GABRIEL PESCHL

# COMPARING RESTRICTED PROPAGATION GRAPHS FOR THE SIMILARITY FLOODING ALGORITHM

Master's dissertation submitted to the Department of Informatics, Federal University of Parana in partial fulfillment of the requirements for the degree of Master in Informatics.
Supervisor: Prof. Ph.D. Marcos Didonet Del Fabro

CURITIBA

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# RESUMO

A Engenharia de Software Orientada a Modelos é uma metodologia que utiliza modelos no processo de desenvolvimento de software. Muitas operações sobre esse modelos são necessárias estabelecer *links* entre modelos distintos, como por exemplo, nas transformação de modelos, nas rastreabilidade de modelos e nas integração de modelos. Neste trabalho, os links são estabelecidos através da operação *matching*. Com os links estabelecidos é comum calcular os valores de similaridades a eles, a fim de se indicar um grau de igualdade entre esses *links*. O *Similarity Flooding* é um algoritmo bem estabelecido que pode aumentar a similaridade entre os *links*. O algoritmo é genérico e está provado sua eficiência. Contudo, ele depende de uma estrutura menos genérica para manter a sua eficiência.

Neste trabalho, foram codificados 9 métodos distintos de propagações para o Similarity Flooding entre os elementos de metamodelos e modelos. Esses elementos compreendem classes, atributos, referências, instâncias e o tipo dos elementos, por exemplo, *Integer*, *String* ou *Boolean*. A fim de verificar a viabilidade desses métodos, 2 casos de estudos são discutidos. No primeiro caso de estudo, foram executados os métodos entre os metamodelos e modelos de *Mantis* e *Bugzilla*. Em seguida, foram executados os métodos entre os metamodelos e modelos de *AccountOwner* e *Customer*. Por fim, é apresentado um estudo comparativo entre os métodos de propagações codificados com um método genérico, com o objetivo de verificar quais métodos podem ser mais (ou menos) eficiente para o Similarity Flooding, dentre os metamodelos e modelos utilizados. De acordo com os resultados, utilizando técnicas restritas de propagações do SF, as similaridades entre os links melhoraram em relação a execução genérica do algoritmo. Isso porque diminuindo a quantidade de links o SF pode ter um melhor desempenho.

# ABSTRACT

In Model-Driven Software Engineering (MDSE), different approaches can be used to establish links between elements of different models for distinct purposes, such as serving as specifications for model transformations. Once the links have been established, it is common to set up a similarity value to indicate equivalence (or lack of) between the elements. Similarity Flooding (SF) is one of the best known algorithms for enhancing the similarity of structurally similar elements. The algorithm is generic and has proven to be efficient. However, it depends on graph-based structure and a less generic encoding.

We created nine generic methods to propagate the similarities between links of elements of models. These elements comprise classes, attributes, references, instances and the type of element, e.g., Integer, String or Boolean. In order to verify the viability of these methods, 2 case studies are discussed. In the first case study, we execute our methods between metamodels and models of Mantis and Bugzilla. In the following, the metamodels and models of AccountOwner and Customer are used.

At the end, a comparative study of the metamodel-based encoding is presented for the purpose of verifying whether a less generic implementation, involving a lesser number of model elements, based on the metamodel and model structures, might be a viable implementation and adaptation of the SF algorithm. We compare these methods with an implementation comprising all the propagation strutures (non-restricted propagation), which are more similar (though not equivalent) to the original SF implementation.

According to the results, using the restricted propagation graphs of the SF, the similarity values between the links has increased in relation to the non-restricted algorithm. This is because reducing the amount of links, will increase the propagation values between the links of elements.

# CHAPTER 1

# INTRODUCTION

In Model-Driven Software Engineering (MDSE) models are considered first-class entities [10] [5], i.e., they can be modified, updated or processed throughout software development processes [5]. A model, in the context of this work, represents a computational system. An example of a computational system is an academic system, where there could be one element *teacher* refering to a class and the elements *name* and *grade* as the attributes [14].

In MDSE scenarios, it is necessary to establish links (relationships) between elements belonging to different models, such as data interoperability, model transformation or model traceability. To establish and create these links, a match operator is often executed [23] [4]. A match may be performed manually; however, this task can be tedious or error prone in a large models [23]. Consequently, several works have proposed solutions to automate this process [23]. The matching returns sets of mappings, or alignments, with a similarity value indicating how one element relates to another element [23]. These similarity values can be discrete or continuous and it may be calculated using different methods, such as String Edit Distance [23].

To increase the initial link similarities, the Similarity Flooding algorithm (SF) [18] can be applied. This is one of the best know algorithms for improving links similarity. SF propagates the similarities of links models over all link models, considering a previously established alignment [18]. The link similarities 'flow' in two ways according to graph propagation structures: incoming propagation and outgoing propagation. The use of propagation algorithms may increase the similarities between the models elements [4] [8] [18]. For examples of propagation techniques, we can cite Del Fabro [4], Faller [8] and Melnik [18]. With the technique proposed by Del Fabro [4], after the matching execution, it is possible to propagate the similarities from links between classes to links between attributes.

## 1.1 Motivation

This work is motivated by the results reported by Didonet Del Fabro's [5] and Melnik's thesis [18]. Melnik [18] proposed the Similarity Flooding algorithm. However, Didonet Del Fabro [5], created restrictions to execute the propagations of SF [4]. Thus, one of the main advantage of this implementation is execution in generic metamodels.

Our work is not only executed in metamodel, but the method comprises instances of attributes of models. Applying the SF in metamodels, we have a set of results that could be used in model transformation or model traceability. Moreover, in the results from models we could be use their in data integration.

Most of the cited works do not report which propagation techniques are the most appropriate. However, we provide a discussion covering as much as possible the propagation technique between links of elements of models and metamodels. This enables the identification of the most suitable propagation technique for each especific use.

## 1.2 Objective

The objective of this dissertation is to implement different propagation methods for the SF in order to execute them between metamodels and models links. Thus, we compared to what extent the similarities of the links have increased (or decreased) in comparison with an implementation comprising all the propagation structures, which are more similar (though not equivalent) to the original SF implementation.

We present nine methods to propagate the similarities in links of metamodels and models below. This decomposition considers specific structures of (meta)models (e.g., attributes or references) or a type of a given element (e.g. String or Integer). These methods change the way as the propagation graphs are executed in a specific kind of link. In order to present a discussion at the end. Our contribution is to verify whether the development of restricted propagation methods is advised, which could be tailored and applied to several MDSE operations.

1. Propagation from links between Classes to links between Attributes;
2. Propagation from links between Classes to links between References;
3. Propagation from links between Classes to links between Attributes and References;
4. Propagation from links between Classes to links between References and Attributes;
5. Propagation from links between Attributes to links between their Instances;
6. Propagation from links between Classes to links between types regarding Attributes;
7. Propagation from links between Classes to links between types regarding References;
8. Propagation from links between Classes to links between types regarding Attributes and References;
9. Propagation from links between Classes to links between types regarding References and Attributes.

## 1.3 Outline

This dissertation is structured as follows. In chapter 2, we present the state of the art. Chapter 3 explains how we developed the techniques of the SF, when then go on to present a comparison of the results. In Chapter 4, we present the conclusions and future works.

# CHAPTER 2

# STATE OF THE ART

In this chapter, we present the literature review for this dissertation: Model-Driven Software Engineering, the Eclipse Modeling Framework, metamodel and model weaving, the match operator and the Similarity Flooding algorithm.

## 2.1 Model-Driven Software Engineering

Model-Driven Software Engineering (MDSE) is a paradigm that uses models as first-class entities [16] [3] [24]. Thus, developers specify software requirements using models and these models are then transformed into working software [16] [5].

According to Muller et al. [19], no consensus has yet been reach regarding the definition of model. Different authors provide their respective definitions [19] [14]. According to Guemhioui [6], Garces [10], and Jouault [13], a model represents a software, with notations and characteristics of interest. A model also can be describe as a directed labeled multigraph [13], providing a generic strucutre. We present a set of definitions regarding a directed labeled multigraph and model extracted from the work of Jouault [13].

**Definition 2.1.1. (Directed Labeled Multigraph).** *A directed labeled multigraph G = ($N_G$, $E_G$, $\Gamma_G$) consists of sets of nodes $N_G$, sets of edges $E_G$ and a mapping function* $\Gamma_G : E_G, \longrightarrow N_G X N_G$.

**Definition 2.1.2. (Model).** *A model M is a triple (G, $\omega$, $\upsilon$), where G relates to a directed labeled multigraph; $\omega$ is itself a model called the reference model of M and $\omega$ associates with a multigraph $G_\omega = (N_\omega, E_\omega, \Gamma_\omega)$; $\upsilon : N_G \cup E_G \longrightarrow N_\omega$ associates nodes and edges of G to nodes of $G_\omega$.*

MDSE proposes that developers define models by conforming to some more abstract models [3] [5]. This practice is called metamodeling, which consists of using constraints to express a model [6][5].

A model conforms to a metamodel, and this relationship is called *conformance* (this expression is often related as *c2*[5]). While a metamodel conforms to a model, we have the conformance relationship between a metamodel and its definition model, which is called metametamodel [3]. A metametamodel is a model that specifies constraints for all models and metamodels [5]. The metametamodel conforms to itself [5] [3]. The conformance relationships, at all levels, allows for the creation and expression of more accurate models [3]. If this levels are not sufficient, it is possible to create more levels to define the models [3]. However, 3 levels of model are frequently used [3].

The conformance level mentioned above gives the *3-level architecture*, as indicate in Figure 2.1: the 3rd level represents the metametamodel; the 2nd level represents the metamodel, and the 1st level represents the model. Below, we present a formal definition of the 3-level conformance of models, according to Brambilla et al. [3], Del Fabro [5] and Jouault [13].

**Definition 2.1.3. (Metametamodel).** *A metametamodel is a model that defines all other models and metamodels. A metametamodel conforms recursively to itself.*

**Definition 2.1.4. (Metamodel).** *A metamodel defines a set of constraints to define a model. A metamodel conforms to a metametamodel.*

**Definition 2.1.5. (Model).** *A terminal model represents a model and it conforms to a metamodel.*

In order to clarify the concepts mentioned above, we present Figure 2.2, which illustrates a partial example of an academic system. In this example, we can see the *conformance* relationship between elements of the models. Thus, every entity of a given model (*M*) conforms to an entity in the model (*M+1*) [12]. The elements in Figure 2.2 are outlined below. The $\mu$ indicates the conformance relationship . At level *M1* (model), the nodes *CalculusI* and *CalculusII* are of the *Subject* type, while the arrows between the nodes are of the *Depend* type. In other words, *CalculusI* and *CalculusII* are subjects and *CalculusI* depends on *CalculusII*. The *M2* level represents the *Subject* and

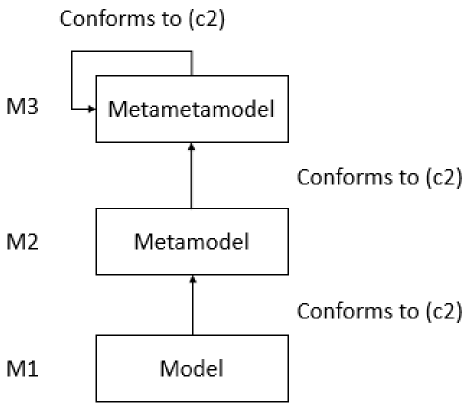


Figure 2.1: 3-level architecture in the MDSE
, [5] [10].

*Depend* nodes, which are the *Class* type. The arrows between these nodes represents the conformance to *Reference* type. However, the next level, M3, represents the types of relationships of *Class* and *Reference* used in this (meta)model. This level ends relationships and conforms recursively to itself.

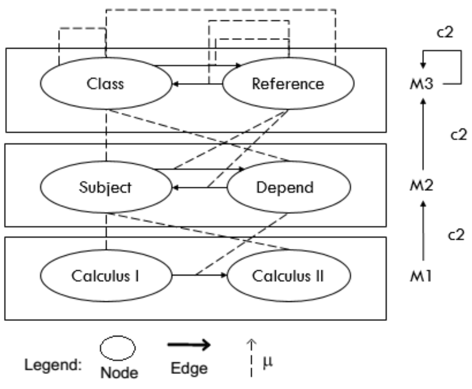


Figure 2.2: A model example according to the 3-level conformance of models

## 2.2 Eclipse Modeling Framework

In order to create and manage models and metamodels, it is necessary to use modeling tools [16]. There are several tools for this purpose, such as the NEO4Emf [1], which models and metamodels are stored in a graph database [1] and XML, which is frequently used to store data.

The Eclipse Modeling Framework (EMF) [1] enables modeling and generating codes from model [14]. This framework is used in this dissertation to manipulate models and metamodels. The EMF uses the ECORE as a metamodel. Its classes are shown in Figure 2.3 and discussed below.

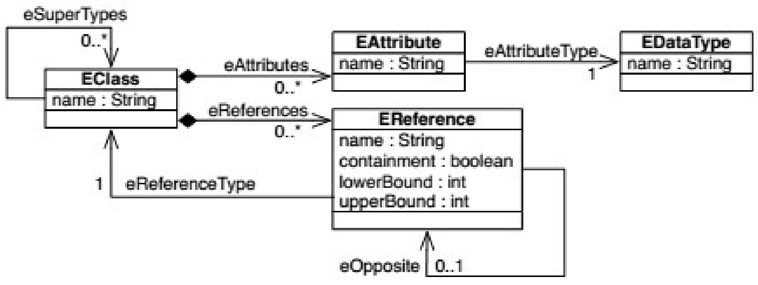
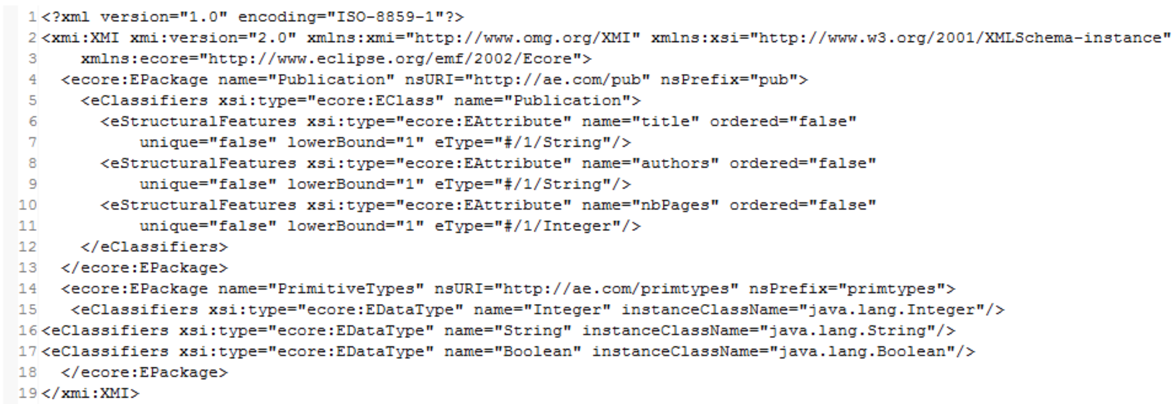


Figure 2.3: Main classes of the Ecore

- **EClass**: used to model classes [14]. EClass has *name* and it may have attributes and references. To support inheritance, one class may refer to many classes of supertype type [27].
- **EAttribute**: used to model attributes [14]. It has *name* and has a *data type* [27];
- **EDatatype**: used to represent atomic data [27]. Data types are identified by *name* [27];
- **EReference**: used to model references between a given class [14]. If a bidirectional association is required, this model can be modeled using two instances of EReference type, which are connected by opposing references [27] and multiplicities may be specified. EReference has *name.*

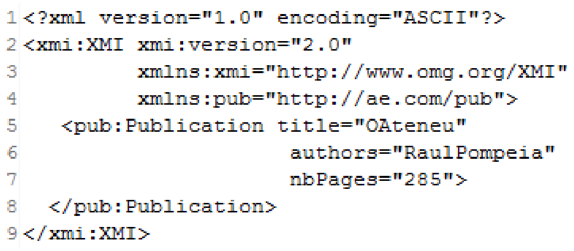
EMF uses XMI (XML Metadata Interchange) to serialize a model and metamodel. One example of metamodel using XMI is shown in Figure 2.4, which has a *title*, *author* and the *number of pages*. *EPackage* groups classes and data of the same types [26]. Figure 2.5 shows the model of the Publication instantiated.

