"workflow matching"	31	5	11	9	1	127
"process model" AND "comparison"	37,701	71	13,484	11	9	715,000
"workflow" AND "comparison"	29,887	75	12,615	35	37	19,500,000

process models," "distance" AND "process models," "dissimilarity" AND "process models," "process model" AND "clustering," "process correspondence," "workflow matching," "workflow similarity," "process model" AND "comparison," "workflow" AND "comparison."

Besides the term "similarity," we especially used the term "matching" as it states a basic technique to determine a similarity value between process models, which is used in many approaches. This helped in finding appropriate literature that does not contain the term "similarity" as, for example, Wombacher et al. (2004). The number of search results for these search terms within the used literature databases are presented in Table 1.

Due to the very high number of search results for some databases, the analysis of search results was skipped for searches leading to more than 250 hits (search results sorted by relevance calculation of each literature database). For those searches, we finished the search after three result pages without a relevant publication. Depending on the search engine, this means that at least 30 consecutive irrelevant hits were examined before the search of a database was canceled. Afterwards, a selection of the identified literature was conducted based on the abstracts. Thus, only articles with a focus on both process models and similarity were considered for the detailed analysis.

Since we further focus on imperative process models, publications considering similarity measurement between declarative process models were ignored. This is grounded on the fact that, on the one hand, declarative models can partially be transformed into imperative models (Prescher et al. 2014), thus allowing corresponding similarity measures to be applied. And on the other hand, if this is not possible or desired, the rule logic of declarative models leads to new challenges for similarity measurement, which are not part of the work at hand. Furthermore, we did not consider publications related to the similarity of scientific workflow models as these differ considerably in their focus. While scientific workflows describe the setup of scientific experiments, that is, they describe the dataflow necessary for an experiment, business process models describe the processes of companies or other organizations focusing on the order of activities, roles, and events. And although the measures calculating a similarity value between scientific workflow models use a subset of the basic techniques used for business process model similarity measurement (see, e.g., the overview in Starlinger et al. (2014)), we do not consider such publications due to the differing focus.

Eventually, the number of resulting hits for the classification and comparative analysis was 195, of which 123 articles were finally selected. Some articles had to be excluded as they, for example, described the usage of an already published similarity measure in a different context, calculated the similarity of process model instances, were a literature survey itself, or described an evaluation of different measures without contributing a similarity measure. Moreover, some articles, such as, for instance, Dijkman (2008), Pietsch and Wenzel (2012), Conforti et al. (2015), Ivanov et al. (2015), and Armas-Cervantes et al. (2016), propose approaches for visualizing the structural or behavioral differences and similarities between business process models. Of course, this is a very important aspect of similarity analyses as, for example, the differences between two models could be visually presented to modelers to ease the examination of deltas. At the same time, the survey at hand focuses on the similarity measurement itself. Hence, only contributions quantifying the similarity of process models are being considered.

To classify the different articles, two authors classified each article independently according to the literature classification criteria described in Section 5. If there was no agreement on the classification, then the different views were discussed until a consensus was reached. Then, a morphological box containing seven analysis aspects and 23 characteristics overall was developed in a theoretical, conceptual way, which serves as a framework for the comparative analysis in Section 7.

5 LITERATURE CLASSIFICATION CRITERIA

The following criteria form the framework for the classification of the publications identified in the literature search. The criteria cover a broad range of aspects related to similarity measurement of process models and refer to the context of similarity measurement as well as to the specifics of the measures. These criteria were determined through an inductive and deductive procedure. That is, after reading the publications, we inductively defined the criteria according to the aspects mentioned in the literature. Afterwards, we deductively added the *Input* criterion and the *Human estimation* aspect for the *Dimensions* criterion to provide for a complete characterization of the similarity measures as these criteria are only rarely mentioned explicitly in the literature. For the purpose of a better comprehensibility of the different criteria, common practices identified in the literature are mentioned for each of them. All criteria were finally combined in the morphological box described in Section 7.1. Results of an analysis of the classification itself are described in Section 7.2. Thus, the classification criteria are an outcome of the literature review as well as a means for classifying the similarity measures.

5.1 Goals Associated with Similarity Measurement of Process Models

In the research literature, the calculation of similarity values for business process models has been associated with different aims. We analyze which and how often goals are pursued by the various similarity measures. Besides, we assess whether the evaluations described in the publications also take the aim into account. In the following paragraphs, the goals found in the literature are categorized and described.[3] Figure 2 provides an overview of the categories and their various sub-goals.

Conformance: One category of goals is the conformance of one model to another. It can be further differentiated between two different sub-goals: On the one hand, the fit of a model to a given reference model is measured, while, on the other hand, differences between different arbitrary models are quantified.

[3]Note that we did not include references to specific publications addressing these goals in the following paragraphs due to space restrictions. These can be found in the online appendix.

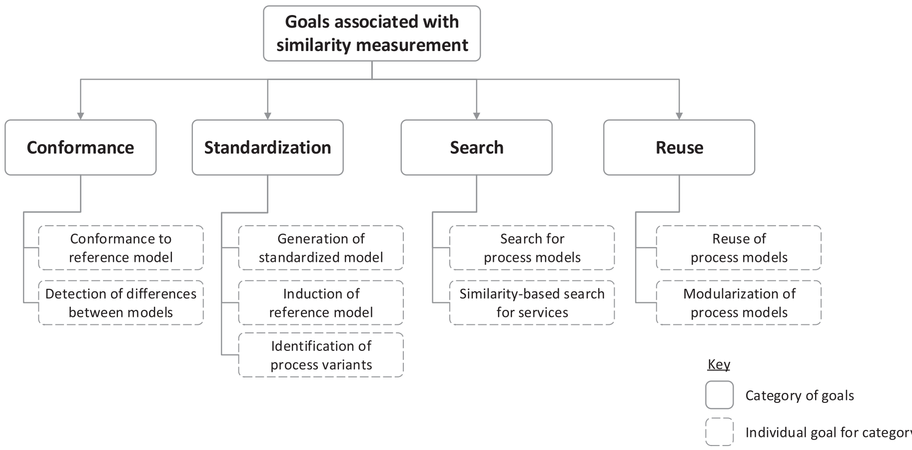

Fig. 2. Goals associated with business process model similarity measurement.

Thereby, the first sub-goal supports two important applications. The similarity measurement can be used to determine the conformance of a model to a reference model in a regulatory sense. In this case, the reference model can be seen as some kind of law or rule that an actual process should adhere to. The second application refers to reference models seen as best practices. Through similarity measurement, differences between a model and a best practice reference model could be used to analyze a model or to find opportunities for process improvement.

Regarding the second sub-goal, the detection of differences is not restricted to reference models only, but arbitrary other models are used. This could be useful in the context of a multinational company executing the same process in different countries according to different models. Differences found through similarity analysis could be used by process analysts for the unification of such processes or process improvement.

Standardization: The second category of goals is related to cases like mergers and acquisitions of enterprises, the restructuring of similar processes of different departments in an organization, and inter-organizational collaborations with the aim to standardize or harmonize several business processes. The ultimate aim is to generate one standardized process model from different process model variants or versions. In this context, process model similarity measures are used to identify processes that can be harmonized in the described way by, for example, applying process model merging approaches.

The inductive generation of reference models can also be seen as an application of process model similarity measures. In this context, the measures can be used to identify corresponding process models of different organizations or different reference models to inductively generate a reference model containing, for example, the best-performing fragments of the input models.

A further application scenario is the identification of process variants. Organizations store different variants of a process model related to, for example, different groups of customers or legal rules in a repository as separate process models. Changing legal regulations or business rules might make it necessary to adapt or standardize these variants to fulfill new requirements. Similarity measures can help to determine affected processes through the identification of related process models.

Search: A third, frequently mentioned goal for the application of process model similarity measures is to facilitate the search for process models in a repository. Organizations have large model repositories containing hundreds or even thousands of models (Dijkman et al. 2011; Houy et al. 2011), which serve as knowledge base for process execution and further business process management activities. In such repositories, model searches could be useful for several reasons and should provide a list of models that are similar to a given process model or process model fragment. A general search could, for instance, be conducted by employees to find the models of the processes they are involved in.

A process model search might also be applied in the context of similarity-based search for services. One of the main ideas of service-oriented architectures is the substitutability of services. If a service procedure is available as a (part of a) process model, then a similarity search may be able to identify candidates for such an exchange. It could also be possible to identify processes that could benefit from an integration of those standardized software services. Hence, as long as similarity measurement between services or the search for services is based on the underlying process, such works could, in principle, be applied to the similarity measurement of process models. Thus, our analysis includes research works focusing on the “process similarity” aspect of services and not on service-specific aspects.

Reuse: A fourth category related to process modeling itself is the reuse of process models. As the modeling of processes is regarded as time-consuming and costly (Becker et al. 2010), this activity could be performed more efficiently through partly or entirely reusing already existing process models. During the modeling activity, a model editor could recommend existing models, which could then be reused by the modeler. Such a recommender function typically uses a similarity measure to propose only suitable models from a repository (Koschmider et al. 2011).

Another application scenario in the reuse category is the modularization of process models. In this scenario, similarity measures are used to detect similar sub-graphs of different process models. These sub-graphs might subsequently be extracted into a new process model to improve the comprehensibility, consistency, and maintainability of process models.

5.2 Dimensions for the Definition of Similarity Measures

There are several different dimensions, which can be used as a foundation for quantifying the similarity between business process models or between their elements. These dimensions form the second investigated criterion and are depicted in Figure 4. While these dimensions are not dimensions in a strong mathematical sense, they focus on different aspects of process models for similarity calculation. This is illustrated in the following with Figure 3, taken and slightly adapted from Fettke et al. (2012).

In Figure 3, three process models are shown referring to the processes of buying and selling products. In *seller process 1* and *seller process 2*, the contained activities have identical labels. Hence, a reasonable similarity value would be 1 when only considering the natural language dimension. Yet, their graph structure and behavior are slightly different. For example, in *seller process 1* the activity “send invoice” is always executed before “ship products” while this is not necessarily true for *seller process 2*, so the final similarity value might be less than 1. When looking at the process models *seller process 2* and *buyer process*, they are identical with respect to the graph structure dimension. Hence, again, a reasonable similarity value would be 1 when only considering this dimension. But regarding the natural language dimension some differences can be observed in the labels (e.g., “receive order” vs. “place order”), which should result in a lower similarity value. Further examples for similarity estimations when considering different dimensions can be found in van der Aalst et al. (2006) for the graph structure and behavior dimensions.

In essence, these illustrative examples show that there are different aspects of a process model that can be used for the calculation of a similarity value. The following descriptions will introduce the dimensions in more detail.

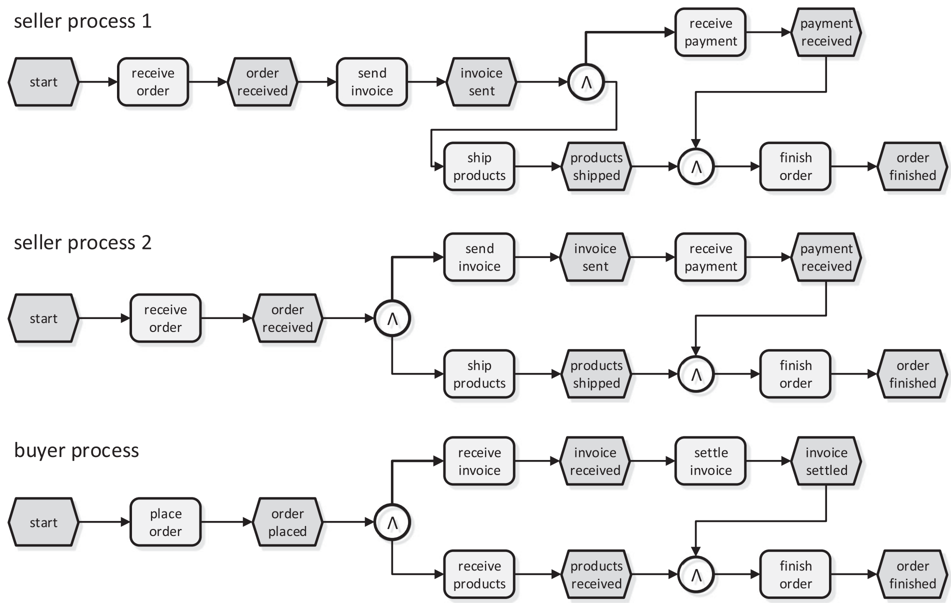

Fig. 3. Illustration of different dimensions used for similarity measurement.

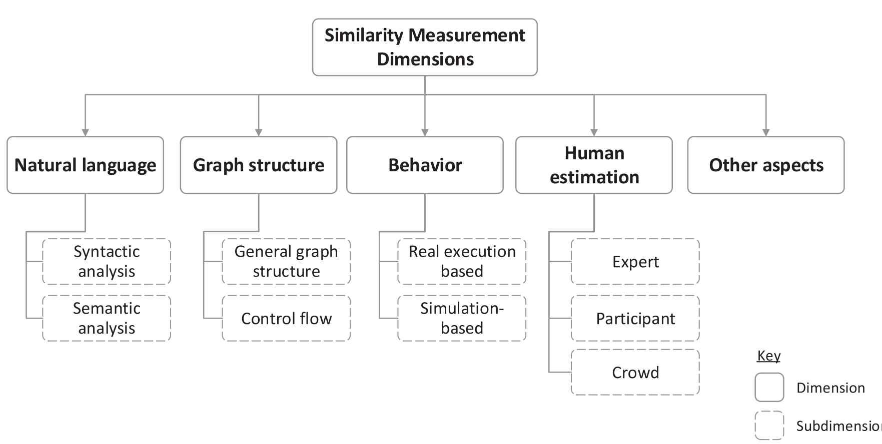

Fig. 4. Dimensions of business process similarity measurement.

Natural language: Generally, natural language is of major importance in the context of business process models (Leopold 2013) as it is, for example, used for labeling the elements contained in a model. Such labels serve as one of the most important sources for process model similarity measurement and are analyzed with regard to syntactic and semantic aspects. While the syntactic analysis focuses on the characters, respectively the string edit distance between two labels, the semantic analysis aims at understanding the meaning of a label based on the used words and the grammar to quantify the similarity of models. Thereby, labels usually consist of few words or short sentences (Koschmider et al. 2015).

In models, labels are usually associated with events, activities and (as conditions when a particular path should be taken) with the directed edges. The labels themselves describe what the corresponding model element consists of. Additionally, roles and business objects can be included and labeled in a model. Furthermore, the similarity measurement can be based on textual metadata associated to process models. Such metadata can, for example, comprise of the name of a model or associated keywords.

For the syntactic analysis sub-dimension, exemplary techniques applied by various similarity measures are the determination of identical labels or the calculation of the Levenshtein distance (Levenshtein 1966) between labels. Regarding the semantic similarity analysis, techniques from the field of NLP are utilized. These comprise, for instance, word stemming, finding synonyms in labels using WordNet (Fellbaum 1998), or determining the closeness between terms using the similarity measure described in Lin (1998).

Graph structure: The relevant aspects of this category arise from graph theory and can be divided into general graph structure-based and business process-aware control flow similarity measures. The general graph structure-based similarity between models can be quantified by, for example, the size (in terms of the number of nodes and edges) of the largest common sub-graph of two models. Since general graph-based algorithms do not consider any connectors (which are very common in the context of business process models), such connectors are either ignored or the existing measures are extended to handle them.

The similarity of two process models regarding the control flow aspect is calculated with respect to the position and kind of the various control flow connectors present in models. For example, it is determined how similar two models are with respect to the order of activities and connectors. La Rosa et al. (2013) use a concept called *context similarity* in their approach for process model merging, in which preceding and succeeding activities of connectors are used to determine the similarity between such connectors.

Techniques belonging to this dimension are, for example, the calculation of (error correcting) graph edit distance or graph isomorphism between the graph structure of process models. Alternatively, the construction of special graph-like representations as, for instance, trees to determine the similarity between such representations are used (see, e.g., Fu et al. (2012) or Bae et al. (2006)). Other techniques taking into account the control flow perspective of process models use, for instance, a block structure representing the control flow of process models (Gater et al. 2011) or the cophenetic distance, a concept from computational phylogenetics, adapted to process models (Sánchez-Charles et al. 2016).

Behavior: This aspect of similarity calculation focuses on execution traces of processes as specified in Definition 2.2. Such execution traces can be generated through simulation runs or during the actual execution of a process and are usually stored in a log for further analysis. In the context of similarity measurement, the number of identical execution sequences in a log can, for instance, be used to determine the similarity between two models. Thereby, characteristics of possible execution sequences as, for example, the length of the longest common subsequence or causal footprints (van Dongen et al. 2008) are also considered.

Techniques used regarding this dimension determine, for example, the similarity between the possible execution sequences of different process models using precision and recall measures (van der Aalst et al. 2006) or the longest common subsequence of execution sequences (Wang et al. 2010). Besides these, the calculation of behavioral profiles that focus on the order of possible execution sequences of process activities are utilized (Kunze et al. 2011).

Human estimation: Another important aspect of similarity measurement is the human judgment on how similar process models are. People are able to subjectively quantify the similarity between process models based on their individual knowledge. One can differentiate three types of human estimation based on the knowledge of the people involved: (1) process experts, (2) process participants, and (3) crowd. Process experts have a grounded knowledge of the process landscape of a company or its divisions, while process participants are specialists for particular processes or process parts. Thus, it can be assumed that process experts quantify the similarity from a more general point of view, while process participants adopt a more detailed perspective. In contrast to that, the crowd solely gains its knowledge from the process description (e.g., business process models). Therefore, the crowd quantifies the similarity according to its own individual interpretation of the process descriptions.

Possible similarity measures taking this aspect into account might include some kind of "learning" algorithm that uses human input on the correctness of automated similarity calculations. Alternative approaches might be the incorporation of human input through Gamification methods and crowd-based similarity estimation.

Currently, only three approaches use a technique fitting into this category. In Klinkmüller et al. (2014), the input of user feedback is used to improve the matching of process model elements, whereas Rodriguez et al. (2016) uses a crowd-based determination of matches. Finally, Laue and Becker (2012) compares tags associated with process models to determine a similarity value.

Other aspects: Finally, other aspects for calculating a similarity value, which are described in the literature, are collected in this group as they do not appear frequently or are specific to a certain similarity measurement approach. Examples are the usage of ontology alignment techniques (Brockmans et al. 2006), process model metric values (Melcher and Seese 2008), and web service descriptions (Huang et al. 2004).

Techniques used regarding this dimension are, for example, the transformation of a process model into an OWL representation (Brockmans et al. 2006) and a measure for the compatibility between web services (Antonellis et al. 2003).

5.3 Input for Similarity Analysis

Another classification criterion investigated is the input on which similarity measures operate. In our analysis, we differentiate between four distinct granularity levels of similarity analysis: (1) similarity between (sets of) model elements, (2) similarity between sub-graphs, (3) similarity between two models, and (4) similarity between sets of models. Thereby, (1) corresponds to the matching of process model elements in Section 2.4 and (3) corresponds to the similarity description in Section 2.3. The granularity levels (2) and (4) resemble a restriction and an extension compared to (3). Granularity level (4) might be useful in cases that require the determination of similarity values for large amounts of process models as similarity values do not have to be calculated pairwise. Instead, similarity between multiple models can be determined at once. This might lead to reductions in effort and time consumption for similarity analysis.

In case a similarity measure calculates a similarity value on multiple granularity levels, all levels applied are marked in the literature analysis table (see online appendix). Additionally, it should be noted that the sub-graph granularity level is only marked when a similarity measure explicitly calculates the similarity value of sub-graphs. Similarity measures that could be adapted to calculate such a sub-graph similarity value but do not actually measure it are not marked. The same applies for similarity calculations between sets of models.

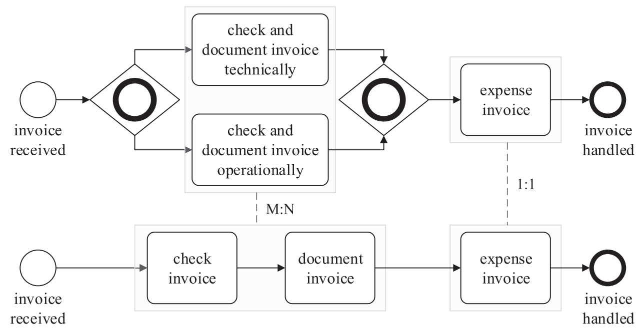

Fig. 5. Node matching cardinality example.