[1]The Eclipse Modeling Framework is a plug-in for Eclipse and is available at http://eclipse.org/modeling/emf/



```
<?xml version="1.0" encoding="ISO-8859-1"?>
<xmi:XMI xmi:version="2.0" xmlns:xmi="http://www.omg.org/XMI" xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
    xmlns:ecore="http://www.eclipse.org/emf/2002/Ecore">
  <ecore:EPackage name="Publication" nsURI="http://ae.com/pub" nsPrefix="pub">
    <eClassifiers xsi:type="ecore:EClass" name="Publication">
      <eStructuralFeatures xsi:type="ecore:EAttribute" name="title" ordered="false"
          unique="false" lowerBound="1" eType="#/1/String"/>
      <eStructuralFeatures xsi:type="ecore:EAttribute" name="authors" ordered="false"
          unique="false" lowerBound="1" eType="#/1/String"/>
      <eStructuralFeatures xsi:type="ecore:EAttribute" name="nbPages" ordered="false"
          unique="false" lowerBound="1" eType="#/1/Integer"/>
    </eClassifiers>
  </ecore:EPackage>
  <ecore:EPackage name="PrimitiveTypes" nsURI="http://ae.com/primtypes" nsPrefix="primtypes">
   <eClassifiers xsi:type="ecore:EDataType" name="Integer" instanceClassName="java.lang.Integer"/>
<eClassifiers xsi:type="ecore:EDataType" name="String" instanceClassName="java.lang.String"/>
<eClassifiers xsi:type="ecore:EDataType" name="Boolean" instanceClassName="java.lang.Boolean"/>
  </ecore:EPackage>
</xmi:XMI>
```

Figure 2.4: A metamodel of Publication in an XMI file



```
<?xml version="1.0" encoding="ASCII"?>
<xmi:XMI xmi:version="2.0"
         xmlns:xmi="http://www.omg.org/XMI"
         xmlns:pub="http://ae.com/pub">
  <pub:Publication title="OAteneu"
                        authors="RaulPompeia"
                        nbPages="285">
  </pub:Publication>
</xmi:XMI>
```

Figure 2.5: A model of Publication in an XMI file

## 2.3 The match operator

The match operator performs semantics and syntactic correlations between (meta)models, ontology and schema database [10] [23] [18]. We consider this the first step to integrating data or to performing a model transformation [7]. In accordance with Del Fabro [4] and Melnik [18], we present the concept of *match* and *matching* as follows:

**Definition 2.3.1. (Match).** *Match is an operator that takes two models as input and produces alignments (links) as output.*

**Definition 2.3.2. (Matching).** *Matching establishes semantic correlations between model elements belonging to different models.*

A match system has two scenarios as input: metamodels or models. In the first scenario, we have to take metamodels into account as input. In the second one, we need a model as input [10]. A match generates alignments (or links) as output. Links have similarity values in a range from 1 to 0 [10][23], which means *in commom* or *not in commom* regarding 2 elements of model. This similarities can be calculated using an Edit

String Distance, Phonetic Similarity or similarity based on constraints [10] [23]. In the follow, we present the definition about similarity between 2 strings.

**Definition 2.3.3. (Similarity between 2 strings).** *Given 2 strings: $\omega_1$ and $\omega_2$, the similarity between them corresponds to a value indicating how equivalent $\omega_1$ is to $\omega_2$.*

We illustrate the matching of two models in Figure 2.6: *Book* and *Publication.* The links represent the correspondence between two elements [5], and they are assigned with a similarity value, for example, the link between "title x title" is 1. This value is calculated using the Levenshtein Edit Distance and it is normalized in relation to the all links. In Figure 2.6, the class *Book* matches to the class *Publication* and the same situation occurs with the elements of these classes.

A filter may be applied to select the best links. The most used filter tecnhique is to set up a minimun treshold value and, then, the links that have the similarity value higher than this threshold are returned [5]. Below, we define the *filter.*

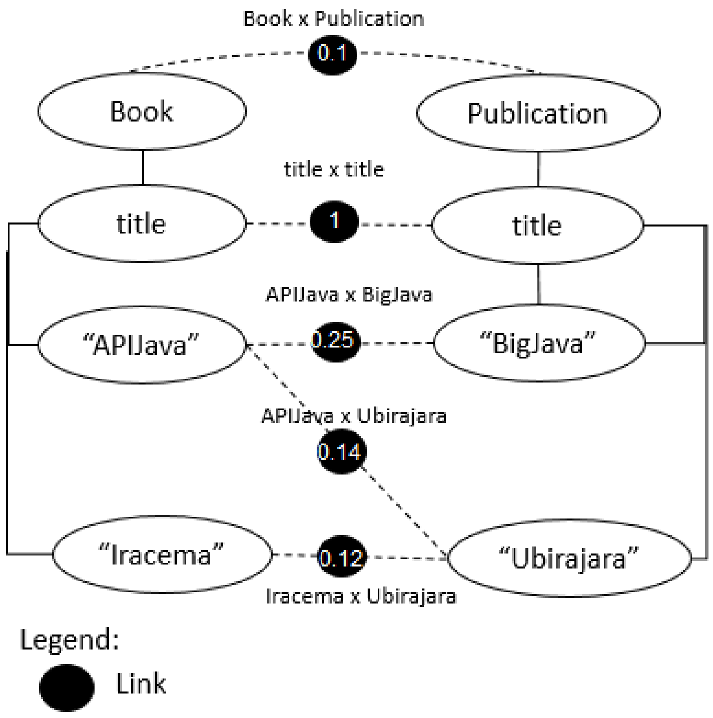


Figure 2.6: Matching example between Book and Publication model

**Definition 2.3.4. (Filter).** *A filter is a method that receives a threshold as input to select the links with similarities higher than (or equal to) this threshold.*

To follow, Figure 2.7 shows the filter aplication in the *Book* and *Publication* model. The threshold defined is 0.25, as it returns the links similarity value bigger than the threshold. These links are often called the best links. In works in the data interoperability domain, for example, the links with the highest similarity are frequently accepted [5]; Because we need the links that are as similar as possible for an accurate operation to be executed. The similarities were calculated using the Levenstein Edit Distance, then they are normalized to a value between 0 to 1.

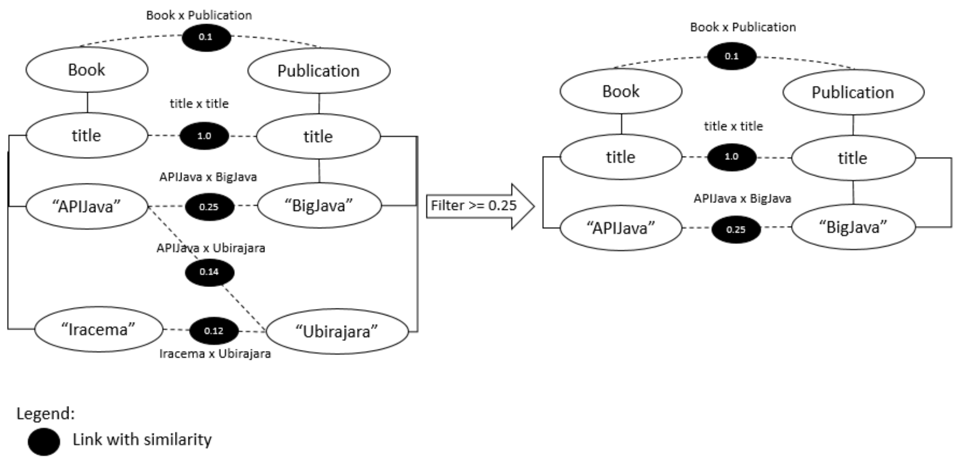


Figure 2.7: Links filtered between models

## 2.4 Weaving Metamodel and Model

After two models have matched in the matching phase, the links produced are stored in the weaving model. A weaving model [5] consists of a model to store correspondences between elements of models. A weaving model conforms to a weaving metamodel and it provides constraints to create links [5].

In accordance with Didonet del Fabro [5], definitions about the weaving metamodel and the weaving model are listed below.

**Definition 2.4.1. (Weaving Metamodel).** *A weaving metamodel is a model* $MM_W = (G_M, \omega_M, \mu_M)$ *that defines link types:*

- $G_M = (N_M, E_M, \Gamma_M)$*, as already presented in definition 2.1.1.*

- $N_M = (N_L \cup N_L E \cup N_O)$, *$N_L$ is the link type; $N_L E$ is the link endpoint type and $N_O$ is the other auxiliary node.*

- $\Gamma_M : E_M \longrightarrow (N_L X N_L E) \bigcup (N_O X N_M)$ *is a link type that refers to multiple link endpoint types and the auxiliary node refers to any kind of node.*

The definition mentioned above is an algebric representation of the weaving metamodel. However, the elements (core) of weaving metamodel are shown in Figure 2.8. The core has one link (*WLink*), and it contains two endpoints (WLinkEnd) - in which the first endpoint refers to an element in *LeftMM*, and the second endpoint refers to an element in *RightMM* [5]. These links are used for distinct purposes, such as the specification of model transformations, model traceability or data integration. The elements that compose the metamodel weaving are listed below:

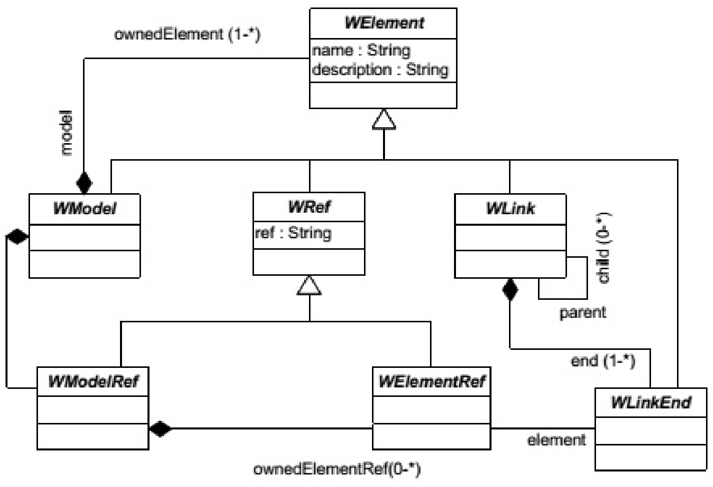


Figure 2.8: The core of the Metamodel Weaving

- **WElement**: the main element where all elements inherit [2]. It is composed by the weaving elements and the reference to corresponded models [5].

- **WModel**: this represents all model elements [5].

- **WLink**: this class represents links between model elements [5]. It also refers to multiple endpoints [2].

- **WLinkEnd**: this class represents the type of linked elements [2]. It allows the definition of N-ary links [5].

- **WElementRef**: this class sets an unique ID for a linked element [2].
- **WModelRefs**: this defines the WLinkEnd and the WElementRef for models as a whole [2].

**Definition 2.4.2. (Weaving Model).** *A weaving model is a model* $M_W = (G_W, \omega_W, \upsilon_W)$*, a graph* $G_W = (N_W, E_W, \Gamma_W)$*, such that its reference model is a weaving metamodel* $(\omega_W, MM_W)$*.*

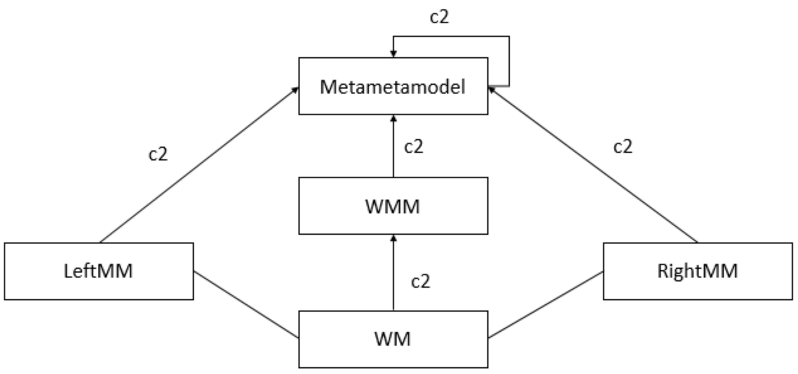


Figure 2.9: Conformance to the weaving metamodel
, [2]

The composition of 2 different models produce a weaving model: a source metamodel (LeftMM) and a target metamodel (RightMM) [2] (Figure 2.9). Figure 2.9 shows the conformance to the model weaving in a generic way. The *LeftMM* and *RightMM* conform to the Weaving Model (WM) and Weaving Metamodel (WMM). The WM conforms to the WMM, which, in its turns, conforms to the Weaving Metametamodel (WMMM) [5]. The WMMM conforms itself.

The SF [18] attempts to increase the initial similarity and, consequently, better links are produced. This situation enables the production of better results in operations of the MDSE (e.g. model transformation). The SF [18] is explained as follows.

## 2.5 The Similarity Flooding algorithm

The Similarity Flooding algorithm (SF) [18] is a well-known algorithm that propagates the similarity between model elements in a graph form, which are connected by the same labeled-edge [4] in a fixed-point computation [18]. The SF is frequently used in matching between metamodels, models, ontologies and data-schemas. For example, consider two models: A and B. We perform the match between (A x B) in order to establish the links. The similarities between links may be calculated using an Edit String Distance, as presented in the previous sections. These values are the initial input for the SF. However, in an iterative sum, the values between these links are propagated until the minimum delta value is reached. At the end of this process, the similarities are normalized and filtered. We explain an example of the SF using real models at the end of this section.

Before executing SF, it is necessary to establish relationships between models elements to produce a *pairwise connectivity graph* (PCG). Each node of the PCG is a map pair -or link [18]. The SF depends on this structure to propagate the similarity values along the graph, through a propagation graph [18]. The propagation graph goes in opposite directions in the links: incoming propagation and outgoing propagation [18] [8]. In Figure 2.12 we can see the propagation graphs. Acording to Melnik [18], the propagation graph is defined below:

**Definition 2.5.1. (Propagation Graph).** *The propagation graph is an auxiliary data structure that stores the proapgation values (weights) used to propagate the similarities between links of matched models.*

We work with the concept of the restricted propagation graph. The restricted propagation graph propapagates the similarities to an specific kind of link of a matched model, for example, the propagation only between links of attributes or the propagation only between links in references. The definition of the restricted propagation graph is given as follows [5]:

**Definition 2.5.2. (Restricted Propagation Graph).** *The restricted propagation graph is an auxiliary data structure that stores the propagation values (weights) used to propagate the similarities between specific links of matched models.*

Weights placed in the propagation graph (or in the restricted propagation graph) indicate the propagation coefficient, i.e., how much the similarity of a given link is propagated

[18]. Melnik [18] defines 7 ways of calculating the propagation coefficients ($\pi$) of the propagation graphs. One of the fix-point formulas proposed by Melnik [18] is calculated over the inverse-product of the number of links of a matched class. It is used in this dissertation and shows more accurate results [18] [8].

The similarity propagation may be executed several times, until a given *delta* is no longer achieved. The *delta* is a treshold value previously defined between iterations, which allows the iteration of the SF to be stopped [18]. This treshold may be defined if the difference between the similarities regarding iterations is too small, we stop the execution of the SF. At the end of each iteration of SF, the values are normalized [18].

Finally, the generalized version of SF is $\sigma_{i+1} = targetLink_i + (sorceLink_i * \pi)$, where the $\sigma$ relate as a link (alignment), the *targetLink* and the *sourceLink* indicate the incoming and outgoing propagation, respectively, and $\pi$ indicates the propagation coefficient [18].

We illustrate one execution of the SF as follows. Consider 2 metamodels: *Book* and *Publication*. According to Figure 2.10, the *Book* metamodel contains the class *Book*, which has 1 attribute: *title*, and 1 reference *chapters* to class *Chapter*. The class *Chapter* contains the following attributes: *title*, *nbPages*, *author*, *book*. Class *Chapters* has one reference *book* to class *Book*. We present the metamodel of *Publication* in Figure 2.11, which has 3 attributes: *title*, *authors*, *nbPages*.

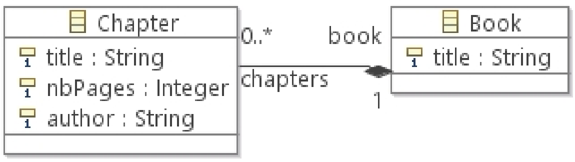


Figure 2.10: Book metamodel

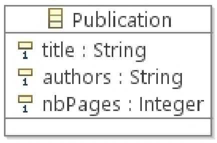


Figure 2.11: Publication metamodel

To create the links, we execute a Cartesian Restrict Product. We calculated the similarities of these links using the Levenshtein Edit Distance [15]. These values initialize

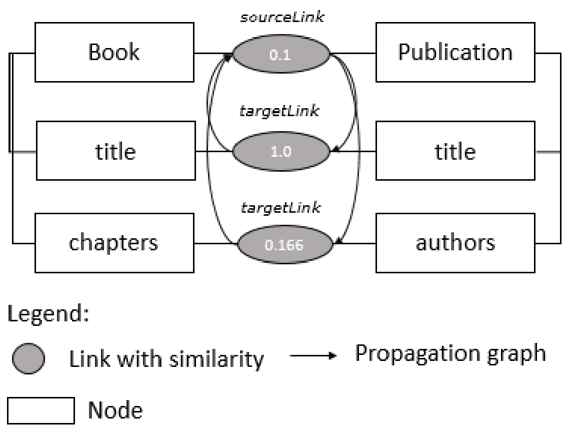


Figure 2.12: Partial links between Book and Publication

the SF. The Levenshtein Edit Distance is an algorithm frequently used in academia and several works. However, we chose this algorithm to illustrated the execution of the SF. Figure 2.12 provides an overview of the links that were created. As already stated, the formula for the SF is: $\sigma^{i+1} = targetLink^i + (sourceLink^i * \pi)$; where, *targetLink* refers to the links that receive the propagation graph and the *sourceLink* is the link that the propagation graph leaves.

| **Links** | **Initial Similarity** | $\pi$ | **1st** | **3rd** | **6th** |
|---|---|---|---|---|---|
| Book x Publication | 0.1 | 0.16666 | 0.465 | 0.466 | 0.465 |
| title x title | 1 | 0.166 | 0.26 | 0.12 | 0.083 |
| title x authors | 0.142 | 0.1666 | 0.040 | 0.068 | 0.076 |
| chapters x authors | 0.1666 | 0.1666 | 0.046 | 0.069 | 0.076 |
| Chapter x Publication | 0.09 | 0.083 | 1 | 1 | 1 |
| title x authors | 0.142 | 0.083 | 0.038 | 0.072 | 0.081 |
| authors x nbPages | 0.125 | 0.083 | 0.033 | 0.070 | 0.081 |

Table 2.1: Partial match for Book and Publication

Now we execute the first iteration from the link *Book X Publication* - *sourceLink*, to *title X title* - *targetLink*. The iterations are important because they change the similarities between links. The *sourceLink* has similarity equal to 0.1, and the *targetLink* has similarity equal to 1. The propagation coefficient is 0.1666, as we have 6 links in the matched class, so, $\frac{1}{6} = 0.1666$. Replacing in the formula, $\sigma^1 = 1 + (0.1 * 0.1666)$, $\sigma^1 = 1.01666$. Thus, the new similarity of the link *title x title* is $\cong 1.01666$. We add all the similarity values that "arrive" at the link *Book x Publication*. This produces the new similarity value for the link of the matched class *Book X Publication*. Table 2.1 shows a partial result for the matching between *Book X Publication*, after executing the SF. We stopped the execution of the SF at the 6th iteration because the delta value was achieved in the links, valuing $\cong 0.001$. At the end of each iteration, the similarity values were normalized.