5.4 Cardinality of Corresponding Nodes

In most cases, process model similarity measures are based on node matching. Thus, the cardinality of these matches is of major importance. Since existing measures use different matching techniques, they also differ with respect to the cardinality ($1:1$, $1:N$, $M:N$) of correspondences. $1:1$ (elementary match) means that for each node of one model a matching algorithm computes at most one corresponding node in the other model. $1:N$ (complex match) is a generalization of this basic case: For each node in one model, one or more corresponding nodes in the other model are identified. This is generally the case when models express a business process on different levels of granularity. An example might be the activity "check invoice" in the lower model in Figure 5 in contrast to the two activities "check and document invoice technically" and "check and document invoice operationally" in the upper model. The $M:N$ cardinality (complex match) generalizes even further: For M nodes of one model, N corresponding nodes in the other model are identified. A sample of a node matching with both, $1:1$ and $M:N$ matches, is visualized in Figure 5. As one can see in Becker and Laue (2012), at the time of this survey, most similarity measures used matching approaches solely creating elementary matches. However, recent works in the field of business process model matching show a focus on complex matches (Cayoglu et al. 2014; Antunes et al. 2015).

5.5 Restrictions Regarding Modeling Language

A lot of similarity measures are defined for certain modeling languages like Petri Nets, EPC or BPMN. As several notations exist in the business process modeling community, the question of whether similarity measures could be applied to models in different notations arises. In theory, problems can occur if one modeling construct or characteristic of a modeling language is not supported by another. If, for example, one similarity measure would require the formal execution semantics of Petri Nets, then this measure could possibly not be applicable to EPC models.

Through this criterion, we assess whether similarity measures are limited by such restrictions. We provide an overview of the restrictions found in the literature and deduce if there are similarity measures that could be applied to heterogeneous process model repositories, that is, repositories with models in different languages.

5.6 Evaluation

Regarding the evaluation criterion, we analyze whether similarity measures have been evaluated against some data sets or not. The goal is to assess whether the empirical usefulness of such measures was evaluated as well as to determine the maturity of these evaluations in general. We distinguish between real life and synthetic data sets. While real life data sets are process models that actually exist, for example, in companies or public administrations, synthetic data sets contain models that were specifically generated for evaluation purposes. Besides this distinction, we also analyze the amount of models used for evaluations as well as the evaluations' aims.

5.7 Implementation

Finally, the implementation criterion describes whether a tool implementing a similarity measure is publicly available as an executable application for practical usage. This might be useful to conduct comparisons between multiple similarity measures, which are currently missing in the research literature. In this context, publicly available means that (1) an implementation does exist, (2) the implementation is working, and (3) the implementation is accessible. To be able to adapt a technique regarding specific requirements, it might also be meaningful to distinguish between open and closed source implementations.

6 BASIC TECHNIQUES FOR SIMILARITY MEASUREMENT

As mentioned above, there are several different dimensions used as a foundation for quantifying the similarity between business process models. In the following, the most common basic techniques addressing these dimensions are explained in detail. Hence, it is not the intention to present an exhaustive overview of all existing formal approaches, but to provide details on basic approaches that are often used in the literature. Thus, the above mentioned dimension *Other* is disregarded as it contains no common techniques by definition.

6.1 Natural Language Dimension

6.1.1 String Edit Distance. Given two labels $l_1, l_2 \in L$, the string edit distance $dist(l_1, l_2)$ is defined as the minimum number of character edit operations transforming l_1 into l_2. One of the simplest and most common set of edit operations is the one defined by Levenshtein (1966) consisting of *insertion*, *deletion*, and *substitution*. In the definition of Levenshtein, all those operations are equally weighted by 1. However, the operations may also be weighted by other non-negative numeric values.

Generally, an edit distance value can also be transformed to a similarity value, which covers the focus of the work at hand. Therefore, the distance value is being divided by the length of the longer label (in case of the Levenshtein distance), which is also the maximum distance value, if all characters differ from each other:

$$sim(l_1, l_2) = \frac{dist(l_1, l_2)}{max(len(l_1), len(l_2))}$$

6.1.2 Word Edit Distance. The word edit distance works analogously to the string edit distance. First, the labels of all nodes of the considered process models are tokenized, which means that the single words of labels are being extracted. For example, the label "check and document invoice technically" is divided into the tokens "check," "and," "document," "invoice," and "technically." The distance is then calculated based on the word edit operations instead of the single characters. Thus, like in the string edit distance case, prior focus is on measuring the similarity of nodes (respectively their labels) to identify correspondences (process model matching). Those correspondences serve as a basis for subsequently quantifying process model similarity.

The technique can be enhanced by removing stop words so only relevant terms are considered (Cayoglu et al. 2014). Furthermore, reduction of the single words to their stems is common practice, which leads to an abstraction from the particular word form (Cayoglu et al. 2014; Antunes et al. 2015).

6.1.3 Semantic Similarity. Semantic similarity refers to similarity quantification of natural language labels by considering *word similarities* (Lin 1998) of the words contained in different labels or more generally the *meaning* of labels. Such a similarity calculation is typically necessary to account for the usage of synonyms and homonyms in labels. For example, when considering the labels "send invoice" and "transfer invoice," both are concerned with sending an invoice to a customer, yet they use synonymous words. While the string edit and word edit distances are big, semantic similarity measures can detect the synonyms and, therefore, assign a high similarity value to the labels.

Regarding the semantic similarity quantification, process model similarity measures utilize various approaches for calculating the semantic similarity of words and sentences. For instance, the WordNet Similarity Score (Pedersen et al. 2004) is used by La Rosa et al. (2013), matching approaches published in Antunes et al. (2015) use additional linguistic databases like Wiktionary[4] or the similarity measure for words described in Lin (1998), and Gacitua-Decar and Pahl (2009) utilize a similarity measure for sentences (Li et al. 2006).

Furthermore, since the semantic similarity aims at considering the meaning of a label, some approaches consider the grammar of labels. For this purpose, common NLP techniques, especially part of speech tagging (POS) and natural language parsing, are applied. The POS assigns a part of speech as, for example, verb, noun, or punctuation mark to each token of a label, whereas natural language parsing aims at deriving the grammatical structure of a label to identify, for example, the subject, the predicate and the object. The matching approach described in Leopold et al. (2012) uses such techniques to determine action, business object, and an optional fragment in labels to calculate matches. Thus, these techniques require specifics for different languages, since there are individual grammatic structures and word forms. Besides, that is also the case for word stemming, which is the reason for the existence of different stemming algorithms for different languages (e.g., the Porter-Stemmer (Porter 1980) for English).

6.1.4 Similarity of Virtual Documents/Bag of Words. A traditional technique from information retrieval is determining the relevance (similarity) of a document with regard to an input document based on the used terms. In the context of business process models, all words contained in all labels are being listed and possibly weighted by the number of their occurrences. Consequently, in case of weighting, the more frequently a word is contained in the process models, the more relevant or irrelevant it is. Such lists are then compared to quantify the similarity between two models, since it is assumed that process models using the same terms describe similar processes (Weidlich et al. 2010). The techniques are often enhanced by additional NLP-techniques, such as stemming and stop word removal. One example is described in Schoknecht et al. (2016), which relies on a vector space representation of process models based on virtual documents. Besides, in contrast to the techniques mentioned above, this approach does not require a particular node matching.

6.2 Graph Structure Dimension

6.2.1 Similarity based on Common Nodes and Edges. One of the graph structure–based similarity measurement techniques is to count the number of common nodes and edges of two process models and relate them to the overall number of nodes and edges (Minor et al. 2007):

$$sim(M_1, M_2) = \frac{2 \cdot (|N_1 \cap N_2| + |A_1 \cap A_2|)}{|N_1| + |N_2| + |A_1| + |A_2|}.$$

[4]Wiktionary: http://www.wiktionary.org.

Since the edges of a process model specify its control flow, they cover the aspect of graph structure. Hence, it might also be possible to solely consider the edges if they are defined through their start and end nodes.

6.2.2 Graph and Tree Edit Distance. Similarly to the above-mentioned string and word edit distances, the graph (tree) edit distance quantifies the similarity between two graphs (trees) based on the minimum amount of operations necessary to transform one process model (respectively, its tree representation) into the other (e.g., Dijkman et al. (2009, 2011)): $dist(M_1, M_2) = (|N_1 \setminus N_2| + |N_2 \setminus N_1|) + (|A_1 \setminus A_2| + |A_2 \setminus A_1|)$. Again, a similarity value can easily be calculated by dividing the distance with the maximum possible distance:

$$sim(M_1, M_2) = \frac{dist(M_1, M_2)}{|N_1| + |A_1| + |N_2| + |A_2|}.$$

This technique can be enhanced by additionally considering the similarity between the individual similarity values of the corresponding nodes.

6.2.3 Feature-Based Similarity. Another technique to quantify the similarity between process models is to use structure-related information in the context of their nodes (called *features*). One example of an existing technique is the feature-based similarity estimation of Yan et al. (2010), which uses five roles $R = \{start, stop, split, join, regular\}$ to characterize a node. With $|\bullet n|$ being the number of preceding nodes of n and $|n\bullet|$ being the number of succeeding nodes of n, for each node $n \in N$, the function $roles : N \rightarrow \mathcal{P}(R)$ assigns the roles, such that

$$\begin{aligned} start \in roles(n) &\Leftrightarrow |\bullet n| = 0, \\ stop \in roles(n) &\Leftrightarrow |n\bullet| = 0, \\ split \in roles(n) &\Leftrightarrow |n\bullet| \geq 2, \\ join \in roles(n) &\Leftrightarrow |\bullet n| \geq 2, \\ regular \in roles(n) &\Leftrightarrow |\bullet n| = 1 \wedge |n\bullet| = 1. \end{aligned}$$

Then, for each node pair (n_1, n_2) with $n_1 \in N_1$ and $n_2 \in N_2$ and the set $croles := roles(n_1) \cap roles(n_2)$, the role feature similarity is defined as:

$$rsim(n_1, n_2) := \begin{cases} 1, & \text{if } start \in croles \wedge stop \in croles, \\ 1 - \frac{||n_1\bullet| - |n_2\bullet||}{2(||n_1\bullet| + |n_2\bullet||)}, & \text{if } start \in croles \wedge stop \notin croles, \\ 1 - \frac{||\bullet n_1| - |\bullet n_2||}{2(||\bullet n_1| + |\bullet n_2||)}, & \text{if } start \notin croles \wedge stop \in croles, \\ 1 - \frac{||n_1\bullet| - |n_2\bullet||}{2(||n_1\bullet| + |n_2\bullet||)} - \frac{||\bullet n_1| - |\bullet n_2||}{2(||\bullet n_1| + |\bullet n_2||)}, & \text{if } otherwise. \end{cases}$$

Two nodes (n_1, n_2) are now considered as equivalent iff both the syntactic label similarity (Levenshtein) and the role feature similarity surpass an individual threshold. Finally, the similarity between two models M_1 and M_2 is defined as the number of corresponding nodes related to the overall number of nodes of both models:

$$sim(M_1, M_2) := \frac{2|N_1 \cap N_2|}{|N_1| + |N_2|}.$$

Apart from this concrete sample technique, a structure-based similarity quantification is also possible based on values of business process model metrics as described in Melcher and Seese (2008). The metrics' values serve as features of a vector describing a process model, which are compared afterwards. A distance, respectively, a similarity value can be calculated using, for instance, particular generic distance measures, such as Euclidean, Hamming, or Jaccard distance.