## 2.6 Related works

In this section, we explain different ways to encoded the propagation graphs of the SF, in addition to other algorithms to propagate similarities - beyond what has been proposed by Melnik [18].

Didonet del Fabro [4] [5] proposes the use of the variants for the propagations in links of metamodels. This approach allows different ways of propagating similarities considering structural relationships of different metamodels [4] [10]. The propagations techniques that were developed are listed below:

- **Containment-tree propagation**: this allows the propagation of the similarities from links between classes to links between attributes and/or from links between classes to links between references [4]. For example, consider two matched classes and the links between them. This method propagates the similarities between links of attributes and/or references [4].

- **Relationship-tree propagation**: this allows the propagation of the similarities to links of references between classes [4]. Consider two matched classes and the links between them. This methods only propagates between links of references [4].

- **Inheritance-tree propagation**: this allows the propagation of the similarities between links of references with inheritance relationship [4]. For example, this method extends the Relationship-tree propagation, however, it takes into account the inheritance of the references [4].

Falleri et al. [8] encoded metamodels into 6 different graph structures in order to execute the propagations of the SF algorithm. According to Falleri et al. [8], these approaches are more detailed than proposed in Didonet del fabro [4]. The implementations of the metamodels are:

- **Minimal configuration**: this requires that we have one labeled node of the graph created for each *EClass* [8]. The name of the nodes are the same of the elements, for example, an element $X$ (an *Eclass*) with name $m$ is represented by a node $N$ with label $m$ [8]. According to Falleri et al. [8], this configuration showed the worst result in the Similarity Flooding, due to its simplicity.

- **Basic configuration**: A labeled name is linked to a unique identified $ID$ [8]. Thus, it allows frequency of a used given name to be know [8]. This frequency can be exploited by the SF [8]. For example, an Eclass $Ec$ is presented by a node $N$ labeled by a unique $ID$, and linked to a node labeled $n$ with an arc *label* [8].

- **Standard configuration**: this obtain the similarities in types and attributes [8]. For example, a node that represents an element $x$ is linked by a labeled node *kind* to a node $x$ representing the type of this element [8].

- **Full configuration**: this extends the Standard configuration as it takes the EAttributes and EReferences into account [8]. For example, all the nodes that represent an EAttribute or EReference are included an node labeled called *derived*, giving this node Boolean conditions (true or false) as to whether the element is derived [8].

- **Flattened configuration**: this extends the Full configuration, although it deals with inheritance relationships [8]. For example, the nodes representing *supertypes* are deleted from the graph [8]. Thus, it is possible to connect nodes representing an *EClass* to nodes representing the *EAttributes* [8]. When an *EReference*is typed as an abstract *EClass*, a node *type* is created [8].

- **Saturated configuration**: this extends the Flattened configuration [8]. For example, the nodes that represent the *EClass* are linked in a *supertype* node [8]. It represents all the super-classes of this *EClass* [8]. *EClass* are also linked in nodes that represents *EAttributes*. The node that represents an *EReference* are created and linked to the node representing the *EClass*, as well as the nodes representing the super-class of the *EClass* [8].

Zhang, Yuan and Huan [32] implemented the SF for the MapReduce. Thus, each iteractive sum of the Similarity Flooding is a MapReduce job. They applied it in a large-scale graph datasets. Experimental results show that this implementation can work in big graph datasets [32].

Truong et al. [29] implemented a new version for SF in the context of integration of the ontologies. This approach consists of three steps:

1. Ontologies models are encoded into a direct labeled graph [29];
2. The method of *concept classification* is applied to increase the precision and reduce the process of the SF [29]. According to Truong et al. [29] this method avoids an exhaustive comparison of all the nodes of the models;
3. Finally, the Similarity Flooding and a filter are applied [29].

The Uppropagation [7] - which is used in context of database schema and is implemented in Coma++, propagates the similarities in a bottom-up manner, i.e., from child-nodes to main-nodes [7]. The authors defend the idea that the similarity propagates directly to main-node because the child-nodes have a strong relationship [7]. The propagated similarity to the main-node is the average of the highest similarity for each child-nodes [7].

Lily [30] creates alignments between heterogeneous, distributed and large-scale ontologies. In the matching phase, Lily exploits both linguistic and structural information of ontology to generate initial alignments [30]. If it is necessary to produce more alignments, a strategy of similarity propagation is applied [17].

### 2.6.1 Discussion

We show a comparative table and discuss the propagation techniques presented in section 2.6. Table 2.2 summarizes how the propagation of the SF works in the presented approaches. Column *approach* mentions the author (or the proposed framework); The *Prop. Technique* elucidates the technique proposed; The *scope* shows the field of application; and the *Similarity Flooding* indicates whether the approach is the Similarity Flooding algorithm or a variant of it.

Del Fabro and Valduriez [4] proposed ways to propagate the link similarity in a metamodel. The authors proposed a propagation metamodel that is used to propagate the similarity in metamodels. On the other hand, Falleri et al. [8] proposed 6 strategies to encode a given metamodel in a graph structure. These methods may provide a better comprehension of the structure of the metamodel, as the metamodel elements are more detailed [8]. In the aproach of Del Fabro and Valduriez [4] the lower the quantity of links, the better the result of the SF, whereas the aproach of Faller et al. [8] may requires a large amount of elements for the SF to sucess.

Zhang, Yuan and Huan [32] used the MapReduce jobs to iterate the results of the SF. Truong et al. [29] presented a new version for the Similarity Flooding algorithm, in which they used the "classification concepts", thereby avoiding the exhaustive matching between elements in ontologies [29].

Other similarity propagation techniques, showing the close of the SF, have also been studied by researchers. Uppropagation [7], which is used in schema matching, attempts to minimize the maximum possible loss of similarities when executing the propagations, using the average of the highest similarity for each element [7]. The propagation is the type of bottom-up, i.e., from a child-node to a main-node of a given schema model, in a graph representation. Lily [30], applied to ontologies, uses a *decision-maker* in order to perform the propagation of similarity, i.e., if there are few alignments, the similarities are then propagated to obtain more alignments [30].

We note most of these implementations have a common goal: to attempt to produce the best alignments to integrate data or process models, and also to explore various elements present in the formalism in order to perform the best propagation of similarities [4] [8] [29] [7] [30] [18] [10]. To follow, we positioned our approach in comparison with the solutions mentioned above, reporting on the main differences between implementations:

1. Melnik [18] proposes the SF. However, we create restricted propagation graphs for this algorithm. Therefore, we can verify whether it is suitable to execute the SF in a lesser amount of links;

2. As in Didonet del Fabro [4] [5], we create restricted propagation graphs in order to execute the SF. However, we developed the propagation less generically, i.e., involving less elements as possbile. This granularity allows us to compare how the propagation technique may be advantageous for the SF;

3. Falleri et al. [8] indicated 6 ways to encode a metamodel in a graph structure, then, the SF is applyed. Unlike this approach, we considered one graph codification regarding a metamodel (or model) and 9 restricted propagation graphs to execute the SF;

4. Compared to Zhang, Yuan and Huan [32] and Coma++ [7], our approach deals with instances of a given model;

5. Unlike Truong et al. [29], we do not consider the use of ”concept of classification”. However, we apply a filter that returns the best links. This may avoid a repetitive matching task between metamodels and models;

6. Unlike Lily [30], we do not consider the use of a propagation method to create more links. Our approach attempts to increase the similarities between the links of metamodels and models.

According to our knowledge, these are between the most representative approaches in its field of study. Whereas they all have propagation similarities, it is difficult to compare them, because the scenarios, the model encodings and the propagation techniques have differences on the conceptual design and implementation. We gathered some simple techniques and provide a comparison.

| Approach / Author | Prop. Technique | Scope | Similarity Flooding |
|---|---|---|---|
| Del Fabro and Valduriez [4] | This takes into account semantic and structural information of a metamodel. The technique may require a small number of elements for a better performance of the SF. | MDSE | X |
| Falleri et al. [8] | Encoded a metamodel in 6 graph manners: *minimal*, *basic*, *standard*, *full*, *flattened* e *satured*. The configuration with more elements provides the best results for the SF. | MDSE | X |
| Zhang, Yuan and Huan [32] | The algorithm is enconded into a MapReduce environment. Each job of the Mapreduce is a new iterative sum of the algorithm. | Data Schema | X |
| Truong et al. [29] | This consists of applying a concept of classification to increase precision and try to reduce the processment time of the algorithm. | Ontology | X |
| *UpPropagation* [7] | This is used in propagating instances of scheme data. The algorithm propagates the average of the highest similarity values of the instances to the attributes. | Data schema | |
| Lily [30] | If the first step does not produce sufficient alignments, a similarity propagation strategy is applied to obtain more alignments. | Ontology | |

Table 2.2: Propagation approaches

# CHAPTER 3

# METAMODEL-BASED SIMILARITY PROPAGATION

In this chapter [1], we present and discuss different ways to implement the propagation methods of the SF. In section 3.1, the methodology workflow of this work is given, in which the steps are sufficiently detailed to permit reproduction and enable a comparison with other propagation approaches. Following this, in section 3.2, we explain nine distinct ways of encoding the SF. For these codification, as already stated, we use information on the structures of metamodels and models to develop of the propagation methods. This could permit a reduction in the amount of links and number iterations of the SF in a single link, which increases the similarity of this related link in as litte iteration possible. In section 3.3, we present the metamodels and models used to execute the propagation methods. However, in subsection 3.3.3, we compare of how much these similarities have been increased (or reduce) in comparison with an implementation comprising all the propagation methods, which is more similar (though not equivalent) to the original SF implementation.

## 3.1 Methodology workflow

The methodology employed in this work is organized in accordance with to Figure 3.1 and may be outlined as follows:

1. **Loading metamodels:** we load pairs of models with their respective metamodels;
2. **Matching:** we execute the matching aiming for the creation of the links between the metamodels and models loaded in step 1. Our motivation is focused on the match operator, because it is the way to create links in a semi-automatic way. In addition to the match, there are several operations for establishing links, such as,

[1]This chapter was partially published in the proceedings of the XVIII Ibero-American Conference on Software Engineering, 2015 [21]

diff, copy or merge [18] [5]. However, we use the match operator because it returns the alignments (links) between 2 models [18] [5];

3. **Links creation:** the links between (meta)models are established. Therefore, similarities can be assigned to them. These links can be stored in a weaving model to serve as input for the next steps [4];

4. **Calculating the similarities:** we calculate the similarities between links. There are various ways to calculate their similarities, such as using a String Edit Distance [23] [18]. In our work, we use a String Edit Distance, which provides the best sequence of edit operations to convert a string from $x$ to $y$ [31]. As edit operations, we can outline insertion, deletion and substitution [31]. There are several Edit Distance functions, e.g., Hamming Distances [11], Longest Commom Subsequence [20], Smith-Waterman distance [25], Jaro-Winkler distance [31] or String$_{sim}$ function [28]. To calculate the similarities between links, we use a well-know String Edit Distance called the Levenshtein Edit Distance [15]. The values returned are the initial input values for the SF. We do not consider the similarities between synonyms. In this way, a dictionary should be implemented.

5. **Link with similarity:** the links are assigned to their respective similarity values. Thus, we can begin the propagation methods, which are explained below;

6. **Executing the propagation methods of SF:** the methods of the propagation are executed. We divided these executions into 2 groups according to the configuration of two filters. A filter only selects links with a similarity higher than a given value. According to Melnik [18], SF has a good performance when dealing with a fewer elements. Therefore, each filter configuration enables a reduction in the number of processed links. The filter settings can be described as follows. In the *(I) first filter configuration*, a filter is applied after running SF. This technique is related to the works of Falleri et al. [8], Del Fabro [4] and Melnik [18]. In the *(II) second filter configuration*, a filter is applied before the SF run. This allows the propagation methods to be applied to the fewest possible links and, thus, this

may increase the similarities in a fewest iterations of the SF due to the smallest number of links in a matched class. However, this implies that a good threshold value should be chosen. At the end, we compared to what extent the similarity of these elements has increased, taking into account the propagation methods used: restricted propagations $X$ comprising all the propagations methods.

7. **Storage in a weaving model:** the links are stored in a weaving model. In this dissertation, the weaving model is persisted in the memory.

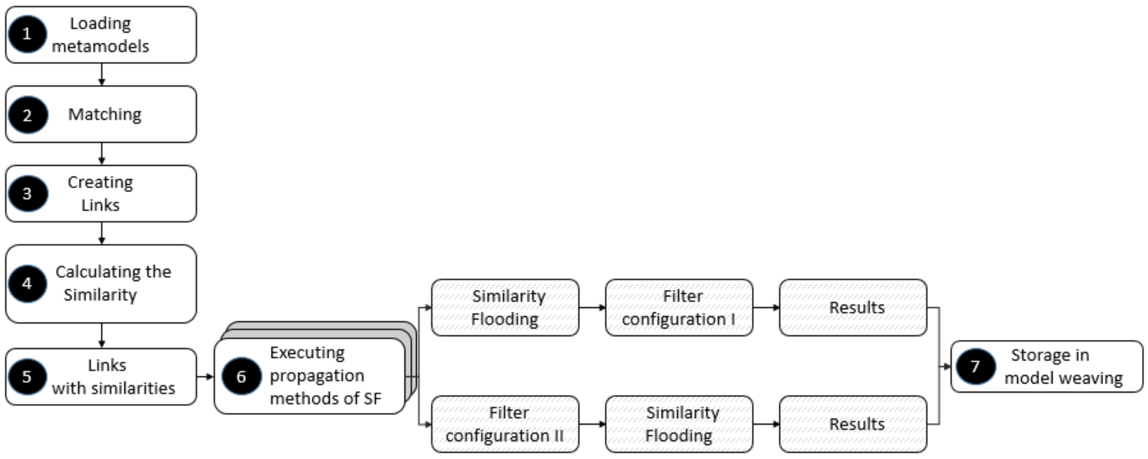


Figure 3.1: Methodology workflow

## 3.2 Implemented methods

We developed 9 ways of execute the restricted propagation according to the structural information of elements of a given (meta)model: classes, attributes, references, instances of attributes and the type of these elements (links between String or Integer). These methods change the direction of the propagation graphs. Then, it is created restriction on the propagation graphs. We implement the methods in Java language and the metamodels and the EMF is used to handle the metamodels and models.

We choose these methods because the links are created by matching the elements of a model and a metamodel as much as possible; giving a representative number of the links to be compared. This situation enables a comparison of the results at the end. Furthermore, we can verify if the restricted propagation graphs are viable in comparison to the non-restricted approach. Note that the propagation methods are restricted to a given type of element and, therefore, cannot be used in any situation.

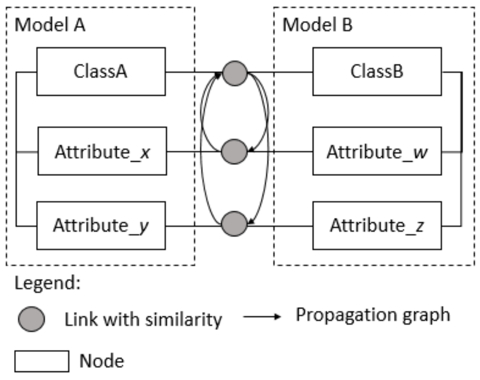


Figure 3.2: Propagation from links between Classes to links between Attributes

- **Propagation from links between Classes to links between Attributes:** this propagates the similarities from links between Classes to links between Attribute belonging to the same matched classes (Figure 3.2). The propagation is calculated as: $\pi = 1/L_x$, where $L_x$ indicates the number of links between attributes belonging to *Class A* and *Class B* matched, with $L_x \neq 0$. For example, considering 2 matched metamodels, this method propagates the similarities from links between classes to only links of attributes.

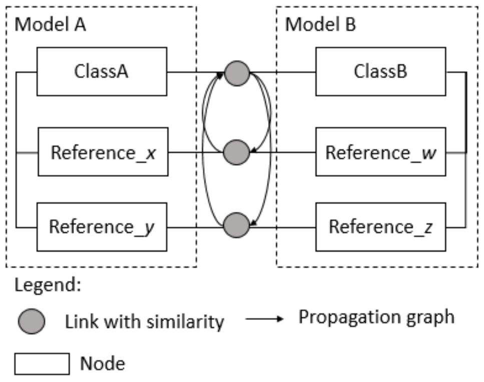


Figure 3.3: Propagation from links between Classes to links between References

- **Propagation from links between Classes to links between References:** this propagates the similarities from links between classes to links between references belonging to the same matched classes (Figure 3.3). This is very similar to the previous propagation method but, in this related propagation, links between references are considered. The propagation is calculated as: $\pi = 1/L_y$, where $L_y$ is the number of links between references of *Class A* and *Class B* matched, with $L_y \neq 0$. For example, considering 2 matched metamodels, this method propagates the similarities from links between classes to only links of references.

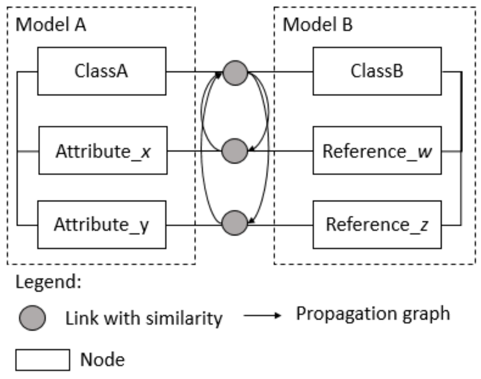


Figure 3.4: Propagation from links between Classes to links between Attributes and References

- **Propagation from links between Classes to links between Attributes and References:** this propagates the similarities from links between Classes to links between Attributes and References belonging to the matched class (Figure 3.4). The formula of the propagation is: $\pi = 1/L_{xy}$, where $L_{xy}$ is the amount of the links between attributes and references of *Class A* and *Class B* matched, with $L_{xy} \neq 0$. For example, considering 2 matched metamodels, this method propagates the similarities from links between classes to only links of attributes and references.

- **Propagation from links between Classes to links between References and Attributes:** this propagates the similarities from links between Classes to links between References matched with Attributes of the same class (Figure 3.5). It changes the propagation direction in comparison with the previous method. The propagation is $\pi = 1/L_{yx}$, where $L_{yx}$ is the amount of links between references regarding *Class A* and *Class B* matched, with $L_{yx} \neq 0$. For example, considering 2 matched metamodels, this method propagates the similarities from links between classes to only links of references and attributes.

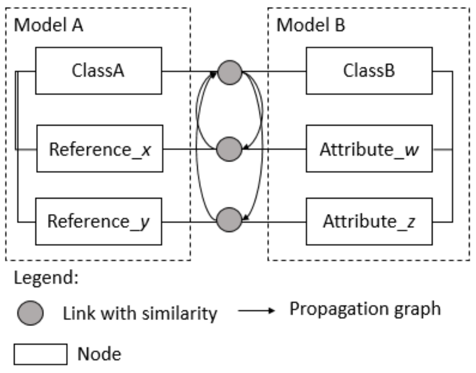


Figure 3.5: Propagation from links between Classes to links between References and Attributes

- **Propagation from links between Attributes to links between their Instances:** the similarities between links of attributes are propagated to links of their respective instances (Figure 3.6). The propagation is $\pi = 1/L_\iota$, where $L_\iota$ designates the amount of instances of a given attributes regarding *Class A* and *Class B* matched, with $L_\iota \neq 0$. For example, considering 2 matched models, this method propagates the similarities only in links of attributes to links of their instances.

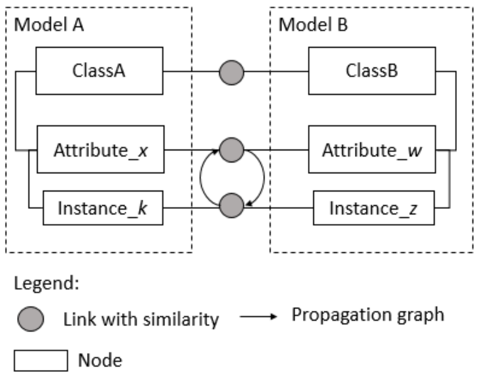


Figure 3.6: Propagation from links between Attributes to links between their Instances

The propagation between links of type belonging of a link are considerate, e.g. *Integer*, *String* or *Float*. In this case, the similarity of the link between classes is propagated to the link between types. The methods are detailed as follows:

- **Propagation from links between Classes to links between types of the Attributes:** this propagates the similarities from links between Classes to links between types of the Attributes (Figure 3.7). The propagation is calculated as:

$\pi = 1/L_{type_x}$, where $L_{type_x}$ indicates the number of links between types belonging to *Attribute A* and *Attribute B* matched, with $L_{type_x} \neq 0$. For example, considering 2 matched metamodels, this method propagates the similarities from links between classes to only links of types of attribute.

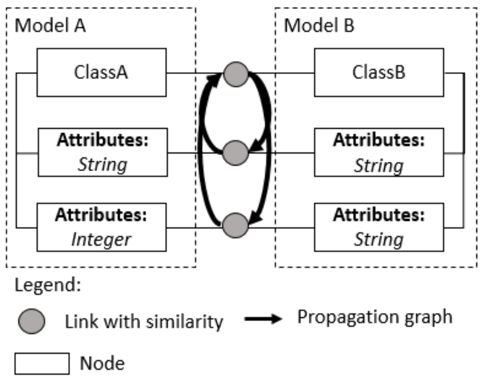


Figure 3.7: Propagation from links between Classes to links between types of the Attributes

- **Propagation from links between Classes to links between types of the References:** this propagates the similarities from links between Classes to links between types of the References (Figure 3.8). The propagation is calculated as: $\pi = 1/L_{type_y}$, where $L_{type_y}$ indicates the number of links between a type belonging to *Reference A* and *Reference B* matched, with $L_{type_y} \neq 0$. For example, considering 2 matched metamodels, this method propagates the similarities from links between classes to only links of types of references.

- **Propagation from links between Classes to links between types of the Attributes and links between types of the References:** this propagates the similarities from links between Classes to links between types of Attributes and References (Figure 3.9). The propagation is calculated as: $\pi = 1/L_{type_xy}$, where $L_{type_xy}$ indicates the number of links between types belonging to *Attribute A* and *Reference B* matched, with $L_{type_xy} \neq 0$. For example, considering 2 matched metamodels, this method propagates the similarities from links between classes to only links of types of attribute and types of references.

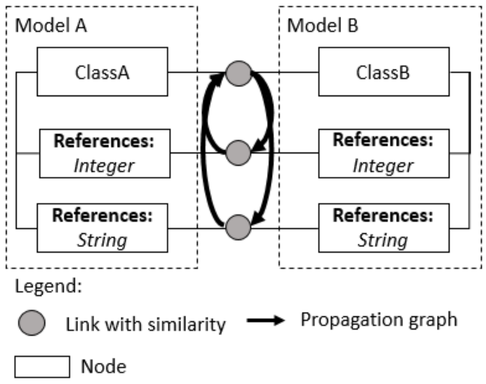


Figure 3.8: Propagation from links between Classes to links between types of the References

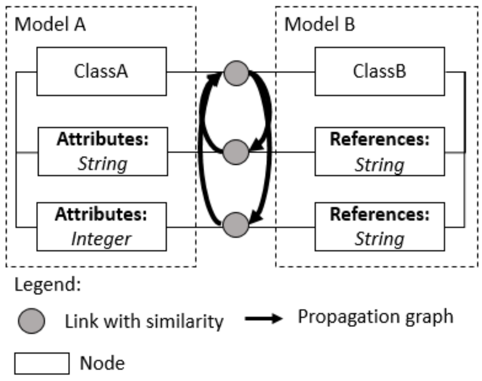


Figure 3.9: Propagation from links between Classes to links between types of the Attributes and links between types of the References

- **Propagation from links between Classes to links between types of the References and links between types of the Attributes:** this propagates the similarities from links between Classes to link between types belonging to References and Attributes (Figure 3.10). The propagation is calculated as: $\pi = 1/L_{type_y x}$, where $L_{type_y x}$ indicates the number of links between types belonging to *Reference A* and *Attribute B* matched, with $L_{type_y x} \neq 0$. For example, considering 2 matched metamodels, this method propagates the similarities from links between classes to only links of types of references and types of attributes.

## 3.3 Case study

In this section, we present 2 case studies involving the methods of the propagation. The (meta)models were chosen because they are frequently used in academia [18] [5].

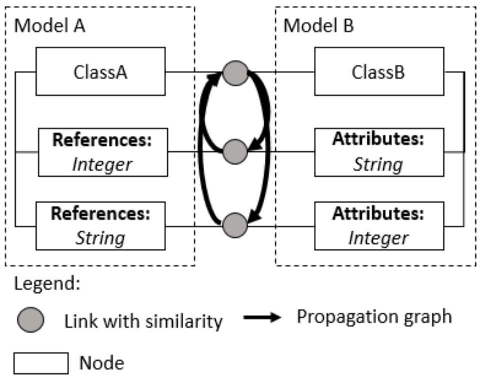


Figure 3.10: Propagation from links between Classes to links between types of the References and links between types of the Attributes

The first case study is related to the matching between partial (meta)models of the Mantis and Bugzilla. Mantis is a web-based bug-tracking system; Bugzilla serves the same purpose, although new modules can be added on it [5]. The objective of this matching is to illustrate the possibility of creating weaving models to integrate 2 different kinds of software. This practice is important when companies need to integrate their software or data [5]. This study is outlined in subsection 3.3.1.

In the second case study, we present the matching between two partial (meta)models: AccountOwner and Customer. These are used in electronic documents for e-business [18]. The objective of this matching is the same as given in sub-subsection 3.3.1: to produce a weaving model to integrate both (meta)models. We have outlined this study in sub-subsection 3.3.2.

### 3.3.1 Propagation between Mantis and Bugzilla

We have outlined the (meta)models as follows [2]. The Mantis' metamodel has 9 classes, 15 attributes and 10 references. The main classes of Mantis are shown in Figure 3.11. The Bugzilla's metamodel has 9 classes, 39 attributes and 8 references and the main classes of it are available in Figure 3.12.

According to Table 3.1, the amount of links generated in the matching of these metamodels and models is shown. We also indicate the number of links after the filter applica-

[2]The metamodels of Mantis and Bugzilla are available at http://www.emn.fr/z-info/atlanmod/index.php/Ecore

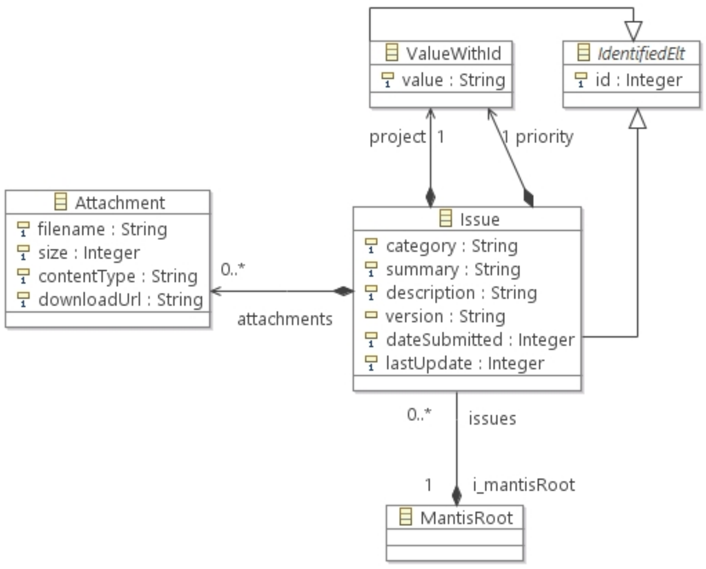


Figure 3.11: Main classes of Mantis metamodel

tion, which the threshold is 0.5. We selected this threshold because it returned the best links according to the calculus of the Levenshtein Edit Distance, after some executions of the SF. If another technique of the calculus of the similarity is applied, another threshold should be defined.

| **Links Matched** | **Amount of Links Generated** | **Amount of Links Filtered** |
|---|---|---|
| Links between classes | 81 | 11 |
| Links between attributes | 585 | 21 |
| Links between references | 80 | 2 |
| Links between attributes and references | 46,800 | 2 |
| Links between references and attributes | 46,800 | 10 |
| Links between types of attributes | 585 | 21 |
| Links between types of references | 80 | 2 |
| Links between types of attributes and references | 46800 | 2 |
| Links between types of references and attributes | 80 | 10 |

Table 3.1: Amount of links generated in the matching phase: Mantis and Bugzilla

Whereas an instance is explicitly related to a class, we make a distinction between the model elements representing a class (called a class instance) and the model elements representing the values of the attributes (called an attribute instance). The Mantis' model has 5 classes instances, 12 attributes with 1 attribute for each instance. The Bugzilla's model has 4 instances of a classes and 31 attributes instances with 1 attribute per instance. According to Table 3.2, the matching generated:

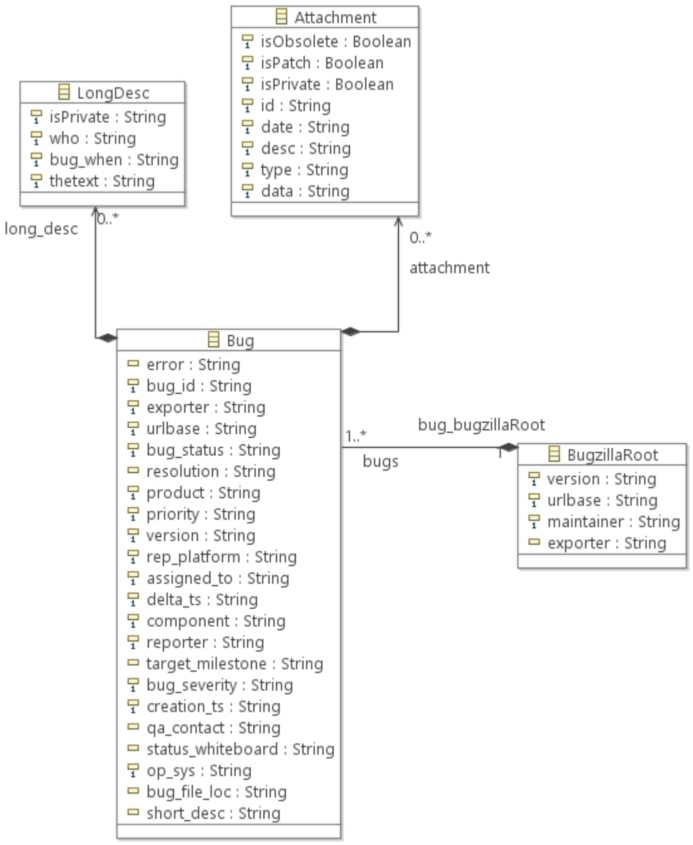


Figure 3.12: Main classes of Bugzilla Metamodel

| Links Matched | Amount of Links Generated | Amount of Links Filtered |
|---|---|---|
| Links between instances of attributes | 372 | 22 |

Table 3.2: Amount of links of instances generated in the matching phase: Mantis and Bugzilla

Table 3.3 and 3.4 show the results according to each propagation method and in Table 3.5 shows the results comprising all the propagation methods. Table 3.6 shows the propagation values according to the type of a given element and Table 3.7 shows the propagation comprising all the methods regarding the type of link. All the tables display the results of the (I) first filter and (II) filter configurations; $\pi$ indicates the propagation coefficient; the link with $(*)$ represents the links between classes or links between attributes. The settings of iterations for the Similarity Flooding are 1, 3 and 6.

The value of the $\pi$ differs for the number of links according to the filter configuration. For example, the link of the class *IdentifiedElt x LongDesc* has 4 links in the first filter configuration; thus, $\pi = 1/L_x = \frac{1}{4} = 0.25$. On the other hand, the same link, in the second filter configuration, has 1 link to execute the propagation; thus, $\pi = 1/L_x = \frac{1}{1} = 1$. This logic ensues for all other links of model elements.

### 3.3.2 Propagation between AccountOwner and Customer

To follow, we present the elements of AccountOwner and Customer [18]. The AccountOwner's metamodel (Figure 3.13) has 2 classes, 7 attributes and 2 references. The Costumer's metamodel (Figure 3.14) has 2 classes, 5 attributes and 2 references. According to Table 3.8, the matching between both metamodels is shown. We also indicate the number of the links after the filter application, which the threshold is 0.25. We selected this threshold because it returned the best links according to the calculus of the Levenshtein Edit Distance, after some executions of the SF. If another technique of the calculus of the similarity is applied, another threshold should be defined.

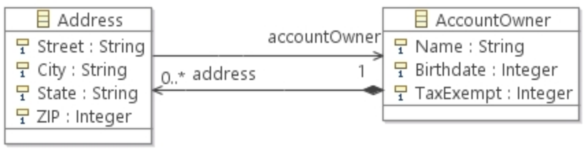


Figure 3.13: AccountOwner Metamodel

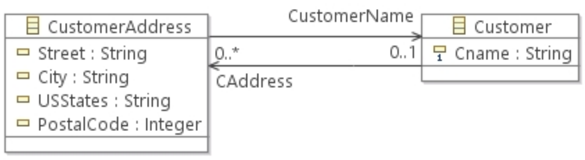


Figure 3.14: Customer Metamodel

In the model of AccountOnwer, we have 2 instances of classes and 7 instances of attributes. In the model of Customer, we have 2 instances of classes and 5 instances of attributes. Table 3.9 shows the amount of links generated in the match phase. In this case, due to a limited number of elements, we do not use filters in the propagation.

Table 3.10 shows the results of restricted propagation between links of AccountOwner x Customer, according to the specific filter configuration. We set the threshold for the filter valuing 0.125. The propagation executing all the methods are shown in Table 3.11. The restricted propagation results between types of links are shown in Table 3.12 and the propagation involving all the propagation methods is shown in Table 3.13.