6.3 Behavior Dimension

6.3.1 Longest Common Subsequence of Traces. The approach of Gerke et al. (2009) uses the traces of two process models to quantify their similarity. Therefore, the two components trace compliance degree $cd_{trace}(\sigma_1, \sigma_2)$ and trace maturity degree $md_{trace}(\sigma_1, \sigma_2)$ are used, whereby σ_1 is a trace of M_1 and σ_2 is a trace of M_2. The trace compliance degree covers the extent to which a process adheres to ordering rules of activities, while the trace maturity degree covers the extent to which the activities of the other model are recalled. Both components are defined based on the length of their longest common subsequence lcs, such that $cd_{trace}(\sigma_1, \sigma_2) = \frac{len(lcs(\sigma_1, \sigma_2))}{len(\sigma_2)}$ and $md_{trace}(\sigma_1, \sigma_2) = \frac{len(lcs(\sigma_1, \sigma_2))}{len(\sigma_1)}$. Based on that, the compliance and maturity degree between two process models are defined as the sum of the maximum trace compliance and trace maturity degrees:

$$cd(M_1, M_2) = \frac{\sum_{\sigma_2 \in \Sigma_{M_2}} max_{\sigma_1 \in \Sigma_{M_1}}(cd_{trace}(\sigma_1, \sigma_2)))}{|\Sigma_{M_2}|},$$
$$md(M_1, M_2) = \frac{\sum_{\sigma_1 \in \Sigma_{M_1}} max_{\sigma_2 \in \Sigma_{M_2}}(md_{trace}(\sigma_1, \sigma_2)))}{|\Sigma_{M_1}|}.$$

Thus, the authors did not present a consolidated similarity value but two components expressing in how far the traces of one model are reflected by the traces of another model.

6.3.2 Similarity of Causal Footprints. A causal footprint (van Dongen et al. 2008) of a process model M and its set of activities $F \subseteq N$ is a tuple (Lk_{lb}, Lk_{la}) with $Lk_{lb} \subseteq (\mathcal{P}(F) \times F)$ the set of look-back links and $Lk_{la} \subseteq (F \times \mathcal{P}(F))$ the set of look-ahead links. A tuple (Θ, f) with $\Theta \in \mathcal{P}(F)$ and $f \in F$ belongs to Lk_{lb} if each occurrence of f is preceded by an occurrence of a $\theta \in \Theta$ in each trace of F such that $\sigma_i =< \ldots, \theta, \ldots, f, \ldots >$ holds. Analogously, a tuple (f, Θ) belongs to Lk_{la} if each occurrence of f is followed by an occurrence of θ such that $\sigma_i =< \ldots, f, \ldots, \theta, \ldots >$ holds. To calculate the similarity between two process models, the causal footprints are represented as vectors of index terms. The set of index terms for two process models $M_1 = (N_1, A_1)$ and $M_2 = (N_2, A_2)$ are defined as $\Omega = N_1 \cup N_2 \cup L_{la}^{M_1} \cup L_{la}^{M_2} \cup Lk_{lb}^{M_1} \cup Lk_{lb}^{M_2}$, so Ω contains all nodes, look-ahead and look-back links of both process models. Let $\lambda : \Omega \rightarrow \mathbb{N}$ be an indexing function that assigns a running index to each index term. The process models M_i with $i \in 1, 2$ are then represented as footprint vectors $\vec{g}_1 = (g_{1,1}, \ldots g_{1,j}, \ldots, g_{1,|\Omega|})$ and $\vec{g}_2 = (g_{2,1}, \ldots g_{2,j}, \ldots, g_{2,|\Omega|})$, with

$$g_{i,\lambda(\omega)} := \begin{cases} 0, & \text{if } \omega \notin (N_i \cup Lk_{la}^{M_i} \cup Lk_{lb}^{M_i}), \\ \frac{1}{2^{|\Omega|-1}}, & \text{if } \omega \in (Lk_{la}^{M_i} \cup Lk_{lb}^{M_i}), \\ 1, & \text{if } \omega \in N_i. \end{cases}$$

The similarity between both process models is then defined as the cosine of the angle between their footprint vectors, such that

$$sim(M_1, M_2) := \frac{\vec{g}_1 \cdot \vec{g}_2}{|g_1| \cdot |g_2|} = \frac{\sum_{j=1}^{|\Omega|} g_{1,j} \cdot g_{1,j}}{\sqrt{\sum_{j=1}^{|\Omega|} g_{1,j}^2} \cdot \sqrt{\sum_{j=1}^{|\Omega|} g_{2,j}^2}}.$$

Thus, already the calculation of the footprint vectors requires a node matching, respectively, a quantification of the correspondence between the particular nodes of M_1 and M_2. Otherwise, the similarity between arbitrary process models would be zero, since the footprints would be disjoint. Therefore, the authors propose an additional metric quantifying the similarity between activities of process models. This semantic similarity score bases on the node labels, which are split into words. Identical words are rated with an equivalence score of 1; synonyms are rated with a score of 0.75. Let $f_1 \in F_1$ and $f_2 \in F_2$ be two activities of two different process models with f_1 and f_2 being the sets of words of the corresponding activity labels in this case. The function $synonym(w_1, w_2)$ returns 1 if the given words from the labels are synonyms and 0 if they are not. Formally, the node similarity score is defined as

$$sem(f_1, f_2) := \frac{1.0 \cdot |f_1 \cap f_2| + 0.75 \cdot \sum_{(w_1, w_2) \in F_1 \setminus F_2 \times F_2 \setminus F_1} synonym(w_1, w_2)}{max(|f_1|, |f_2|)}.$$

These similarity values (within $[0, 1]$) are subsequently used for weighting the elements of the footprint vectors.

6.3.3 Similarity of Behavioral Profiles. In Weidlich et al. (2010), the behavior of a process model is conceptualized as dependencies between activities of a set of execution traces, which are derived from the model's execution log. For all $f_i, f_j \in F$, the dependencies are expressed by four different relations, the resulting set of relations is called causal behavioral profile.

- Strict order relation: f_i and f_j are in strict order relation, iff in all traces $\sigma \in \Sigma$ containing both f_i and f_j, f_i is always executed before f_j.
- Exclusiveness relation: f_i and f_j are in exclusiveness relation, iff there is no trace $\sigma \in \Sigma$ containing both f_i and f_j.
- Interleaving order relation: f_i and f_j are in interleaving order relation, iff in the set of traces $\sigma \in \Sigma$ containing both f_i and f_j there is at least one trace $\sigma_i =< \ldots, f_i, \ldots, f_j, \ldots >$ and at least one trace $\sigma_j =< \ldots, f_j, \ldots f_i, \ldots >$.
- Co-occurrence relation: f_i and f_j are in co-occurrence relation, iff all traces $\sigma \in \Sigma$ containing f_i also contain f_j and vice versa.

Based on the causal behavioral profiles and a predefined activity mapping, the authors define a similarity measure (degree of profile consistency of alignment) as follows: Let Λ_{M_1,M_2} be the set of matches between M_1 and M_2. Then $F_1^{\sim} = \{f^{M_1} \in F_1 | \exists f^{M_2} \in F_2 : (f^{M_1}, f^{M_2}) \in \Lambda_{M_1,M_2}\}$, $F_2^{\sim}$ is defined analogously. Let further the set of consistent pairs $(f_1^{M_1}, f_2^{M_1}) \in P_1$ with $P_1 \subseteq F_1^{\sim} \cdot F_1^{\sim}$ contain activity pairs, for which their counterparts $(f_1^{M_2}, f_2^{M_2}) \in P_2$ with $P_2 \subseteq F_2^{\sim} \cdot F_2^{\sim}$ and $(f_1^{M_1}, f_1^{M_2}), (f_2^{M_1}, f_2^{M_2}) \in \Lambda_{M_1,M_2}$ are in the same relations. Then, the similarity between M_1 and M_2 is defined as

$$sim(M_1, M_2) = \frac{|P_1| + |P_2|}{|F_1^{\sim} \cdot F_1^{\sim}| + |F_2^{\sim} \cdot F_2^{\sim}|}.$$

As one can see in the formalization, the behavioral profiles cannot only be calculated based on the execution logs of a business process but based on the process model as well. Another important differentiation to the other mentioned similarity measurement approaches is the ability to handle complex node matches. Thus, $|F_1^{\sim}|$ is not necessarily equal to $|F_2^{\sim}|$.

6.4 Human Estimation Dimension

6.4.1 Crowd-Based Similarity Estimation. Social tagging of process models is considered in Laue and Becker (2012) to calculate the similarity between process models. The basic idea is that models are more similar to each other the more common tags they share. Hence, the similarity of a model M_1 with a multiset of tags $Tags_1$ and a model M_2 with a multiset of tags $Tags_2$ is calculated as $sim(M_1, M_2) = \frac{2|Tags_1 \cap Tags_2|}{|Tags_1| + |Tags_2|}$ using Dice's coefficient (Dice 1945). $|Tags_i|$ is the number of elements in the tag list $Tags_i$.