### 3.3.3 Discussion

We implemented 9 restricted propagation graphs between structures based on the metamodel and model elements to propagate similarities between their links. In addition, we execute these propagations using two different filter configurations: after and before the execution of the SF (as illustrated in Figure 3.1).

We use 4 sets of metamodels in our experiments: *Mantis x Bugzilla* and *AccountOwner x Customer*. The methods and (meta)models are rather simple, but executing them enables some conclusions to be drawn regarding the propagation of similarity process. In the following case, we compared the restricted methods with a combined propagation. The combined propagation executes all the propagation methods together (non-restricted propagation). This method show close as proposed in Melnik [18].

We summarize the percentage of the gain of the similarities for the metamodels of Mantis x Bugzilla and AccountOwner x Customer in Table 3.14 and Table 3.15, respectively. We compare the mean of the similarities of each restricted propagation graph with the non-restricted propagation. Therefore, the higher the similarity percentage, the better the restricted propagation technique is in relation to non-restricted propagation.

We discuss the results of the propagation between links of *Mantis x Bugzilla*. Table 3.14 provides a big picture of the results of each propagation methods compared with a combined propagation method. This table shows the mean percentage gain over the iteration of the SF in accordance to the results of *(I) filter configuration* and *(II) filter configuration*. The best implementation for the SF are related to the *propagation from links between Classes to links between References* and *propagation from links between Classes to links between types of References* in the 6th iteration of *(I) filter configuration*, and in the 1st iteration of *(I) filter configuration*, respectively, due to the small number of the links. While the worst similarities avarege comes from the methods which were executed in a large number of the links in a matched classes, e.g., *propagation from links between Classes to links between References and Attributes* in any iteration of *(II) filter* *configuration* and *propagation from links between Classes to links between of types of References and Attributes* in the 1st iteration of *(II) filter configuration.*

According to the *AccountOwner x Customer* metamodels and models, we have insights, which are disscused below. A summary of the percentage of the mean between the methods is provided in Table 3.15. The best propagation techique is the *propagation from links between Classes to links between References.* The avarege of the similarities values increased in the 6th iteration of *(I) filter configuration.* According to the propagation between the *types* of the links, the best propagation method is the *propagation from links between Classes to links between types of References.* The avarege of the similarities values increased in the 6th iteration of *(I) filter configuration.* In these configurations, the restricted propagation reduced the number of the links and then increased the average of the similarities. The worst results come from the *propagation from links between Classes to links between Attributes* and *propagation from links between Classes to links between types of Attributes*, in the 1st iteration of *(II) filter configuration* and in the 3rd iteration of *(II) filter configuration*, respectively, due to the high value of the total number of the links.

The *second filter configuration* acted as a constraint, reducing the number of the links. Therefore, we did not find a significant increase relative to the average of the similarity in comparison with the combined method, with the average of the similarities remaining constant for each iteration of the SF. However, by comparing the filter configurations, regardless of the propagation methods, there is an increase in the similarities between the links or no change in the similarities in the iterations of the SF.

In both metamodels (Mantis x Bugzilla or AccountOwner x Customer) in the *propagation from links between Attributes to links between their Instances*, we observed that the similarities are unable to 'flow' between links, where the propagation coefficient is equal to 1. For example, from the link *'version x version'* to the link *'Beta x beta'*, the same similarity of the link of the attribute is equal to the similarity of the link of the instance, in any iteration (Table 3.14). Due to the reduced number of the links, the *(II) filter configuration* has no effect on the iterations.

In all metamodels and models, from the 6th iteration, the values of the similarities between the links began to gradually decrease, when the delta value has a treshold value of $\cong 0.001$. Thus, we stopped the execution of the SF. The SF tends to propagate the similarity to a class or element that has the highest number of links. For this reason, after each iteration and normalization of the results, the similarity increased in a single kind of link, e.g., the link between classes *Address x CustomerAddress* in the *propagation from links between Classes to links between Attributes* or *Issue x Bug* in the propagation comprising all the propagation methods. Therefore, similarity values of 1 were assigned to these elements in every iteration. Due to this behavior of the SF, in some iterations the similarities between the links were reduced due to these (meta)models being more connected, e.g., the *propagation from links between Classes to links between Attributes* in the 3rd interation of *Mantis x Bugzilla*. By the best filter technique, it may be possible to disconnect the (meta)models. Thus, the results will not tend to be concentrated in a single link. However, it is important to know the nature of the metamodels and models in order to choose the best propagation method.

Analyzing the formula of the SF we can deduce the behavior of the algorithm in (meta)models in different situations. The formula returns the final similarity between links in accordance with the propagation coefficient multiplied by the similarity of the links between classes, plus the similarity of the links between attributes and/or references, thus SF = targetLink + (sourceLink * propagationCoefficient). The propagation coefficient is directly related to the inverse amount of links to a matched class, thus, 1/amountofLinks. However, the smaller the amount of links, the better the result of the SF may be. This situation is shown in both (meta)models used. It is also necessary take into account the similarity value of the sourceLink, because if this value equals 0, the result may be the targetLink. Nevertheless, if the targetLink is equal to 0, the result of SF may be the (sourceLink * propagationCoefficient). Consequently, it is necessary to apply the best filter techniques when the number of the links is unknown to return the links with the best similarities, which may increase the result of SF. In this work, we know the number of links prior to the filter application. However, when using large-scale (meta)models, it is recommend that the number of the links of each matched class be reduced, which may improve their results.

The links and the weaving model are persisted in memory, which could allow the weaving model to be handled faster than a model stored in a file. The EMF has specific *classes* to persist the weaving model in an XMI file. The weaving model was implemented using Java language.

Our work does not target only MDSE applications. The methods developed may be used to discover mutual friends in a social network [18] or to unveil cartels in public bids [9]. The high similarity may indicates a strong friendship between people [18] or may indicate fraud in public tenders [9], respectively. This will depend on the enconding of the similarity values, for example, the use of the Edit Distance. The restricted propagation methods also may be applied to the Geographic Information System, in which it may be possible to match schemas of maps [22].

The advantage of the use of restricted propagation graphs is that they can be applied in different metamodels and models [4]. These methods also may reduce the links of a matched class, thus, enhancing the similarities between the links. A limitation of this study is that our implementation does not deal with links concerning inheritance propagation. However, it can be inferred that abstract classes with a generic structure (e.g. an 'Object' class), would have several links and the similarity of this class would greatly increase. The way the links were filtered is also a limitation. Del Fabro and Valduriez [4] show that such an implementation can be a disadvantage, since the limit value for the filter is known. After analysis, these values returned the links with a best match. The evaluation of the similarities should be calculated using Precision and Recall to ensure greater reliability. Finally, we could implement a dictionary, using ontology, in order to handle with synonyms.

## 3.4 Summary

In this chapter, we presented the methodology for comparing the executions of the SF. We compare the average of the similarity of each restricted propagation graph with the propagation executing all the methods (shown as closely as proposed by Melnik [18]). We utilize 4 metamodels to execute the propagation: matching between Mantis with Bugzilla and matching between AccountOwner x Customer. The propagation using the restricted propagation graphs increase the similarities between the links because they reduce the number of the links of a matched class.

We also apply 2 variants of filters configuration: before and after the execution of the SF, as in Figure 3.1. The application of the filter before of the SF enables a comparison if the number of the links of a matched class is diminished, it is possible increase the similarity between the links. Applying the filter after the SF only selects the links with the best similarities, and they have no effect on the propagations. According to our experiments, the choice of the filter configuration increases the similarities between links, mainly if we execute the filter after the execution of the SF, because this reduces the number of the links.

Tables 3.14 and 3.15 show the percent of the gain of similarity. The comparison is the average of the similarities of the restricted graph propagation with the average of the similarities of the non-restricted propagation. Therefore, the higher the percentage, the better the similarity improvement of the application of the restricted propagation graphs. We executed the iterations of the SF until the 50th iteration. However, the results are showed to be more appropriate up to the 6th iteration, due to the limit of the delta value. Therefore the similarities between the links has decreased progressively.

The advantage of using the restricted propagation graph is that this method may increase faster the similarities between the links, in comparison with a non-restricted propagation. On the other hand, we must know the features of the metamodels and models before apply the restricted propagation method in order to provide the best result.

| **Links** | $\pi$ | | **Similarities** | **1st** | | **3rd** | | **6th** | |
|---|---|---|---|---|---|---|---|---|---|
| | ***I*** | ***II*** | | **I** | **II** | **I** | **II** | **I** | **II** |
| **Propagation from links between Classes to links between Attributes** | | | | | | | | | |
| IdentifiedElt x LongDesc* | *0.25* | *1* | 0.091 | 0.047 | 0.195 | 0.047 | 0.195 | 0.047 | 0.195 |
| id x who | *0.25* | *1* | 0.250 | 0.019 | 0.195 | 0.014 | 0.195 | 0.012 | 0.195 |
| IdentifiedElt x Attachment* | *0.125* | *1* | 0.091 | 0.154 | 0.623 | 0.154 | 0.623 | 0.154 | 0.624 |
| id x id | *0.125* | *1* | 1.000 | 0.070 | 0.623 | 0.032 | 0.623 | 0.021 | 0.624 |
| Issue x BugzillaRoot* | *0.04166* | *1* | 0.083 | 0.244 | 0.619 | 0.244 | 0.619 | 0.244 | 0.619 |
| version x version | *0.04166* | *1* | 1.000 | 0.069 | 0.619 | 0.025 | 0.619 | 0.012 | 0.619 |
| Issue x Bug* | *0.007575* | *1* | 0.200 | 1.000 | 0.686 | 1.000 | 0.686 | 1.000 | 0.686 |
| version x version | *0.007575* | *1* | 1.000 | 0.069 | 0.686 | 0.023 | 0.686 | 0.009 | 0.686 |
| ValueWithId x StringElt* | *1* | *1* | 0.083 | 0.074 | 0.619 | 0.074 | 0.619 | 0.074 | 0.617 |
| value x value | *1* | *1* | 1.000 | 0.074 | 0.619 | 0.074 | 0.619 | 0.074 | 0.619 |
| ValueWithId x Attachment* | *0.125* | *1* | 0.091 | 0.100 | 0.195 | 0.100 | 0.195 | 0.100 | 0.195 |
| value x date | *0.125* | *1* | 0.250 | 0.018 | 0.195 | 0.014 | 0.195 | 0.013 | 0.195 |
| Note x LongDesc* | *0.25* | *1* | 0.143 | 0.056 | 0.225 | 0.056 | 0.225 | 0.056 | 0.225 |
| text x thetext | *0.25* | *1* | 0.250 | 0.020 | 0.225 | 0.015 | 0.225 | 0.014 | 0.225 |
| Note x Attachment* | *0.125* | *0.5* | 0.111 | 0.108 | 0.349 | 0.108 | 0.349 | 0.108 | 0.349 |
| text x desc | *0.125* | *0.5* | 0.250 | 0.018 | 0.175 | 0.014 | 0.175 | 0.014 | 0.175 |
| text x type | *0.125* | *0.5* | 0.25 | 0.018 | 0.175 | 0.015 | 0.174 | 0.014 | 0.175 |
| Attachment x Attachment* | *0.03125* | *0.333* | 1 | 0.348 | 1.000 | 0.348 | 1.000 | 0.348 | 1.000 |
| size x id | *0.03125* | *0.333* | 0.25 | 0.019 | 0.333 | 0.013 | 0.333 | 0.011 | 0.333 |
| size x date | *0.03125* | *0.333* | 0.25 | 0.019 | 0.333 | 0.013 | 0.333 | 0.011 | 0.333 |
| size x type | *0.03125* | *0.333* | 0.25 | 0.019 | 0.333 | 0.013 | 0.333 | 0.011 | 0.333 |
| **Propagation from links between Classes to links between References** | | | | | | | | | |
| Issue x Bug* | *0.0142857* | *1* | 0.2 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| attachments _ attachment | *0.0142857* | *1* | 0.5 | 0.065 | 1.000 | 0.027 | 1.000 | 0.016 | 1.000 |
| **Propagation from links between Classes to links between Attributes and References** | | | | | | | | | |
| IdentifiedElt x Bug* | *0.142857* | *1* | 0.071 | 0.243 | 1 | 0.243 | 1.000 | 0.243 | 1.000 |
| id_cc | *0.142857* | *1* | 0.333 | 0.080 | 1 | 0.046 | 1.000 | 0.036 | 1.000 |
| **Propagation from links between Classes to links between References and Attributes** | | | | | | | | | |
| Issue x Bug* | *0.0045* | *0.25* | 0.2 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| project x product | *0.0045* | *0.25* | 0.333 | 0.013 | 0.162 | 0.007 | 0.228 | 0.005 | 0.247 |
| priority x priority | *0.0045* | *0.25* | 1 | 0.039 | 0.444 | 0.013 | 0.298 | 0.006 | 0.256 |
| reporter x exporter | *0.0045* | *0.25* | 0.333 | 0.013 | 0.162 | 0.007 | 0.228 | 0.005 | 0.247 |
| assignedTo x assigned_To | *0.0045* | *0.25* | 0.5 | 0.019 | 0.232 | 0.008 | 0.246 | 0.005 | 0.249 |
| Issue x BugzillaRoot* | *0.025* | *1* | 0.0833 | 0.183 | 0.176 | 0.183 | 0.176 | 0.183 | 0.176 |
| reporter x exporter | *0.025* | *1* | 0.333 | 0.013 | 0.176 | 0.007 | 0.176 | 0.005 | 0.176 |
| Issue x Attachment | *0.0125* | *1* | 0.1 | 0.373 | 0.148 | 0.373 | 0.148 | 0.373 | 0.148 |
| notes x date | *0.0125* | *1* | 0.25 | 0.010 | 0.148 | 0.006 | 0.148 | 0.005 | 0.148 |
| **Propagation from links between Attributes to links between Instances** | | | | | | | | | |
| version x version * | *1* | - | 1 | 1 | - | 1.000 | - | 1.000 | - |
| Beta x beta | *1* | - | 1 | 1 | - | 1.000 | - | 1.000 | - |
| category x exporter * | *1* | - | 0.111 | 0.180 | - | 0.181 | - | 0.181 | - |
| website x teste | *1* | - | 0.25 | 0.180 | - | 0.181 | - | 0.181 | - |
| category x product* | *1* | - | 0.111 | 0.555 | - | 0.556 | - | 0.556 | - |
| website x website | *1* | - | 1 | 0.555 | - | 0.556 | - | 0.556 | - |
| version x exporter* | *1* | - | 0.111 | 0.180 | - | 0.181 | - | 0.181 | - |
| Beta x teste | *1* | - | 0.25 | 0.180 | - | 0.181 | - | 0.181 | - |
| version x version * | *1* | - | 1 | 1 | - | 1.000 | - | 1.000 | - |
| Beta x beta | *1* | - | 1 | 1 | - | 1.000 | - | 1.000 | - |
| value x component * | *1* | - | 0.111 | 0.180 | - | 0.181 | - | 0.181 | - |
| High x link | *1* | - | 0.25 | 0.180 | - | 0.181 | - | 0.181 | - |
| value x value * | *1* | - | 1 | 0.625 | - | 0.625 | - | 0.625 | - |
| High x link | *1* | - | 0.25 | 0.625 | - | 0.625 | - | 0.625 | - |

Table 3.3: Propagations from links between Mantis and Bugzilla metamodels and models

| Links | $\pi$ |  | Similarities | 1st |  | 3rd |  | 6th |  |
|---|---|---|---|---|---|---|---|---|---|
|  | *I* | *II* |  | I | II | I | II | I | II |
| **Propagation from links between Attributes to links between their Instances** |  |  |  |  |  |  |  |  |  |
| value x exporter * | *1* | - | 0.125 | 0.1875 | - | 0.188 | - | 0.188 | - |
| low x abc | *1* | - | 0.25 | 0.1925 | - | 0.188 | - | 0.188 | - |
| value x bug_id * | *1* | - | 0.143 | 0.196 | - | 0.196 | - | 0.196 | - |
| low x 1 | *1* | - | 0.25 | 0.196 | - | 0.196 | - | 0.196 | - |
| value x component * | *1* | - | 0.111 | 0.180 | - | 0.181 | - | 0.181 | - |
| low x link | *1* | - | 0.25 | 0.180 | - | 0.181 | - | 0.181 | - |
| value x target_milestone * | *1* | - | 0.0714 | 0.160 | - | 0.161 | - | 0.161 | - |
| low x v01 | *1* | - | 0.25 | 0.160 | - | 0.161 | - | 0.161 | - |
| value x bug_severity * | *1* | - | 0.083 | 0.541 | - | 0.542 | - | 0.542 | - |
| low x low | *1* | - | 1 | 0.541 | - | 0.542 | - | 0.542 | - |
| value x value * | *1* | - | 1 | 0.625 | - | 0.625 | - | 0.625 | - |
| low x link | *1* | - | 0.25 | 0.625 | - | 0.625 | - | 0.625 | - |
| login x version* | *1* | - | 0.1667 | 0.208 | - | 0.208 | - | 0.208 | - |
| geor x beta | *1* | - | 0.25 | 0.208 | - | 0.208 | - | 0.208 | - |
| value x assigned_to* | *1* | - | 0.0909 | 0.212 | - | 0.212 | - | 0.212 | - |
| George x Jorge | *1* | - | 0.333 | 0.212 | - | 0.212 | - | 0.212 | - |
| login x version* | *1* | - | 0.1667 | 0.208 | - | 0.208 | - | 0.208 | - |
| geor x beta | *1* | - | 0.25 | 0.208 | - | 0.208 | - | 0.208 | - |
| login x bug_severity* | *1* | - | 0.0909 | 0.170 | - | 0.170 | - | 0.170 | - |
| geor x low | *1* | - | 0.25 | 0.170 | - | 0.170 | - | 0.170 | - |
| value x bug_status* | *1* | - | 0.111 | 0.180 | - | 0.181 | - | 0.181 | - |
| null x st_null | *1* | - | 0.25 | 0.180 | - | 0.181 | - | 0.181 | - |
| login x version* | *1* | - | 0.1667 | 0.208 | - | 0.208 | - | 0.208 | - |
| geor x beta | *1* | - | 0.25 | 0.208 | - | 0.208 | - | 0.208 | - |
| value x assigned_to* | *1* | - | 0.0909 | 0.212 | - | 0.212 | - | 0.212 | - |
| George x Jorge | *1* | - | 0.333 | 0.212 | - | 0.212 | - | 0.212 | - |
| login x version* | *1* | - | 0.167 | 0.208 | - | 0.208 | - | 0.208 | - |
| geor x beta | *1* | - | 0.25 | 0.208 | - | 0.208 | - | 0.208 | - |
| login x bug_severity* | *1* | - | 0.0909 | 0.170 | - | 0.170 | - | 0.170 | - |
| geor x low | *1* | - | 0.25 | 0.170 | - | 0.170 | - | 0.170 | - |

Table 3.4: Continuation - Propagation results from links between Mantis and Bugzilla metamodels and models

| **Links** | $\pi$ | | **Similarities** | **1st** | | **3rd** | | **6th** | |
|---|---|---|---|---|---|---|---|---|---|
| | ***I*** | ***II*** | | **I** | **II** | **I** | **II** | **I** | **II** |
| IdentifiedElt x Bug* | *0.34400* | *1.000* | 0.071 | 0.067 | 0.083 | 0.068 | 0.083 | 0.071 | 0.083 |
| id x cc | *0.34400* | *1.000* | 0.333 | 0.006 | 0.083 | 0.003 | 0.083 | 0.003 | 0.083 |
| IdentifiedElt x LongDesc* | *0.25000* | *1.000* | 0.091 | 0.013 | 0.070 | 0.013 | 0.070 | 0.014 | 0.070 |
| id x who | *0.25000* | *1.000* | 0.250 | 0.005 | 0.070 | 0.004 | 0.070 | 0.004 | 0.070 |
| IdentifiedElt x Attachment* | *0.12500* | *1.000* | 0.091 | 0.043 | 0.224 | 0.044 | 0.224 | 0.046 | 0.224 |
| id x id | *0.12500* | *1.000* | 1.000 | 0.019 | 0.224 | 0.009 | 0.224 | 0.006 | 0.224 |
| Issue x Bug* | *0.00202* | *0.143* | 0.200 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| project x product | *0.00202* | *0.143* | 0.333 | 0.006 | 0.074 | 0.003 | 0.126 | 0.002 | 0.141 |
| priority x priority | *0.00202* | *0.143* | 1.000 | 0.019 | 0.211 | 0.006 | 0.160 | 0.003 | 0.145 |
| reporter x exporter | *0.00202* | *0.143* | 0.333 | 0.006 | 0.074 | 0.003 | 0.126 | 0.002 | 0.141 |
| reporter x reporter | *0.00202* | *0.143* | 1.000 | 0.019 | 0.211 | 0.006 | 0.160 | 0.003 | 0.145 |
| version x version | *0.00202* | *0.143* | 1.000 | 0.019 | 0.211 | 0.006 | 0.160 | 0.003 | 0.145 |
| assignedTo x assigned_to | *0.00202* | *0.143* | 0.500 | 0.010 | 0.109 | 0.004 | 0.134 | 0.002 | 0.142 |
| attachments x attachment | *0.00202* | *0.143* | 0.500 | 0.010 | 0.109 | 0.004 | 0.134 | 0.002 | 0.142 |
| Issue x BugzillaRoot* | *0.11700* | *0.500* | 0.083 | 0.193 | 0.291 | 0.193 | 0.291 | 0.193 | 0.291 |
| reporter x exporter | *0.11700* | *0.500* | 0.333 | 0.006 | 0.077 | 0.003 | 0.128 | 0.002 | 0.143 |
| version x version | *0.11700* | *0.500* | 1.000 | 0.019 | 0.214 | 0.007 | 0.163 | 0.003 | 0.148 |
| Issue x Attachment* | *0.07350* | *1.000* | 0.100 | 0.292 | 0.072 | 0.292 | 0.072 | 0.292 | 0.072 |
| notes x date | *0.07350* | *1.000* | 0.250 | 0.005 | 0.072 | 0.003 | 0.072 | 0.002 | 0.072 |
| ValueWithID x StringElt* | *0.50000* | *1.000* | 0.083 | 0.021 | 0.223 | 0.018 | 0.223 | 0.012 | 0.223 |
| value x value | *0.50000* | *1.000* | 1.000 | 0.020 | 0.223 | 0.013 | 0.223 | 0.008 | 0.223 |
| ValueWithID x Attachment* | *0.06250* | *1.000* | 0.091 | 0.028 | 0.070 | 0.024 | 0.070 | 0.016 | 0.070 |
| value x date | *0.06250* | *1.000* | 0.250 | 0.005 | 0.070 | 0.003 | 0.070 | 0.001 | 0.070 |
| Note x LongDesc* | *0.08330* | *1.000* | 0.143 | 0.027 | 0.081 | 0.025 | 0.081 | 0.019 | 0.081 |
| text x thetext | *0.08330* | *1.000* | 0.250 | 0.005 | 0.081 | 0.003 | 0.081 | 0.002 | 0.081 |
| Note x Attachment* | *0.04166* | *0.500* | 0.111 | 0.051 | 0.126 | 0.048 | 0.126 | 0.037 | 0.126 |
| text x desc | *0.04166* | *0.500* | 0.250 | 0.005 | 0.063 | 0.003 | 0.063 | 0.002 | 0.063 |
| text x type | *0.04166* | *0.500* | 0.250 | 0.005 | 0.063 | 0.003 | 0.063 | 0.002 | 0.063 |
| Attachment x Attachment* | *0.02500* | *0.333* | 1.000 | 0.097 | 0.360 | 0.092 | 0.360 | 0.082 | 0.360 |
| size x id | *0.02500* | *0.333* | 0.250 | 0.005 | 0.120 | 0.003 | 0.120 | 0.002 | 0.120 |
| size x date | *0.02500* | *0.333* | 0.250 | 0.005 | 0.120 | 0.003 | 0.120 | 0.002 | 0.120 |
| size x type | *0.02500* | *0.333* | 0.250 | 0.005 | 0.120 | 0.003 | 0.120 | 0.002 | 0.120 |

Table 3.5: Results comprising all the propagation methods between links of Mantis and Bugzilla metamodel

| Links | Type link element | π |  | Similarities | 1st |  | 3rd |  | 6th |  |
|---|---|---|---|---|---|---|---|---|---|---|
|  |  | ***I*** | ***II*** |  | **I** | **II** | **I** | **II** | **I** | **II** |
| **From links between Classes to links between types of Attributes** |  |  |  |  |  |  |  |  |  |  |
| IdentifiedElt x LongDesc* | - | *0.250* | *1.000* | 0.091 | 0.007 | 0.111 | 0.007 | 0.111 | 0.007 | 0.111 |
| id x who | Integer x String | *0.250* | *1.000* | 0.143 | 0.002 | 0.111 | 0.002 | 0.111 | 0.002 | 0.111 |
| IdentifiedElt x Attachment* | - | *0.125* | *1.000* | 0.091 | 0.012 | 0.111 | 0.012 | 0.111 | 0.012 | 0.111 |
| id x id | Integer x String | *0.125* | *1.000* | 0.143 | 0.002 | 0.111 | 0.002 | 0.111 | 0.002 | 0.111 |
| Issue x BugzillaRoot* | - | *0.042* | *1.000* | 0.083 | 0.182 | 0.513 | 0.182 | 0.513 | 0.182 | 0.513 |
| version x version | String x String | *0.042* | *1.000* | 1.000 | 0.011 | 0.513 | 0.008 | 0.513 | 0.008 | 0.513 |
| Issue x Bug* | - | *0.008* | *1.000* | 0.200 | 1.000 | 0.569 | 1.000 | 0.568 | 1.000 | 0.568 |
| version x version | String x String | *0.008* | *1.000* | 1.000 | 0.011 | 0.569 | 0.008 | 0.568 | 0.008 | 0.568 |
| ValueWithId x StringElt* | - | *1.000* | *1.000* | 0.083 | 0.011 | 0.513 | 0.011 | 0.513 | 0.011 | 0.513 |
| value x value | String x String | *1.000* | *1.000* | 1.000 | 0.011 | 0.513 | 0.011 | 0.513 | 0.011 | 0.513 |
| ValueWithId x Attachment* | - | *0.125* | *1.000* | 0.091 | 0.058 | 0.513 | 0.058 | 0.517 | 0.058 | 0.517 |
| value x date | String x String | *0.125* | *1.000* | 1.000 | 0.011 | 0.513 | 0.008 | 0.517 | 0.007 | 0.517 |
| Note x LongDesc* | - | *0.250* | *1.000* | 0.143 | 0.044 | 0.542 | 0.044 | 0.541 | 0.044 | 0.541 |
| text x thetext | String x String | *0.250* | *1.000* | 1.000 | 0.011 | 0.542 | 0.011 | 0.541 | 0.011 | 0.541 |
| Note x Attachment* | - | *0.125* | *0.500* | 0.111 | 0.058 | 1.000 | 0.058 | 1.000 | 0.058 | 1.000 |
| text x desc | String x String | *0.125* | *0.500* | 1.000 | 0.011 | 0.500 | 0.008 | 0.500 | 0.007 | 0.500 |
| text x type | String x String | *0.125* | *0.500* | 1.000 | 0.011 | 0.500 | 0.008 | 0.500 | 0.007 | 0.500 |
| Attachment x Attachment* | - | *0.031* | *0.333* | 1.000 | 0.193 | 0.677 | 0.193 | 0.677 | 0.193 | 0.677 |
| size x id | Integer x String | *0.031* | *0.333* | 0.143 | 0.002 | 0.226 | 0.005 | 0.226 | 0.006 | 0.226 |
| size x date | Integer x String | *0.031* | *0.333* | 0.143 | 0.002 | 0.226 | 0.005 | 0.226 | 0.006 | 0.226 |
| size x type | Integer x String | *0.031* | *0.333* | 0.143 | 0.002 | 0.226 | 0.005 | 0.226 | 0.006 | 0.226 |
| **From links between Classes to links between types of References** |  |  |  |  |  |  |  |  |  |  |
| Issue x Bug* | - | *0.0143* | *1* | 0.2 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| attachments _ attachment | Attachment x Attachment | *0.0143* | *1* | 1 | 0.120 | 1.000 | 0.041 | 1.000 | 0.018 | 1.000 |
| **From links between Classes to links between types of Attributes and References** |  |  |  |  |  |  |  |  |  |  |
| IdentifiedElt x Bug* | - | *0.143* | *1* | 0.071 | 0.171 | 1 | 0.171 | 1 | 0.171 | 1 |
| id_cc | Integer x Cc | *0.143* | *1* | 0.125 | 0.027 | 1 | 0.025 | 1 | 0.025 | 1 |
| **From links between Classes to links between types of References and Attributes** |  |  |  |  |  |  |  |  |  |  |
| Issue x Bug* | - | *0.0045* | *0.2* | 0.200 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| project x product | ValueWithId x String | *0.0045* | *0.2* | 0.091 | 0.004 | 0.148 | 0.004 | 0.187 | 0.005 | 0.198 |
| priority x priority | ValueWithId x String | *0.0045* | *0.2* | 0.091 | 0.004 | 0.148 | 0.004 | 0.187 | 0.005 | 0.198 |
| reporter x exporter | Person x String | *0.0045* | *0.2* | 0.167 | 0.007 | 0.235 | 0.005 | 0.209 | 0.005 | 0.201 |
| reporter x reporter | Person x String | *0.0045* | *0.2* | 0.167 | 0.007 | 0.235 | 0.005 | 0.209 | 0.005 | 0.201 |
| assignedTo x assigned_To | Person x String | *0.0045* | *0.2* | 0.167 | 0.007 | 0.235 | 0.005 | 0.209 | 0.005 | 0.201 |
| Issue x BugzillaRoot* | - | *0.0250* | *1* | 0.083 | 0.184 | 0.284 | 0.184 | 0.284 | 0.184 | 0.284 |
| reporter x exporter | Person x String | *0.0250* | *1* | 0.167 | 0.007 | 0.284 | 0.005 | 0.284 | 0.005 | 0.284 |
| Issue x Attachment* | - | *0.0125* | *1* | 0.100 | 0.358 | 0.276 | 0.358 | 0.276 | 0.292 | 0.276 |
| notes x date | Note x String | *0.0125* | *1* | 0.143 | 0.006 | 0.276 | 0.005 | 0.276 | 0.005 | 0.276 |

Table 3.6: Results of the propagation between types of links of Mantis and Bugzilla metamodels

| **Links** | **Type link element** | $\pi$ | | **Similarities** | **1st** | | **3rd** | | **6th** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | ***I*** | ***II*** | | **I** | **II** | **I** | **II** | **I** | **II** |
| IdentifiedElt x Bug* | - | *0.0344* | *1.000* | 0.071 | 0.030 | 0.140 | 0.031 | 0.140 | 0.032 | 0.140 |
| id x cc | Integer x Cc | *0.0344* | *1.000* | 0.333 | 0.001 | 0.140 | 0.001 | 0.140 | 0.001 | 0.140 |
| IdentifiedElt x LongDesc* | - | *0.2500* | *1.000* | 0.091 | 0.005 | 0.081 | 0.005 | 0.081 | 0.005 | 0.081 |
| id x who | Integer x String | *0.2500* | *1.000* | 0.143 | 0.001 | 0.081 | 0.001 | 0.081 | 0.001 | 0.081 |
| IdentifiedElt x Attachment* | - | *0.1250* | *1.000* | 0.091 | 0.009 | 0.081 | 0.009 | 0.081 | 0.009 | 0.081 |
| id x id | Integer x String | *0.1250* | *1.000* | 0.143 | 0.001 | 0.081 | 0.001 | 0.081 | 0.001 | 0.081 |
| Issue x Bug* | - | *0.0020* | *0.143* | 0.200 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| project x product | ValueWithId x String | *0.0020* | *0.143* | 0.091 | 0.001 | 0.069 | 0.002 | 0.118 | 0.002 | 0.140 |
| priority x priority | ValueWithId x String | *0.0020* | *0.143* | 0.091 | 0.001 | 0.069 | 0.002 | 0.118 | 0.002 | 0.140 |
| reporter x exporter | Person x String | *0.0020* | *0.143* | 0.167 | 0.001 | 0.068 | 0.002 | 0.124 | 0.002 | 0.141 |
| reporter x reporter | Person x String | *0.0020* | *0.143* | 0.167 | 0.001 | 0.068 | 0.002 | 0.124 | 0.002 | 0.141 |
| version x version | String x String | *0.0020* | *0.143* | 1.000 | 0.008 | 0.357 | 0.003 | 0.196 | 0.002 | 0.150 |
| assignedTo x assigned_to | Person x String | *0.0020* | *0.143* | 0.167 | 0.001 | 0.068 | 0.002 | 0.124 | 0.002 | 0.141 |
| attachments x attachment | Attachment x Attachment | *0.0020* | *0.143* | 1.000 | 0.008 | 0.357 | 0.003 | 0.196 | 0.002 | 0.150 |
| Issue x BugzillaRoot* | - | *0.0118* | *0.500* | 0.083 | 0.180 | 0.434 | 0.180 | 0.434 | 0.180 | 0.434 |
| reporter x exporter | Person x String | *0.0118* | *0.500* | 0.167 | 0.001 | 0.072 | 0.002 | 0.181 | 0.002 | 0.212 |
| version x version | String x String | *0.0118* | *0.500* | 1.000 | 0.008 | 0.361 | 0.004 | 0.253 | 0.002 | 0.221 |
| Issue x Attachment* | - | *0.0074* | *1.000* | 0.100 | 0.247 | 0.084 | 0.247 | 0.084 | 0.247 | 0.084 |
| notes x date | Note x String | *0.0074* | *1.000* | 0.143 | 0.001 | 0.084 | 0.002 | 0.084 | 0.002 | 0.084 |
| ValueWithID x StringElt* | - | *0.5000* | *1.000* | 0.083 | 0.008 | 0.376 | 0.007 | 0.376 | 0.005 | 0.376 |
| value x value | String x String | *0.5000* | *1.000* | 1.000 | 0.008 | 0.376 | 0.005 | 0.376 | 0.003 | 0.376 |
| ValueWithID x Attachment* | - | *0.0625* | *1.000* | 0.091 | 0.041 | 0.379 | 0.036 | 0.379 | 0.024 | 0.379 |
| value x date | String x String | *0.0625* | *1.000* | 1.000 | 0.008 | 0.379 | 0.004 | 0.379 | 0.002 | 0.379 |
| Note x LongDesc* | - | *0.0833* | *1.000* | 0.143 | 0.036 | 0.397 | 0.033 | 0.397 | 0.026 | 0.397 |
| text x thetext | String x String | *0.0833* | *1.000* | 1.000 | 0.008 | 0.397 | 0.004 | 0.397 | 0.003 | 0.397 |
| Note x Attachment* | - | *0.0417* | *0.500* | 0.111 | 0.051 | 0.733 | 0.047 | 0.733 | 0.037 | 0.624 |
| text x desc | String x String | *0.0417* | *0.500* | 1.000 | 0.008 | 0.366 | 0.004 | 0.366 | 0.002 | 0.366 |
| text x type | String x String | *0.0417* | *0.500* | 1.000 | 0.008 | 0.366 | 0.004 | 0.366 | 0.002 | 0.366 |
| Attachment x Attachment* | - | *0.1250* | *0.333* | 1.000 | 0.137 | 0.496 | 0.131 | 0.496 | 0.117 | 0.496 |
| size x id | Integer x String | *0.1250* | *0.333* | 0.143 | 0.001 | 0.165 | 0.003 | 0.165 | 0.003 | 0.165 |
| size x date | Integer x String | *0.1250* | *0.333* | 0.143 | 0.001 | 0.165 | 0.003 | 0.165 | 0.003 | 0.165 |
| size x type | Integer x String | *0.1250* | *0.333* | 0.143 | 0.001 | 0.165 | 0.003 | 0.165 | 0.003 | 0.165 |