6.4.2 User Feedback. With respect to the improvement of process model matching the input of user feedback is incorporated in Klinkmüller et al. (2014). Thereby, a user is presented with the

Table 2. Morphological Box for Characterizing Process Model Similarity Measures

Background	**Objective**	Conformance (18.7%)	Standardization (43.9%)	Search (48.8%)	Reutilization (24.4%)	
Conceptualization	**Input**	Model elements (65.0%)	Sub-graphs (12.2%)	Models (81.3%)	Sets of models (4.1%)	
	Dimensions	Natural language (69.1%)	Graph structure (86.2%)	Behavior (31.7%)	Human estimation (2.4%)	Other (18.7%)
	Cardinality	1 : 1 (34.1%)	1 : N (8.9%)	M : N (16.3%)	Other (19.5%)	None (21.1%)
	Restriction	Petri Net (7.3%)	EPC (0.0%)	BPMN (1.6%)	Other (26.8%)	None (64.2%)
Application	**Validation**	Real life data (36.6%)	Synthetic data (31.7%)	None (34.1%)		
	Implementation	Free (15.4%)	Commercial (0.8%)	Unknown (2.4%)	None (82.1%)	

matches of an automatic matching approach and has to remove incorrect matches and add further correct ones. This user input is then passed on to the automatic matching approach, which uses the input to adapt the underlying label similarity calculation.

7 COMPARATIVE ANALYSIS

This section describes the morphological box, an excerpt of the classification data as well as descriptive analyses regarding the literature classification. In the next section, these descriptive analyses are discussed with respect to future research opportunities regarding similarity measurement of business process models.

7.1 Morphological Box and Classification Data Sample

The characteristics mentioned in Section 5 allow the description of business process model similarity measures. Thus, a framework was developed, which is condensed in Table 2. Generally, the morphological box consists of three analysis levels. One is background information on the similarity measures, that is, the objective of a measure. The second refers to the concepts used by the measures and the third contains data related to practical aspects. The percentage values within the brackets explicate the rate of approaches for which a characteristic holds true. Thereby, multiple entries per aspect are possible.

A sample of the classification data can be found in Tables 3 and 4. These data are displayed for illustration purposes, the complete data set can be found in the online appendix. In the tables, the classification data for the publications by Akkiraju and Ivan (2010), Dijkman et al. (2009), Gerke et al. (2009), Minor et al. (2007), La Rosa et al. (2013), Schoknecht et al. (2016), and Yan et al. (2010) are described. Additionally, a complete list of references for the publications analyzed in this review can be found in the online appendix.

Table 3. Sample of Literature Classification Data

ID	Reference	Goals associated with similarity measurement									Input				Implementation
		G1	G2	G3	G4	G5	G6	G7	G8	G9	I1	I2	I3	I4	
3	(Akkiraju and Ivan 2010)					x			x				x		-
24	(Dijkman et al. 2009)						x				x		x		ProM
45	(Gerke et al. 2009)	x											x		-
88	(Minor et al. 2007)								x				x		-
99	(La Rosa et al. 2013)			x							x		x		http://www.processconfiguration.com
103	(Schoknecht et al. 2016)							x					x		butler.aifb.kit.edu/asc/LS3/ls3.html
119	(Yan et al. 2010)						x				x		x		-

Legend: G1 = Conformance to reference model, G2 = Detection of differences between models, G3 = Generation of standardized model, G4 = Induction of reference model, G5 = Identification of process variants, G6 = Search for process models, G7 = Similarity-based search for services, G8 = Reuse of process models, G9 = Modularization of process models. I1 = Similarity of model elements, I2 = Similarity of sub-graphs, I3 = Similarity between models, I4 = Similarity between sets of models.

Table 4. Sample of Literature Classification Data (Continued)

ID	Dimensions							Cardinality	Restrictions	Validation	
	D1	D2	D3	D4	D5	D6	D7			Real-life	Synthetic
3	x							1:1	-	5299 models	-
24	x			x				1:1	-	100 models	-
45					x			-	Workflow net	1 model	-
88			x	x				-	-	37 models	-
99	x	x	x	x				1:1	Explicit logical control flow connectors	-	-
103			x					-	-	80 models	-
119	x		x					m:n	-	10 queries 100 models	-

Legend: D1 = Syntax, D2 = Semantic, D3 = Graph-oriented, D4 = Control flow oriented, D5 = Behavior, D6 = Human estimation, D7 = Further aspects. Cardinality of node matches. Restrictions regarding modeling language.

7.2 Classification Analysis

Generally, research on process model similarity began in the mid '90s with two published articles between 1995 and 1996. Besides these early works, the topic only aroused deeper interest from 2004 on. While three related articles were published in 2004, the number of publications increased significantly from 2006 on with peaks of 18 and 19 publications in 2010 and 2012. Afterwards, the publication count dropped to only eight in 2014, while we discovered nine additional articles published in 2015 and 2016. For an overview on the publication numbers per year see Figure 6.

7.2.1 Goals and Evaluation Status. As described in Section 5.1, various goals have been stated in the literature regarding the application of similarity measures. The most often mentioned objective is the *search for process models* (42 times). With additional 18 publications expressing a *similarity-based search for services* as their aim, *search* is the category specified most frequently (60 times in total). With 54 publications stating objectives from the *standardization* category, it is ranked

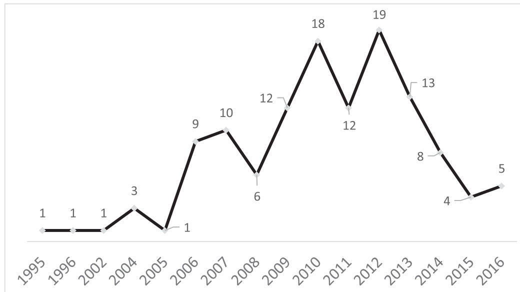

Fig. 6. Publications per year.

second. *Generation of standardized model* is the second most frequently mentioned goal (37 times). Behind these two goals *reuse of process models* and *conformance to a reference model* are ranked third and fourth regarding their occurrence (26 and 20 times). The remaining objectives were mentioned even less frequently: *Identification of process variants* ten times, *induction of reference models* seven times, *modularization of process models* four times, and *detection of differences between models* three times. Besides these frequencies, two publications did not mention any goal.

The status of evaluations of similarity measures is quite weak. Forty-two of the 123 analyzed articles did not provide an evaluation regarding the similarity values of their measures at all. In another 6 articles the description was unclear so no number of models could be determined. Of the remaining publications, 33 articles used 20 or less models for an evaluation (small data set). Medium-sized data sets from 21 to 100 models were used in 17 articles and large data sets above 100 models were used in 25 publications. This essentially means that 34.1% of the analyzed articles did not provide an evaluation regarding their similarity values. Besides that, only a few articles provide an evaluation comparing different similarity measures, although such comparisons can be very insightful as could be seen by the process model matching contests (Antunes et al. 2015; Cayoglu et al. 2014). Two notable exceptions are Dijkman et al. (2009) and Thaler et al. (2016) in which different measures and the calculated similarity values are compared to each other. This lack of comparative evaluations might be caused by missing readily available implementations (see Section 7.2.5).

The analysis results regarding a combined examination of evaluation status and goals also show quite a weak support. Only 44 of the 75 publications providing an evaluation consider the objectives according to which the similarity measure was developed for. Thereby, mostly similarity measures developed for search have been evaluated with respect to the objective. This can probably be attributed to a relatively straightforward evaluation setting, whereby a list of process models is ranked by process experts according to their perceived similarity to a query model. Afterwards, this ranking is compared to a ranked list of models returned by an automatic similarity calculation approach. A comparative overview of similarity measures for certain goals allowing us to assess how they perform against each other is missing, too. It would be interesting to compare, for example, the rankings of different similarity measures in a search scenario to a common model data set. Right now, it is unclear whether these rankings would differ from each other. Another aspect would be to assess in how far and how effectively similarity measures support modelers during their modeling task by, for example, providing model recommendations.

7.2.2 Dimensions used for Similarity Measurement. Regarding the dimensions used for similarity measurement, some are used often, while others have mostly been neglected until now. The syntactic dimension is used most frequently (76 times), while the human estimation dimension is used least of all with only three measures fitting into this category. Interestingly, there seem to be some combinations of dimensions that are used quite frequently together, while other combinations seem to be excluding each other. Measurement techniques related to the graph structure, the control flow and the behavior dimensions are seldom used together. Only one measure uses techniques from all these dimensions and only five and twelve measures use combinations of control flow and behavior or graph structure and behavior dimensions, respectively. With 21 measures, the combination of graph structure and control flow dimensions is a bit more common.

In contrast to that, the combination of different natural language techniques (syntactic and semantic analysis) is much more common with 39 similarity measures utilizing such a combination. Bearing in mind that only 45 measures use a semantic analysis, the combination of syntactic and semantic analysis seems to be a “natural” fit. This can be explained by the recognized fact that process models typically do not contain exactly the same terms in labels, even if they describe the same process. One case of difference can be the usage of synonyms, for instance. Semantic analysis techniques can help to mitigate such challenges.

Another interesting aspect is that only six measures solely rely on a semantic analysis neglecting a syntactical analysis. Hence, the semantic analysis does not replace the syntactic analysis until now. Also, syntactic analysis is commonly used together with techniques from the graph structure and control flow dimensions (29 and 44 times), while the behavior dimension is used less frequently with only 20 measures. Astonishingly, only five publications described similarity measures including all of the three main dimensions natural language, graph structure and behavior.

7.2.3 Input and Cardinality of Node Matches. As expected, most similarity measures calculate or require an explicit matching of nodes for the calculation of a similarity value. Only 26 of the 123 analyzed articles do not utilize such a matching, but employ other means such as the calculation of process model metrics with cluster analysis (Melcher and Seese 2008) or the comparison of vectors in a vector space (Schoknecht et al. 2016) instead. In 84 measures, elementary or complex node matching is used while the remaining 13 approaches calculate other kinds of correspondences. Such correspondences include, for example, the comparison of languages generated by finite state automata (Wombacher and Rozie 2006) or the matching of execution sequences (Belhoul et al. 2012).

Besides, almost all analyzed similarity measurement approaches calculate the similarity between two process models. Such a calculation is described in 100 articles. Interestingly, only 25 of them do not rely on a matching of model elements, that is, do not calculate the similarity between single process model elements. They resort to other means such as the approach described in Malinova et al. (2013a), in which process models are represented by word vectors that are clustered through the application of k-means algorithm (MacQueen 1967). Yet, in total, 79 approaches explicitely describe how to calculate the similarity between model elements. Additionally, 15 approaches determine the similarity of sub-graphs and five approaches calculate a similarity value between sets of models. One example for the similarity calculation between sets of models is the measure described in Uba et al. (2011) applied to detect clones in process model repositories utilizing a graph structure. Through this graph structure, all clones in a model repository can be found at once. Finally, 16 measures only calculate a similarity value between model elements and do not provide a formula for the similarity of two process models. Hence, these approaches focus on the process model matching part. Notably, one measure does not determine any similarity values as process model metrics and a cluster algorithm are used for determining similar models (Melcher and Seese 2008).

7.2.4 Restrictions Regarding Modeling Language. The analysis regarding the modeling language restrictions showed that most similarity measures can be applied independently of the used modeling language or other specific restrictions (79 of 123). This is less surprising as it might seem as the most frequently used similarity calculation dimensions comprise the labels of process model elements and the general graph structure of a model. Such techniques can be applied or transferred to all of the common business process modeling languages. For example, the syntactic or semantic analysis of transition labels in Petri Nets can be applied to the analysis of functions or activities in EPCs or BPMN diagrams. The other approaches require various features such as Pr/T nets, finite state automata, BPMN 2.0, explicit control flow connectors, or execution logs.

7.2.5 Implementation Availability. Based on the literature overview, all articles for which an existing implementation is mentioned in the article or known from an alternative source were marked. This resulted in 22 implementations, which were also available as executable applications. Of these, one was distributed under a commercial license, while 18 were distributed freely. For the three remaining implementations, no explicit license could be found. Overall, the non-availability of implementations poses a drawback regarding the comparison and evaluation of similarity measures. This becomes even more severe as we discovered that a few implementations could not be used. Hence, the availability of implementations for the various published similarity measures is very limited.

8 DISCUSSION

Concerning the results of our analysis presented in the previous three sections and possible future research, we discuss central aspects in the following. These central aspects comprise: (1) The need for further comparative analyses of similarity measures to achieve a better understanding of the commonalities and differences between the various measures; (2) the possible integration of human input into the techniques for process model similarity and matching calculation; (3) the need for a deeper analysis of the different usage scenarios and their requirements to evaluate in how far similarity measures support these usage scenarios.

(1) Need for comparative analyses: The conceptual analysis shows that the existing similarity measures are very manifold and highly divergent in the identified dimensions. Besides, the implementations of particular dimensions differ to a high degree. For example, there are different possibilities of analyzing the natural language semantics. While one approach analyzes the words used for labeling the elements of a process model by means of string-difference only, another also takes synonyms, the word context or additional sources into account.

Furthermore, high differences in the computational complexity of the similarity measurement approaches have been identified ranging from linear to NP-complete as well as in the resource intensity in terms of memory and time consumption (Thaler et al. 2016). In fact, these aspects are closely related to each other. However, it should be mentioned that some approaches are characterized by a high computation effort while others produce a mass of data without being of high computational complexity. Both effects lead to trouble in the context of a practical application culminating in non-applicability (Thaler et al. 2016). Yet, other approaches are able to calculate a similarity value within short time and with only little resources.

What also becomes apparent through the analysis is that nearly all analyzed approaches that calculate the similarity between process models base on matches between the elements of process models (mostly the activities). This means that the actual similarity measurement is more like a function on these matches. As a result, it is necessary to divide the process model similarity measurement for such approaches into two components—(1) the node matching and (2) the calculation of an aggregated similarity value. We identified 54 "distinct" approaches[5] that calculate the

[5]Different approaches were merged if one adapted the other. For example, in case one measure would calculate node matches only based on a syntactical analysis of node labels while another one would add a semantic analysis, the two approaches would be merged into one.

similarity of process models of which only seven do not base on an underlying matching. Additionally, we only identified one measure that uses both proceedings, that is, this measure combines the two variants illustrated in Figure 1. In Qiao et al. (2011) a clustering technique, which does not rely on matches, is combined with a structure-based similarity calculation that uses matches. Hence, this approach performs a two step procedure for finding similar models, whereby the first one does not need a matching while the second one does.

These two aspects—highly diverging computational complexity and differences regarding an underlying matching—call for further comparative assessments. Although two comparative evaluations of similarity measures have been published (Dijkman et al. 2011; Thaler et al. 2016), these compare only a limited number of approaches due to missing implementations. Yet, there should be more measures included in such evaluations to provide a comprehensive overview as has been the case in the Process Model Matching Contests. As Thaler et al. (2016) showed that most similarity values of the compared approaches (all based on matches) highly correlate, it would be interesting to assess whether the similarity values of measures not requiring matches differ. Similarity calculation without requiring matches could also be interesting from a computational point of view due to the high effort needed for determining matches, which leads to non acceptable calculation times in real-world settings with possibly hundreds of process models (Thaler et al. 2016). At least for some of the objectives mentioned in Section 5.1 matching nodes might not be necessary so corresponding measures might mitigate the computation challenge. Alternatively, it might be possible to combine similarity measures that are not based on matches with measures requiring them as demonstrated in Qiao et al. (2011). The requirements for certain objectives are also discussed in the third point.

Another aspect that has been mostly neglected until now is the comparison of similarity values calculated by automated approaches and the subjective judgment by humans (See Wombacher (2006) and Dijkman et al. (2011) as exemplary studies). Currently, in the context of similarity measurement for searching process model collections, the models retrieved by such a similarity-based search functionality have been compared to the results expected by humans (sometimes also taking the ranking of returned models into account). Yet, this is just an indirect way of determining the appropriateness of similarity measures as not the similarity values themselves are compared, but the outcome of a more complex procedure (e.g., the results of a search). We think that there should be more research devoted to understand how humans subjectively rate the similarity of models and in how far existing measures cover the subjective measurement or how this can be appropriately implemented in an automatic similarity measure.

(2) Integration of human input: Currently, the usage of human input into process model matching and similarity techniques is only described in three publications as the analysis in Section 7.2 showed. In our opinion, methods and techniques from, for example, gamification research, which include human input, could be utilized to improve similarity calculation. Such input might be used in some kind of (machine) learning algorithm to improve the accuracy of similarity techniques. At the moment, such techniques are not utilized at all. Users could, for example, provide an estimation as input for such a technique, whether a matching of process model elements is correct or not, possibly based on the semantics of labels or the order of activities. Such an input could be used by a learning algorithm in future similarity techniques. One research question in this case would be how contradictory user inputs could be handled.

User input might be especially useful for matching model elements as the determination of correct matches is still an open challenge (Antunes et al. 2015) and as it still needs to be clarified what constitutes a match. Imagine different application processes of universities in which some universities interview the applicants while others prefer aptitude tests. One could argue that these procedures correspond to each other, since both serve as an instrument for selecting adequate applicants. But one might also argue that there is no correspondence as these are different procedures (Thaler et al. 2014). Against this background, it is necessary to obtain a deeper understanding on what should be understood as a correspondence and what types of correspondences do exist. Depending on the application scenario, these aspects are of major importance for the similarity measurement and might only be reliably identified by humans.

Regarding the integration of humans, another point of view might be worth investigating. Until now, publications related to the similarity measurement of process models are, besides some surveys or evaluations, only considering concrete measures. What is currently not in the scope of interest is how the results of similarity measurement can be used in practice. If, for instance, the objective of similarity measurement is to determine compliant and non-compliant process models, then how should users of a similarity measure exploit the similarity results? That is, which similarity threshold can be applied to distinguish between compliant and non-compliant processes to, for example, speed up a manual analysis? The general question here refers to how similarity measurement results can be presented to users, helping them to easily distinguish between models that are relevant to them and those that are not.

(3) Need for an analysis of different usage scenarios: As mentioned in Section 5, there exist a lot of conceivable application scenarios for business process similarity measures. To address the specific characteristics of these usage scenarios, it is necessary to analyze them with regard to their requirements concerning similarity measurement. For example, in the case of a general similarity-based search for process models it might be sufficient to compare the natural language dimension to assess the similarity of models without calculating matches. This would lead to faster calculation times, which might be more important in the search case than calculating possibly more precise similarity values. On the contrary, in case of conformance checking the calculation of matches might be unavoidable to compare sequences of activities. This argumentation also holds regarding the metric properties of similarity measures and their corresponding distance functions. As the example described in Section 2.3 illustrates, there might be good reasons for violating certain properties in a specific usage scenario. Such usage scenario analyses could then help practitioners to identify suitable similarity measures for their use cases.

From a research point of view it is necessary to analyze in how far particular similarity measures match the requirements of specific usage scenarios and whether it is meaningful to apply different similarity measures to different scenarios. This might also be helpful to specify the underlying calculation techniques needed for similarity assessment (examples of such techniques are described in Section 6). A scenario might be the similarity analysis of process models that are derived from the instance logs of information systems (Process Mining). Since the data basis is generated automatically, the contained information is linguistically harmonized or even cryptic. Against that background, the analysis of node labels with NLP techniques to detect, for example, synonymous words is of minor importance, while the usage of further information like system handbooks might be relevant.

9 CONCLUSION

In this article, we described the state of the art related to calculating the similarity of business process models. For this purpose, 123 publications have been analyzed with respect to three research questions: (1) Which similarity measures do exist in the literature? (2) How can they be characterized and what are their limitations? (3) What are possible future research directions?

(1) Similarity measures overview: It can be stated that there exists a multitude of similarity measures, which cover different application areas and similarity measurement techniques. During our literature search, we found 123 publications describing a process model matching or similarity measure. Besides, a few articles were published that either describe evaluation results or provide another survey with a different focus than our article.

(2) Similarity measures characterization: To sum up the interesting aspects of the state of the art analysis, first, the objectives for which similarity measures are typically developed are similarity-based search for and the standardization of process models. Yet, it is still unclear in how far these goals are reached as only about two thirds of the publications provide an evaluation. Furthermore, only 55% of these publications provide an evaluation regarding the similarity measurement goal. Second, typical dimensions utilized for the calculation of a similarity value are natural language, the graph structure, and the behavior of process models. On the contrary, the human estimation dimension has mostly been neglected with only three publications fitting into this category. Another interesting fact is that techniques from the graph structure and behavior dimensions are almost never combined while techniques for the analysis of natural language are almost always applied. Third, as expected, an overwhelming majority of similarity measures calculates a similarity value between two process models, which is arguably the ultimate goal of business process model similarity research. Yet, some measures only provide model element matching procedures. Hence, these need to be extended to provide results for a similarity measure on process models. Regarding the cardinality of node matches, again, almost all similarity measures use elementary or complex node matches. Only few measures are not based on them and utilize other means for similarity calculation. Fourth, only 44 similarity measures cannot be used independently of a certain modeling language. That is, they need certain characteristics of a modeling language such as explicit control flow connectors or Pr/T nets. And finally, the availability of similarity measure implementations is quite limited. Only 22 implementations were mentioned in the publications. In our opinion, this hampers the analysis of similarity measures as it is not easily possible to compare different measures in evaluation settings or practical experiments.