Table 3.7: Results comprising all the propagation methods between types of links of Mantis and Bugzilla

| **Links Matched** | **Amount of Links Generated** | **Amount of Links Filtered** |
|---|---|---|
| Links between classes | 2 | 2 |
| Links between attributes | 35 | 25 |
| Links between references | 4 | 1 |
| Links between attributes with references | 14 | 5 |
| Links between references with attributes | 10 | 4 |
| Links between types of attributes | 35 | 25 |
| Links between types of references | 4 | 1 |
| Links between types of attributes with reference | 14 | 7 |
| Links between types of references with attributes | 10 | 5 |

Table 3.8: Amount of links generated in the matching phase: AccountOwner and Customer

| **Links Matched** | **Amount of Links Generated** | **Amount of Links Filtered** |
|---|---|---|
| Links between instances of attributes | 10 | 10 |

Table 3.9: Amount of links of instances generated in the matching phase: AccountOwner and Customer

| **Links** | $\pi$ | | **Similarities** | **1st** | | **3rd** | | **6th** | |
|---|---|---|---|---|---|---|---|---|---|
| | **I** | **II** | | **I** | **II** | **I** | **II** | **I** | **II** |
| **Propagation from links between Classes to links between Attributes** | | | | | | | | | |
| AccountOwner x Customer * | *0.333* | *0.500* | 0.143 | 0.203 | 0.196 | 0.203 | 0.196 | 0.203 | 0.196 |
| name x Cname | *0.333* | *0.500* | 0.500 | 0.126 | 0.146 | 0.082 | 0.110 | 0.069 | 0.099 |
| birthdate x Cname | *0.333* | *0.500* | 0.125 | 0.040 | 0.050 | 0.061 | 0.086 | 0.067 | 0.096 |
| AccountOwner x CustomerAdress* | *0.083* | *0.143* | 0.071 | 0.376 | 0.285 | 0.376 | 0.285 | 0.376 | 0.285 |
| name x street | *0.083* | *0.143* | 0.167 | 0.040 | 0.045 | 0.033 | 0.042 | 0.032 | 0.285 |
| name x city | *0.083* | *0.143* | 0.200 | 0.047 | 0.054 | 0.035 | 0.044 | 0.032 | 0.041 |
| name x USStates | *0.083* | *0.143* | 0.143 | 0.034 | 0.039 | 0.032 | 0.040 | 0.031 | 0.041 |
| birthdate x street | *0.083* | *0.143* | 0.125 | 0.030 | 0.034 | 0.031 | 0.039 | 0.031 | 0.041 |
| birthdate x city | *0.083* | *0.143* | 0.125 | 0.030 | 0.034 | 0.031 | 0.039 | 0.031 | 0.040 |
| birthdate x USStates | *0.083* | *0.143* | 0.143 | 0.034 | 0.039 | 0.032 | 0.040 | 0.031 | 0.041 |
| taxExempt x street | *0.083* | *0.143* | 0.143 | 0.034 | 0.039 | 0.032 | 0.040 | 0.031 | 0.041 |
| Address x Customer * | *0.250* | *0.250* | 0.111 | 0.206 | 0.228 | 0.206 | 0.228 | 0.206 | 0.228 |
| street x Cname | *0.250* | *0.250* | 0.167 | 0.045 | 0.050 | 0.050 | 0.055 | 0.051 | 0.057 |
| city x Cname | *0.250* | *0.250* | 0.200 | 0.053 | 0.058 | 0.052 | 0.057 | 0.052 | 0.057 |
| state x Cname | *0.250* | *0.250* | 0.250 | 0.053 | 0.058 | 0.055 | 0.060 | 0.052 | 0.057 |
| ZIP x Cname | *0.250* | *0.250* | 0.167 | 0.045 | 0.050 | 0.050 | 0.055 | 0.051 | 0.057 |
| Address x CustomerAddress* | *0.063* | *0.083* | 0.111 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| street x street | *0.063* | *0.083* | 1.000 | 0.232 | 0.257 | 0.105 | 0.127 | 0.068 | 0.089 |
| street x city | *0.063* | *0.083* | 0.143 | 0.035 | 0.039 | 0.056 | 0.072 | 0.062 | 0.082 |
| street x USStates | *0.063* | *0.083* | 0.167 | 0.040 | 0.045 | 0.057 | 0.074 | 0.062 | 0.082 |
| city x street | *0.063* | *0.083* | 0.143 | 0.035 | 0.039 | 0.056 | 0.072 | 0.062 | 0.082 |
| city x city | *0.063* | *0.083* | 1.000 | 0.232 | 0.257 | 0.105 | 0.127 | 0.068 | 0.089 |
| city x USStates | *0.063* | *0.083* | 0.125 | 0.030 | 0.034 | 0.054 | 0.071 | 0.062 | 0.082 |
| state x street | *0.063* | *0.083* | 0.250 | 0.059 | 0.066 | 0.062 | 0.079 | 0.062 | 0.083 |
| state x city | *0.063* | *0.083* | 0.200 | 0.048 | 0.053 | 0.059 | 0.076 | 0.062 | 0.082 |
| state x USStates | *0.063* | *0.083* | 0.250 | 0.059 | 0.066 | 0.062 | 0.079 | 0.062 | 0.083 |
| state x postalCode | *0.063* | *0.083* | 0.143 | 0.035 | 0.039 | 0.054 | 0.072 | 0.062 | 0.082 |
| ZIP x street | *0.063* | *0.083* | 0.143 | 0.035 | 0.039 | 0.056 | 0.072 | 0.062 | 0.082 |
| ZIP x city | *0.063* | *0.083* | 0.250 | 0.059 | 0.066 | 0.062 | 0.079 | 0.062 | 0.083 |
| **Propagation from links between Classes to links between References** | | | | | | | | | |
| AccountOwner x Customer* | *1* | *1* | 0.143 | 1 | 1 | 1 | 1 | 1 | 1 |
| address x Caddress | *1* | *1* | 0.5 | 1 | 1 | 1 | 1 | 1 | 1 |
| **Propagation from links between Classes to links between Attributes and References** | | | | | | | | | |
| AccountOwner x Customer* | *0.333* | *0.500* | 0.143 | 0.830 | 0.815 | 0.830 | 0.806 | 0.830 | 0.815 |
| name x Caddress | *0.333* | *0.500* | 0.143 | 0.310 | 0.425 | 0.285 | 0.412 | 0.278 | 0.408 |
| TaxExempt x Caddress | *0.333* | *0.500* | 0.125 | 0.281 | 0.390 | 0.278 | 0.403 | 0.277 | 0.407 |
| Address x Customer* | *0.250* | *0.333* | 0.111 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| street x Caddress | *0.250* | *0.333* | 0.143 | 0.277 | 0.357 | 0.257 | 0.339 | 0.251 | 0.334 |
| city x Caddress | *0.250* | *0.333* | 0.125 | 0.248 | 0.322 | 0.250 | 0.330 | 0.250 | 0.333 |
| state x Cadress | *0.250* | *0.333* | 0.125 | 0.248 | 0.322 | 0.250 | 0.330 | 0.250 | 0.333 |
| **Propagation from links between Classes to links between References and Attributes** | | | | | | | | | |
| AccountOwner x Customer * | *1* | *1* | 0.143 | 0.493 | 0.585 | 0.493 | 0.585 | 0.493 | 0.585 |
| address x Cname | *1* | *1* | 0.143 | 0.493 | 0.585 | 0.493 | 0.585 | 0.493 | 0.585 |
| AccountOwner x CustomerAdress* | *0.25* | *0.333* | 0.071 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| address x street | *0.25* | *0.333* | 0.167 | 0.319 | 0.390 | 0.267 | 0.348 | 0.252 | 0.335 |
| address x city | *0.25* | *0.333* | 0.125 | 0.247 | 0.305 | 0.249 | 0.326 | 0.250 | 0.332 |
| address x USStates | *0.25* | *0.333* | 0.125 | 0.247 | 0.305 | 0.249 | 0.326 | 0.250 | 0.332 |
| **Propagation from links between Attributes to links between their Instances** | | | | | | | | | |
| name x Cname* | *1* | - | 0.5 | 1 | - | 1 | - | 1 | - |
| JoÃ£o Silva x Joaquim Silva | *1* | - | 0.2 | 1 | - | 1 | - | 1 | - |

Table 3.10: Propagation results from links between AccountOwner and Customer metamodels using restrictive propagation methods

| Links | $\pi$ | | Similarities | 1st | | 3rd | | 6th | |
|---|---|---|---|---|---|---|---|---|---|
| | ***I*** | ***II*** | | **I** | **II** | **I** | **II** | **I** | **II** |
| AccountOwner x Customer * | *0.125* | *0.167* | 0.143 | 0.365 | 0.428 | 0.365 | 0.428 | 0.365 | 0.428 |
| name x Cname | *0.125* | *0.167* | 0.500 | 0.100 | 0.133 | 0.059 | 0.087 | 0.047 | 0.073 |
| birthdate x Cname | *0.125* | *0.167* | 0.125 | 0.028 | 0.038 | 0.041 | 0.063 | 0.045 | 0.070 |
| address x Caddress | *0.125* | *0.167* | 0.500 | 0.100 | 0.133 | 0.065 | 0.087 | 0.047 | 0.073 |
| name x Caddress | *0.125* | *0.167* | 0.143 | 0.031 | 0.042 | 0.042 | 0.064 | 0.045 | 0.070 |
| TaxExempt x Caddress | *0.125* | *0.167* | 0.125 | 0.028 | 0.038 | 0.041 | 0.063 | 0.045 | 0.070 |
| adress x Cname | *0.125* | *0.167* | 0.143 | 0.031 | 0.042 | 0.042 | 0.064 | 0.045 | 0.070 |
| AccountOwner x CustomerAdress* | *0.05* | *0.100* | 0.071 | 0.488 | 0.391 | 0.488 | 0.391 | 0.488 | 0.391 |
| name x street | *0.05* | *0.100* | 0.167 | 0.033 | 0.044 | 0.027 | 0.040 | 0.025 | 0.039 |
| name x city | *0.05* | *0.100* | 0.200 | 0.039 | 0.053 | 0.028 | 0.043 | 0.025 | 0.040 |
| name x USStates | *0.05* | *0.100* | 0.143 | 0.028 | 0.038 | 0.025 | 0.039 | 0.025 | 0.039 |
| birthdate x street | *0.05* | *0.100* | 0.125 | 0.025 | 0.034 | 0.025 | 0.038 | 0.024 | 0.039 |
| birthdate x city | *0.05* | *0.100* | 0.125 | 0.025 | 0.034 | 0.025 | 0.038 | 0.024 | 0.039 |
| birthdate x USStates | *0.05* | *0.100* | 0.143 | 0.028 | 0.038 | 0.025 | 0.039 | 0.025 | 0.039 |
| taxExempt x street | *0.05* | *0.100* | 0.143 | 0.028 | 0.038 | 0.025 | 0.039 | 0.025 | 0.039 |
| adress x street | *0.05* | *0.100* | 0.167 | 0.033 | 0.044 | 0.027 | 0.040 | 0.025 | 0.039 |
| address x city | *0.05* | *0.100* | 0.125 | 0.025 | 0.034 | 0.025 | 0.038 | 0.024 | 0.039 |
| address x USStates | *0.05* | *0.100* | 0.125 | 0.025 | 0.034 | 0.025 | 0.038 | 0.024 | 0.039 |
| Address x Customer * | *0.1* | *0.143* | 0.111 | 0.306 | 0.328 | 0.306 | 0.328 | 0.306 | 0.328 |
| street x Cname | *0.1* | *0.143* | 0.167 | 0.034 | 0.047 | 0.032 | 0.047 | 0.031 | 0.047 |
| city x Cname | *0.1* | *0.143* | 0.200 | 0.041 | 0.055 | 0.033 | 0.049 | 0.031 | 0.047 |
| state x Cname | *0.1* | *0.143* | 0.250 | 0.050 | 0.068 | 0.036 | 0.052 | 0.031 | 0.048 |
| ZIP x Cname | *0.1* | *0.143* | 0.167 | 0.034 | 0.047 | 0.032 | 0.047 | 0.031 | 0.047 |
| street x Caddress | *0.1* | *0.143* | 0.143 | 0.030 | 0.040 | 0.030 | 0.045 | 0.031 | 0.047 |
| city x Caddress | *0.1* | *0.143* | 0.125 | 0.026 | 0.036 | 0.030 | 0.044 | 0.030 | 0.047 |
| state x Cadress | *0.1* | *0.143* | 0.125 | 0.026 | 0.036 | 0.030 | 0.044 | 0.030 | 0.047 |
| Address x CustomerAddress* | *0.04* | *0.083* | 0.111 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| street x street | *0.04* | *0.083* | 1.000 | 0.194 | 0.257 | 0.079 | 0.127 | 0.045 | 0.089 |
| street x city | *0.04* | *0.083* | 0.143 | 0.028 | 0.039 | 0.037 | 0.072 | 0.040 | 0.082 |
| street x USStates | *0.04* | *0.083* | 0.167 | 0.033 | 0.045 | 0.038 | 0.074 | 0.040 | 0.082 |
| city x street | *0.04* | *0.083* | 0.143 | 0.028 | 0.039 | 0.037 | 0.072 | 0.040 | 0.082 |
| city x city | *0.04* | *0.083* | 1.000 | 0.194 | 0.257 | 0.079 | 0.127 | 0.045 | 0.089 |
| city x USStates | *0.04* | *0.083* | 0.125 | 0.025 | 0.034 | 0.036 | 0.071 | 0.040 | 0.082 |
| state x street | *0.04* | *0.083* | 0.250 | 0.049 | 0.066 | 0.042 | 0.079 | 0.040 | 0.083 |
| state x city | *0.04* | *0.083* | 0.200 | 0.040 | 0.053 | 0.040 | 0.076 | 0.040 | 0.082 |
| state x USStates | *0.04* | *0.083* | 0.250 | 0.049 | 0.066 | 0.042 | 0.079 | 0.040 | 0.082 |
| state x postalCode | *0.04* | *0.083* | 0.143 | 0.028 | 0.039 | 0.037 | 0.072 | 0.040 | 0.083 |
| ZIP x street | *0.04* | *0.083* | 0.143 | 0.028 | 0.039 | 0.037 | 0.072 | 0.040 | 0.082 |
| ZIP x city | *0.04* | *0.083* | 0.250 | 0.049 | 0.066 | 0.042 | 0.079 | 0.040 | 0.083 |