(3) Future research directions: More comparative analyses is therefore one future research direction. As the analyzed similarity measures vary to a high degree, further comparative assessments are necessary to understand commonalities and differences between them. Such analyses should also focus on the goal of similarity measurement to provide further insights in how far certain goals like reuse of models, similarity-based search, or conformance of models are reached and supported by similarity measures. Therefore, a deeper analysis of the various goals with respect to similarity measurement should be conducted to clarify specific requirements.

Another important limitation of existing approaches in the field of business process similarity quantification is the focus on comparing pairs of "flat" process models. In reality, process models are structured in process hierarchies and decomposed into sub process models (Malinova et al. 2013b). This fragmentation varies to a high degree depending on the modeler, the domain, and the modeling target. Thus, business processes are typically described on different hierarchical levels and probably through different sub process models, which requires a corresponding consideration in similarity analyses.

And last, the human judgment on the similarity of process models as well as possible human input into similarity measurement should be researched more intensively. As automatic similarity measurement ultimately aims at supporting humans during tasks in which they subjectively quantify the similarity of models and utilize those quantifications, an in-depth understanding on how humans judge the similarity of models might help in designing appropriate automatic similarity measures. Besides, human input might help to improve the quality of automatic matching and similarity measurement approaches.

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Online Appendix to: Similarity of Business Process Models—A State-of-the-Art Analysis

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A LITERATURE ANALYSIS DATA

This section of the online appendix refers to the literature analysis data. In the two tables below, all publications are listed. The data sets for each publication had to be separated because of space restrictions, but they can be linked by the publication IDs.

The column headers also had to be abbreviated due to space reasons and can be interpreted as follows: G1 = Conformance to reference model, G2 = Detection of differences between models, G3 = Generation of standardized model, G4 = Induction of reference model, G5 = Identification of process variants, G6 = Search for process models, G7 = Similarity-based search for services, G8 = Reuse of process models, G9 = Modularization of process models. I1 = Similarity of model elements, I2 = Similarity of sub-graphs, I3 = Similarity between models, I4 = Similarity between sets of models. D1 = Syntax, D2 = Semantic, D3 = Graph oriented, D4 = Control flow oriented, D5 = Behavior, D6 = Human estimation, D7 = Further aspects.

Furthermore, the full list of publication references used in the state-of-the-art analysis can be found in the reference list at the end of this online appendix.

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ID	Reference	Goals associated with similarity measurement									Input size for Similarity Analysis				Implementation
		G1	G2	G3	G4	G5	G6	G7	G8	G9	I1	I2	I3	I4	
1	[van der Aalst et al. 2006]	x						x					x		ProM
2	[Abbas and Seba 2012]						x				x		x		-
3	[Akkiraju and Ivan 2010]					x			x		x		x		-
4	[Awad et al. 2008]						x				x		x		-
5	[Bae et al. 2006a]						x						x		-
6	[Bae et al. 2006b]			x			x						x		-
7	[Bae et al. 2007]						x						x		-
8	[Baumann et al. 2015]		x	x			x		x				x		-
9	[Becker et al. 2011]	x											x		-
10	[Becker et al. 2012]			x			x				x				-
11	[Belhoul et al. 2012]						x					x	x		-
12	[Belhoul et al. 2015]							x					x		-
13	[Bergmann and Gil 2011]						x		x		x		x		-
14	[Bergmann and Gil 2014]						x		x		x		x		CAKE
15	[Bergmann et al. 2013]						x		x		x		x		-
16	[Branco et al. 2012]				x						x	x			-
17	[Brockmans et al. 2006]			x							x				-
18	[Cao et al. 2016]			x					x		x		x		-
19	[Castano and Antonellis 1996]			x									x		-
20	[Castano and Antonellis 1995]						x						x		-
21	[Cayoglu et al. 2013]	No specific goal mentioned									x x				http://butler.aifb.kit. edu/asc/TripleS.jar
22	[Corrales et al. 2006]							x			x	x	x		-
23	[Dijkman et al. 2009b]		x	x							x		x		ProM
24	[Dijkman et al. 2009a]						x				x		x		ProM
25	[Dijkman et al. 2011]					x				x	x	x	x		-
26	[Dongen et al. 2008]	x		x									x		ProM
27	[Dumas et al. 2013]						x			x				x	-
28	[Ehrig et al. 2007]			x					x		x		x		http://www.sempet.org/
29	[Ekanayake et al. 2012]			x							x		x	x	Apromore
30	[Esgin and Senkul 2011]	x											x		-
31	[Esgin and Karagoz 2013b]	x										x			-
32	[Esgin and Karagoz 2013a]	x										x			-
33	[Eshuis and Grefen 2007]							x			x		x		-
34	[Fengel and Reinking 2012]			x							x				-
35	[Fengel 2014]			x							x		x		-
36	[Fu et al. 2012]	x		x							x		x		-
37	[Gacitua-Decar and Pahl 2009]								x		x				-
38	[Gacitua-Decar and Pahl 2010]								x		x				-
39	[Gao et al. 2007]	x									x		x		-
40	[Gao and Zhang 2009]			x							x		x		-
41	[Gao et al. 2013]			x	x						x		x		-
42	[Gater et al. 2010]					x		x			x		x		-
43	[Gater et al. 2011]			x		x	x				x		x		Bematch platform
44	[Gater et al. 2012]						x				x		x		Bematch platform
45	[Gater et al. 2009]	x											x		-
46	[Gater et al. 2010]			x							x	x	x		-
47	[Gater et al. 2011]			x							x	x	x		-
48	[Grigori et al. 2006]							x			x	x	x		-
49	[Grigori et al. 2008]							x			x	x	x		-
50	[Grigori et al. 2010]							x			x	x	x		-

		Goals associated with similarity measurement									Input size for Similarity Analysis				
ID	Reference	G1	G2	G3	G4	G5	G6	G7	G8	G9	I1	I2	I3	I4	Implementation
51	[Hake et al. 2014]			x	x				x		x				-
52	[Hidders et al. 2005]			x					x		x		x		-
53	[Huang et al. 2009]							x			x		x		-
54	[Huang et al. 2004]							x			x		x	x	-
55	[Humm and Fengel 2012]			x							x		x		-
56	[Jin et al. 2011a]						x				x				-
57	[Jin et al. 2011b]						x				x				-
58	[Jin et al. 2012]						x				x		x		-
59	[Jung and Bae 2006]								x		x		x		-
60	[Jung et al. 2009]								x		x		x		-
61	[Kastner et al. 2009]			x			x		x		x		x		-
62	[Klinkmüller et al. 2013]			x							x				http://code.google.com/p/jpmmt/
63	[Klinkmüller et al. 2014]	x			x		x				x				-
64	[Koschmider and Oberweis 2007]					x					x				http://www.sempet.org/
65	[Kunze and Weske 2010]						x				x		x		-
66	[Kunze et al. 2011a]						x						x		-
67	[Kunze and Weske 2012]						x						x		-
68	[Kunze et al. 2013]						x				x		x		-
69	[Kunze et al. 2011b]						x						x		-
70	[Lam 2009]								x				x		-
71	[Laue and Becker 2012]						x		x				x		-
72	[Leopold et al. 2012]			x			x	x			x				-
73	[Li et al. 2008]	x											x		-
74	[Li et al. 2010]				x						x		x		ADEPT2 Process Template Editor
75	[Ling et al. 2014]	x		x							x		x		-
76	[Liu et al. 2012]						x						x		-
77	[Liu et al. 2014]			x							x	x			-
78	[Lu and Sadiq 2007]					x					x		x		-
79	[Lu et al. 2009]					x					x		x		-
80	[Madhusudan et al. 2004]								x		x		x		-
81	[Mahmod and Chiew 2010]					x			x				x		-
82	[Mahmod and Radzi 2010]					x			x				x		-
83	[Malinova et al. 2013]				x								x		-
84	[Martens et al. 2014]				x						x		x		-
85	[Medeiros et al. 2008]	x						x					x		ProM
86	[Melcher and Seese 2008]	No specific goal mentioned									No similarity values				-
87	[Mendling et al. 2007]			x			x						x		ProM
88	[Minor et al. 2007]								x				x		-
89	[Montani et al. 2015]	x									x		x		-
90	[Nejati et al. 2007]			x							x		x		-
91	[Niedermann et al. 2010]								x		x				-
92	[Niemann et al. 2010]	x									x	x	x		-
93	[Niemann et al. 2012]	x					x				x	x	x		ProMNot available in the plugin list
94	[Pittke et al. 2012]								x	x	x		x		-
95	[Qiao et al. 2011]						x				x		x		-
96	[Rinderle-Ma and Kabicher-Fuchs 2016]	x											x		-
97	[Rodriguez et al. 2016]						x				x				-
98	[La Rosa et al. 2010]			x							x		x		http://www.processconfiguration.com/
99	[La Rosa et al. 2013]			x							x		x		http://www.processconfiguration.com/
100	[La Rosa et al. 2015]			x							x		x	x	Apromore
101	[Sanchez-Charles et al. 2016]		x										x		-
102	[Sarno et al. 2013]			x					x				x		-
103	[Schoknecht et al. 2016]						x						x		butler.aifb.kit.edu/asc/LS3/ls3.html
104	[Srivastava and Mukherjee 2009]								x		x		x		-
105	[Sun 2010]							x				x	x		-
106	[Tka and Ghannouchi 2012]	x									x		x		-
107	[Uba et al. 2011]									x				x	-
108	[Wang et al. 2010]						x						x		-
109	[Wang et al. 2012]	x									x		x		-
110	[Wang et al. 2007]							x	x		x		x		-
111	[Wasser and Lincoln 2013]					x					x		x		-
112	[Weidlich et al. 2010]	x		x							x		x		https://code.google.com/p/process-matching/
113	[Weidlich et al. 2013b]			x			x				x		x		-
114	[Weidlich et al. 2013a]			x			x				x				-
115	[Wombacher et al. 2004]							x					x		-
116	[Wombacher and Rozie 2006]							x					x		-
117	[Wombacher 2006]							x					x		-
118	[Wombacher and Li 2010]							x					x		-
119	[Yan et al. 2010]						x				x		x		-
120	[Yan et al. 2012]						x				x		x		Apromore
121	[Zha et al. 2009]			x			x						x		-
122	[Zha et al. 2010]			x			x						x		-
123	[Zhuge 2002]						x		x		x		x		-

	Relevant Dimensions for the Definition of Similarity Measures									Validation	
ID	D1	D2	D3	D4	D5	D6	D7	Cardinality	Restrictions	Real-life	Artificial
1			x		x			-	Modeling language with executable semantics	-	-
2		x		x				m:n	-	-	100 process graphs
3	x							1:1	-	5299 models	-
4	x	x						1:n	-	-	-
5				x				Calculation based on models represented as vectors of trees, implicit	-	-	-
6				x				Calculation based on a kind of adjacency matrix, implicit	-	-	-
7				x				Calculation based on a kind of adjacency matrix, implicit	-	-	Not clear how many models were used
8			x		x			m:n	-	-	3 models
9	x				x			Calculation based on difference of distributions over activity sequences	Probabilities assigned to paths	-	8 models
10							Simulation of linear transition systems and quantitative bisimulation	1:1	Transformation to labeled transition system required	-	-
11	x				x			1:1 mapping of execution sequences	-	-	623 models
12	x			x	x			1:1 mapping of execution sequences	-	-	240 models
13				x			Usage of ontology-annotated models	1:1 mapping of nodes and edges	-	-	10 queries, 20 models
14				x			Usage of ontology-annotated models	1:1 mapping of nodes and edges	-	-	10 queries, 20 models
15				x			Usage of ontology-annotated models	1:1 mapping of nodes and edges	-	1729 workflow models from cooking recipes	-
16	x			x				1:1, 1:n, m:n	BPMN 2.0	39 models	-
17	x	x	x	x				m:n	Pr/T nets	-	-
18	x		x					1:1	Petri Net	-	100 models
19	x	x						-	-	-	-
20	x	x						-	-	-	-
21	x	x		x				1:n	-	18 models	-
22	x	x		x				1:n	-	-	-
23	x			x				m:n	-	17 pairs of models	-
24	x			x				1:1	-	100 models	-
25	x			x				1:1	Calculation of Refined Process Structure Tree	284 + 604 models	-

ID	Relevant Dimensions for the Definition of Similarity Measures							Cardinality	Restrictions	Validation	
	D1	D2	D3	D4	D5	D6	D7			Real-life	Artificial
26	x	x			x			Calculation based on vector space model, no explicit mapping	-	Not clear how many models were used	-
27	x		x	x				-	Calculation of Refined Process Structure Tree	1474 models, not exactly specified how many queries	-
28	x	x	x					1:1	Pr/T Nets	-	Unclear description
29	x		x	x				1:1	Calculation of Refined Process Structure Tree	958 models	-
30			x		x			-	-	-	3 + 25 models
31			x		x		Genetic algorithm	-	-	-	6 + 25 models
32			x		x		Genetic algorithm	-	-	-	6 + 25 models
33	x		x	x				1:1	BPEL	-	-
34	x	x						1:1	-	1380 models, usage of 8 radom model pairs	-
35	x	x					Ontology transformation of process models	m:n	-	8 model pairs	-
36	x		x	x				1:1	Block-structured process models	-	50 model pairs
37		x	x	x				1:n	-	Not clear how many models were used	-
38				x				1:n	-	-	-
39		x					Data	m:n	-	-	20 model pairs
40	x	x					Data flow	m:n	-	-	20 model pairs
41	x		x					m:n	-	37 models	-
42	x	x		x				1:n	-	-	-
43	x	x		x				m:n	-	-	80 models, 15 queries
44	x	x		x				1:n	-	-	300 models, 30 queries
45					x			-	Workflow net	1 model	-
46				x				1:1	Calculation of fragments	-	-
47	x			x				1:1	Calculation of fragments	-	-
48	x	x		x				1:n	-	-	-
49	x	x		x				1:n	-	-	5 models
50	x	x		x				1:n	-	-	15 models
51	x	x		x				1:1	-	44 models	-
52					x			No explicit mapping of nodes on sets of traces, 1:1 mapping with bisimulation	-	-	-
53					x			1:1	-	-	3 models
54				x			Web-Service descriptions	1:1	Web-Service descriptions required	-	-
55	x	x		x			Model types and element types through static distance values between meta-models	m:n	-	-	6 models

	Relevant Dimensions for the Definition of Similarity Measures									Validation	
ID	D1	D2	D3	D4	D5	D6	D7	Cardinality	Restrictions	Real-life	Artificial
56	x	x	x		x			1:1	Complete prefix unfolding computable	-	-
57	x	x			x			1:1	Complete prefix unfolding computable	-	-
58	x	x			x			1:1	Complete prefix unfolding computable	-	-
59	x		x	x				1:1	-	-	sets of 50, 100, 150, 200, 250 models
60	x			x				1:1	-	-	10 models
61	x		x	x				1:1	Specific workflow meta-model has to be used for similarity measurement	-	129 models
62	x	x						m:n	-	9 models	-
63	x	x	x	x		User feedback		m:n	-	18 models	-
64	x	x	x					1:1	Pr/T Nets	-	-
65	x			x				1:1	-	600 models	-
66	x				x			Mapping prerequisite	Sound workflow net	85 models, 9 queries	-
67					x			Mapping prerequisite	Sound workflow net	-	1 query, 3 models
68	x				x			Mapping prerequisite	Bounded net system	34 models + 10 query models	-
69					x			-	-	-	-
70			x					-	BPMN 1.1 only	-	-
71						Tags		-	-	-	15 models
72	x	x	x				Markov logic networks	1:n	-	9 models	-
73			x		x		Number of change operations	No specific mapping. Matching is achieved through a comparison of order matrices	Block structure representation required	-	7 models
74			x		x			1:1 Mapping prerequisite	-	generation of 1 reference model from 84 variant models	54 groups containing 1 reference model and 100 process variants (5454 models in total)
75	x	x	x	x				m:n	Calculation of Refined Process Structure Tree	-	20 model pairs
76	x				x			-	Data has to be described in a process model	-	-
77	x		x	x				1:1	-	-	-

ID	Relevant Dimensions for the Definition of Similarity Measures D1	D2	D3	D4	D5	D6	D7	Cardinality	Restrictions	Validation Real-life	Artificial
78				x			Comments, modeler, resources, data objects, duration, but not exactly specified how	1:1	-	-	-
79				x			Comments, modeler, resources, data objects, duration, but not exactly specified how	1:1	-	-	-
80	x	x		x				1:1	Arc labels must be available	-	-
81			x	x				-	-	-	-
82			x	x				-	-	-	-
83	x							-	-	604 models	-
84	x			x				1:1	-	generation of 2 reference models out of 20 respectively 10 process models	-
85			x		x			-	Modeling language with executable semantics	-	-
86				x			Process metric values	-	Process metrics must be computable	515 models	-
87					x			Calculation based on vector space model, no explicit mapping	-	7 models	-
88			x	x				-	-	37 models	-
89	x	x	x	x	x		Temporal duration of activities	1:1	Event log necessary for process mining	16 models	-
90	x	x			x			m:n	Statechart definition required	3 model pairs	-
91	x	x						Not clearly described	-	-	-
92	x	x		x			Tagging of clusters with characteristics	1:1	-	-	-
93	x	x		x			Tagging of clusters with characteristics	1:1	-	48 model pairs evaluating node assignments, 110 models for retrieval	-
94		x			x			1:1	-	604 models	-
95	x	x		x				1:1	-	603 + 242 + 180 + 117 models,5 + 10 + 5 + 5 queries	-
96							Number of shared business rules	-	-	108 models, 375 compliance rules	-
97						Crowd		m:n	-	4 models	-
98	x		x	x				1:1	Explicit logical control flow connectors required	-	-

ID	Relevant Dimensions for the Definition of Similarity Measures							Cardinality	Restrictions	Validation	
	D1	D2	D3	D4	D5	D6	D7			Real-life	Artificial
99	x	x	x	x				1:1	Explicit logical control flow connectors required	-	-
100	x		x	x				1:1	Calculation of Refined Process Structure Tree	595 + 363 models	-
101	x			x				1:1	-	700 pairs of models	8 models
102				x	x			-	Coverability tree of Petri nets required	-	28 models
103		x						-	-	80 models	-
104	x				x			m:n	-	240 process definition documents, 325 process flow diagrams	-
105	x				x		Web service model	-	-	-	Collections of services from 100 to 1,000 services
106	x	x		x				1:1	-	-	-
107	x		x	x				-	Calculation of Refined Process Structure Tree	1474 models	-
108					x			-	Coverability tree of Petri nets required	-	6 models
109	x			x	x			1:1	-	-	-
110		x						1:1	ECA rules	-	-
111	x	x	x		x			1:1	-	-	-
112	x	x	x	x			Step-wise approach to matching	1:1, 1:n	-	20 model pairs	-
113	x		x					m:n	-	23 model pairs	-
114	x	x	x	x				m:n	-	-	-
115	x				x			Only calculation of matching based on non-empty intersection of finite state automata	Only finite state automata	-	-
116	x				x			No specific mapping. Matching through comparison of languages generated by finite state automata	Only finite state automata	-	12 models
117	x		x		x			No specific mapping. Matching through comparison of languages generated by finite state automata	Only finite state automata	-	Not clear how many models were used
118	x			x	x		Number of change operations	No specific mapping, 1:1	Only finite state automata	-	Not clear how many models were used

	Relevant Dimensions for the Definition of Similarity Measures									Validation	
ID	D1	D2	D3	D4	D5	D6	D7	Cardinality	Restrictions	Real-life	Artificial
119	x		x					m:n	-	10 queries 100 models	-
120	x		x					m:n	-	10 queries, 100 models + 10 queries, 97 models	-
121					x			-	-	-	4 models
122					x			-	-	10 models	4 models
123	x		x					1:1	-	-	-

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