Table 3.11: Propagation results comprising all the propagation methods from links between AccountOwner and Customer metamodels

| **Links** | **Type link element** | $\pi$ | | **Similarities** | **1st** | | **3rd** | | **6th** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | ***I*** | ***II*** | | **I** | **II** | **I** | **II** | **I** | **II** |
| **From links between Classes to links between types of Attributes** | | | | | | | | | | |
| AccountOwner x Customer* | - | *0.333* | *0.333* | 0.143 | 0.130 | 0.130 | 0.130 | 0.130 | 0.130 | 0.130 |
| name x cname | String x String | *0.333* | *0.333* | 1.000 | 0.096 | 0.096 | 0.056 | 0.056 | 0.045 | 0.045 |
| birthdate x cname | Integer x String | *0.333* | *0.333* | 0.143 | 0.017 | 0.017 | 0.037 | 0.037 | 0.043 | 0.043 |
| taxExempt x cname | Integer x String | *0.333* | *0.333* | 0.143 | 0.017 | 0.017 | 0.037 | 0.037 | 0.043 | 0.043 |
| AccountOwner x CustmerAddress* | - | *0.083* | *0.083* | 0.071 | 0.554 | 0.554 | 0.554 | 0.554 | 0.554 | 0.554 |
| name x street | String x String | *0.083* | *0.083* | 1.000 | 0.092 | 0.092 | 0.058 | 0.058 | 0.048 | 0.048 |
| name x city | String x String | *0.083* | *0.083* | 1.000 | 0.092 | 0.092 | 0.058 | 0.058 | 0.048 | 0.048 |
| name x USStates | String x String | *0.083* | *0.083* | 1.000 | 0.092 | 0.092 | 0.058 | 0.058 | 0.048 | 0.048 |
| name x postalCode | String x Integer | *0.083* | *0.083* | 0.143 | 0.014 | 0.017 | 0.038 | 0.038 | 0.045 | 0.045 |
| birthdate x street | Integer x String | *0.083* | *0.083* | 0.143 | 0.014 | 0.017 | 0.038 | 0.038 | 0.045 | 0.045 |
| birthdate x city | Integer x String | *0.083* | *0.083* | 0.143 | 0.014 | 0.017 | 0.038 | 0.038 | 0.045 | 0.045 |
| birthdate x USStates | Integer x String | *0.083* | *0.083* | 0.143 | 0.014 | 0.017 | 0.038 | 0.038 | 0.045 | 0.045 |
| birthdate x postalCode | Integer x Integer | *0.083* | *0.083* | 1.000 | 0.092 | 0.092 | 0.058 | 0.058 | 0.048 | 0.048 |
| taxExempt x street | Integer x String | *0.083* | *0.083* | 0.143 | 0.014 | 0.017 | 0.038 | 0.038 | 0.045 | 0.045 |
| taxExempt x city | Integer x String | *0.083* | *0.083* | 0.143 | 0.014 | 0.017 | 0.038 | 0.038 | 0.045 | 0.045 |
| taxExempt x USStates | Integer x String | *0.083* | *0.083* | 0.143 | 0.014 | 0.017 | 0.038 | 0.038 | 0.045 | 0.045 |
| taxExempt x postalCode | Integer x Integer | *0.083* | *0.083* | 1.000 | 0.092 | 0.092 | 0.058 | 0.058 | 0.048 | 0.048 |
| Address x Customer * | - | *0.250* | *0.250* | 0.111 | 0.297 | 0.297 | 0.297 | 0.297 | 0.297 | 0.297 |
| street x cname | String x String | *0.250* | *0.250* | 1.000 | 0.094 | 0.094 | 0.079 | 0.079 | 0.075 | 0.075 |
| city x cname | String x String | *0.250* | *0.250* | 1.000 | 0.094 | 0.094 | 0.079 | 0.079 | 0.075 | 0.075 |
| state x cname | String x String | *0.250* | *0.250* | 1.000 | 0.094 | 0.094 | 0.079 | 0.079 | 0.075 | 0.075 |
| ZIP x cname | Integer x String | *0.250* | *0.250* | 0.143 | 0.016 | 0.016 | 0.060 | 0.060 | 0.072 | 0.072 |
| Address x CustomerAddress* | - | *0.063* | *0.063* | 0.111 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| street x street | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| street x city | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| street x USStates | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| street x postalCode | String x Integer | *0.063* | *0.063* | 0.143 | 0.014 | 0.014 | 0.050 | 0.050 | 0.061 | 0.061 |
| city x street | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| city x city | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| city x USStates | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| city x postalCode | String x Integer | *0.063* | *0.063* | 0.143 | 0.014 | 0.014 | 0.050 | 0.050 | 0.061 | 0.061 |
| state x street | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| state x city | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| state x USStates | String x String | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| state x postalCode | String x Integer | *0.063* | *0.063* | 0.143 | 0.014 | 0.014 | 0.050 | 0.050 | 0.061 | 0.061 |
| ZIP x street | Integer x String | *0.063* | *0.063* | 0.143 | 0.014 | 0.014 | 0.050 | 0.050 | 0.061 | 0.061 |
| ZIP x city | Integer x String | *0.063* | *0.063* | 0.143 | 0.014 | 0.014 | 0.050 | 0.050 | 0.061 | 0.061 |
| ZIP x USStates | Integer x String | *0.063* | *0.063* | 0.143 | 0.014 | 0.014 | 0.050 | 0.050 | 0.061 | 0.061 |
| ZIP x postalCode | Integer x Integer | *0.063* | *0.063* | 1.000 | 0.092 | 0.092 | 0.070 | 0.070 | 0.064 | 0.064 |
| **From links between Classes to links between types of References** | | | | | | | | | | |
| Address x CustomerAddress* | - | *1.000* | *1.000* | 0.111 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| accountOwner x CustomerName | AccountOwner x Customer | *1.000* | *1.000* | 0.143 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| **From links between Classes to links between types of Attributes and References** | | | | | | | | | | |
| AccountOwner x CustomerAddress* | - | *0.333* | *0.333* | 0.071 | 0.775 | 0.775 | 0.775 | 0.775 | 0.775 | 0.775 |
| name x customerName | String x Customer | *0.333* | *0.333* | 0.143 | 0.236 | 0.236 | 0.253 | 0.253 | 0.258 | 0.258 |
| birthdate x customerName | Integer x Customer | *0.333* | *0.333* | 0.167 | 0.270 | 0.270 | 0.261 | 0.261 | 0.259 | 0.259 |
| taxExempt x customerName | Integer x Customer | *0.333* | *0.333* | 0.167 | 0.270 | 0.270 | 0.261 | 0.261 | 0.259 | 0.259 |
| Address x CustomerAddress* | - | *0.250* | *0.250* | 0.111 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| street x customerName | String x Customer | *0.250* | *0.250* | 0.143 | 0.242 | 0.242 | 0.248 | 0.248 | 0.250 | 0.250 |
| city x customerName | String x Customer | *0.250* | *0.250* | 0.143 | 0.242 | 0.242 | 0.248 | 0.248 | 0.250 | 0.250 |
| state x customerName | String x Customer | *0.250* | *0.250* | 0.143 | 0.242 | 0.242 | 0.248 | 0.248 | 0.250 | 0.250 |
| ZIP x customerName | Integer x Customer | *0.250* | *0.250* | 0.167 | 0.275 | 0.275 | 0.256 | 0.256 | 0.251 | 0.251 |
| **From links between Classes to links between types of References and Attributes** | | | | | | | | | | |
| AccountOwner x Customer * | - | *1.000* | *1.000* | 0.143 | 0.457 | 0.457 | 0.457 | 0.457 | 0.457 | 0.457 |
| address x Cname | Address x String | *1.000* | *1.000* | 0.143 | 0.457 | 0.457 | 0.457 | 0.457 | 0.457 | 0.457 |
| AccountOwner x CustomerAddress* | - | *0.250* | *0.250* | 0.071 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| address x street | Address x String | *0.250* | *0.250* | 0.143 | 0.257 | 0.257 | 0.252 | 0.252 | 0.250 | 0.250 |
| address x city | Address x String | *0.250* | *0.250* | 0.143 | 0.257 | 0.257 | 0.252 | 0.252 | 0.250 | 0.250 |
| address x USStates | Address x String | *0.250* | *0.250* | 0.143 | 0.257 | 0.257 | 0.252 | 0.252 | 0.250 | 0.250 |
| address x postalCode | Address x Integer | *0.250* | *0.250* | 0.125 | 0.229 | 0.229 | 0.245 | 0.245 | 0.249 | 0.249 |

Table 3.12: Propagation results between types of links of AccountOwner and Customer metamodels

| **Links** | **Type link element** | $\pi$ | | **Similarities** | **1st** | | **3rd** | | **6th** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **I** | **II** | | **I** | **II** | **I** | **II** | **I** | **II** |
| AccountOwner x Customer* | - | 0.125 | 0.25 | 0.14 | 0.1583 | 0.1342 | 0.1583 | 0.1342 | 0.1583 | 0.1342 |
| name x cname | String x String | 0.125 | 0.25 | 1.00 | 0.0842 | 0.0885 | 0.0359 | 0.0473 | 0.0218 | 0.0353 |
| birthdate x cname | Integer x String | 0.125 | 0.25 | 0.14 | 0.0133 | 0.0153 | 0.0182 | 0.0290 | 0.0196 | 0.0330 |
| taxExempt x cname | Integer x String | 0.125 | 0.25 | 0.14 | 0.0133 | 0.0153 | 0.0182 | 0.0290 | 0.0196 | 0.0330 |
| address x Cname | Address x String | 0.125 | 0.25 | 0.14 | 0.0133 | 0.0153 | 0.0182 | 0.0290 | 0.0196 | 0.0330 |
| AccountOwner x CustmerAddress* | - | 0.05 | 0.05 | 0.07 | 0.5965 | 0.6066 | 0.5965 | 0.6066 | 0.5965 | 0.6066 |
| name x street | String x String | 0.05 | 0.05 | 1.00 | 0.0830 | 0.0857 | 0.0431 | 0.0454 | 0.0315 | 0.0336 |
| name x city | String x String | 0.05 | 0.05 | 1.00 | 0.0830 | 0.0857 | 0.0431 | 0.0454 | 0.0315 | 0.0336 |
| name x USStates | String x String | 0.05 | 0.05 | 1.00 | 0.0830 | 0.0857 | 0.0431 | 0.0454 | 0.0315 | 0.0336 |
| name x postalCode | String x Integer | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| birthdate x street | Integer x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| birthdate x city | Integer x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| birthdate x USStates | Integer x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| birthdate x postalCode | Integer x Integer | 0.05 | 0.05 | 1.00 | 0.0830 | 0.0857 | 0.0431 | 0.0454 | 0.0315 | 0.0336 |
| taxExempt x street | Integer x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| taxExempt x city | Integer x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| taxExempt x USStates | Integer x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| taxExempt x postalCode | Integer x Integer | 0.05 | 0.05 | 1.00 | 0.0830 | 0.0857 | 0.0431 | 0.0454 | 0.0315 | 0.0336 |
| name x customerName | String x Customer | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| birthdate x customerName | Integer x Customer | 0.05 | 0.05 | 0.17 | 0.0141 | 0.0146 | 0.0259 | 0.0468 | 0.0293 | 0.0314 |
| taxExempt x customerName | Integer x Customer | 0.05 | 0.05 | 0.17 | 0.0141 | 0.0146 | 0.0259 | 0.0468 | 0.0293 | 0.0314 |
| address x street | Address x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| address x city | Address x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| address x USStates | Address x String | 0.05 | 0.05 | 0.14 | 0.0121 | 0.0125 | 0.0254 | 0.0271 | 0.0293 | 0.0313 |
| address x postalCode | Address x Integer | 0.05 | 0.05 | 0.13 | 0.0106 | 0.0110 | 0.0250 | 0.0267 | 0.0292 | 0.0313 |
| Address x Customer * | - | 0.1 | 0.25 | 0.11 | 0.3080 | 0.2780 | 0.3080 | 0.2780 | 0.3080 | 0.2780 |
| street x cname | String x String | 0.1 | 0.25 | 1.00 | 0.0836 | 0.0878 | 0.0440 | 0.0741 | 0.0325 | 0.0701 |
| city x cname | String x String | 0.1 | 0.25 | 1.00 | 0.0836 | 0.0878 | 0.0440 | 0.0741 | 0.0325 | 0.0701 |
| state x cname | String x String | 0.1 | 0.25 | 1.00 | 0.0836 | 0.0878 | 0.0440 | 0.0741 | 0.0325 | 0.0701 |
| ZIP x cname | Integer x String | 0.1 | 0.25 | 0.14 | 0.0127 | 0.0146 | 0.0263 | 0.0558 | 0.0302 | 0.0678 |
| Address x CustomerAddress* | - | 0.04 | 0.05 | 0.11 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| street x street | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| street x city | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| street x USStates | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| street x postalCode | String x Integer | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| city x street | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| city x city | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| city x USStates | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| city x postalCode | String x Integer | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| state x street | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| state x city | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| state x USStates | String x String | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| state x postalCode | String x Integer | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| ZIP x street | Integer x String | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| ZIP x city | Integer x String | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| ZIP x USStates | Integer x String | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| ZIP x postalCode | Integer x Integer | 0.04 | 0.05 | 1.00 | 0.0831 | 0.0859 | 0.0508 | 0.0572 | 0.0413 | 0.0488 |
| street x customerName | String x Customer | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| city x customerName | String x Customer | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| state x customerName | String x Customer | 0.04 | 0.05 | 0.14 | 0.0122 | 0.0127 | 0.0330 | 0.0389 | 0.0391 | 0.0465 |
| ZIP x customerName | Integer x Customer | 0.04 | 0.05 | 0.17 | 0.0142 | 0.0147 | 0.0335 | 0.0394 | 0.0392 | 0.0466 |

Table 3.13: Propagation results comprising all the propagation methods between types of links of AccountOwner and Customer metamodels

| **Propagation methods** | **1st** | | **3rd** | | **6th** | |
|---|---|---|---|---|---|---|
| | **I** | **II** | **I** | **II** | **I** | **II** |
| Propagation from links between Classes to links between Attributes (%) | 91.460 | 164.439 | 90.797 | 164.450 | 94.164 | 164.412 |
| Propagation from links between Classes to links between References (%) | 734.861 | 515.620 | 758.680 | 515.639 | 782.250 | 515.631 |
| Propagation from links between Classes to links between Attributes and References (%) | 153.394 | 515.620 | 141.988 | 515.639 | 142.778 | 515.631 |
| Propagation from links between Classes to links between References and Attributes (%) | 189.708 | 81.124 | 197.945 | 81.124 | 206.115 | 81.122 |
| Propagation from links between Attributes to links between their Instances (%) | 427.228 | x | 462.018 | x | 483.705 | x |
| Propagation from links between Classes to links between types of Attributes (%) | 38.198 | 63.950 | 40.828 | 65.098 | 45.132 | 67.259 |
| Propagation from links between Classes to links between types of References (%) | 884.425 | 278.437 | 833.999 | 280.933 | 841.704 | 285.919 |
| Propagation from links between Classes to links between types of Attributes and References (%) | 74.235 | 278.437 | 76.281 | 280.933 | 81.285 | 285.919 |
| Propagation from links between Classes to links between types of References and Attributes (%) | 177.990 | 18.087 | 182.809 | 18.865 | 179.094 | 20.421 |

Table 3.14: A comparison between propagation methods of Mantis and Bugzilla metamodels

| **Propagation methods** | **1st** | | **3rd** | | **6th** | |
|---|---|---|---|---|---|---|
| | **I** | **II** | **I** | **II** | **I** | **II** |
| Propagation from links between Classes to links between Attributes (%) | 17.933 | 6.619 | 21.823 | 7.008 | 23.288 | 13.909 |
| Propagation from links between Classes to links between References (%) | 938.113 | 808.441 | 1022.931 | 808.359 | 1052.649 | 802.457 |
| Propagation from links between Classes to links between Attributes and References (%) | 373.800 | 371.068 | 405.177 | 369.880 | 416.353 | 367.978 |
| Propagation from links between Classes to links between References and Attributes (%) | 384.291 | 380.070 | 415.136 | 380.027 | 426.157 | 376.909 |
| Propagation from links between Attributes to links between their Instances (%) | 938.113 | x | 1022.931 | x | 1052.649 | x |
| Propagation from links between Classes to links between types of Attributes (%) | 29.746 | 29.570 | 39.165 | 28.299 | 42.505 | 30.081 |
| Propagation from links between Classes to links between types of References | 1177.503 (%) | 1167.095 | 1270.243 | 1163.257 | 1299.898 | 1177.843 |
| Propagation from links between Classes to links between types of Attributes and References (%) | 403.984 | 399.877 | 440.570 | 398.363 | 452.270 | 404.118 |
| Propagation from links between Classes to links between types of References and Attributes (%) | 431.859 | 189.622 | 470.468 | 425.927 | 482.815 | 432.000 |

Table 3.15: A comparison between propagation methods of AccountOwner and Customer metamodels

# CHAPTER 4

# CONCLUSION AND FUTURE WORKS

We presented 9 propagation methods based on metamodel and model structures in order to execute a variant of the Similarity Flooding Algorithm [18]. Thus, we provided a comparative between the techniques in order to verify whether the development of restricted propagation methods are advised.

The methods may be handled by different existing approaches, although they are not executed separately in order to perform comparisons. The propagation is constituted between nine different kinds of elements, from metamodels or models. The propagations are codificated based on the structural information of a given (meta) model: *class*, *attribute* and *reference*, as well as its type: *Integer*, *String*, *Double*, etc.

The restricted propagation executions had a higher increase in the similarity values. Therefore, these techniques are shown to be feasible because they reduce the number of model elements and, also reduced the amount of iterations of the SF to achieve a better similarity result. In metamodels and models with more connected links, the similarity values tend to concentrate on the element with the highest amount of links.

We also implemented two filters on the Similarity Flooding algorithm results: (a) after executing the Similarity Flooding and, (b) before executing the Similarity Flooding. Both configuration enable a reduction in the number of links involved in the propagation process. However, the choice of the filter value remains empirical. We can clearly see that knowing the models and metamodels in advance may have an influence on the choice of propagation technique, especially to avoid the highly centralized elements. However, this should be tested and developed with bigger models and also models of a different nature.

Our major difficulty was finding large metamodels that comprised all nine techniques stabilized. Therefore, we focused on simple metamodels, but, they were sufficient to conclude this work. We can provide suggestions for future research:

- **Structure of the graphs propagation:** to help increase the similarities between links, emphasis can be placed on the weight of the similarities calculated previously from a String Distance. For example, the links that have the same cardinality are assigned with weight equaling 0.2 [4].

- **Filter technique:** the use of a right filter may increase the final similarity of the SF. Therefore, we should implement a filter based on the heuristics or Artifical Intelligence technique;

- **Comparing with large models:** we recommed testing the restricted propagations in large (meta)models and with differents natures, in order to analyse the behavior of the similarities in these environment;

- **Graphical User Interface, G.U.I., and Plug-in:** the use of a graphic user interface would improve user experience, showing the results over the iterations of the SF. Therefore, the user can stop the propagation in the best result. Furthermore, a user can easily customize settings related to the propagation method, filter configuration and export the results. The EMF permits the creation of plug-ins. However, it is possible to integrate the propagation methods in the EMF as a plug-in and making the tool more complete.

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