# A Method for Estimating Potential Knowledge Increase after Updating Ontology Mapping

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Abstract: In the modern days, users cannot expect that ontologies in their initial states won't remain static throughout the lifespan of their application, therefore a tool for managing appearing alterations is necessary. In our previous work, we have prepared a solid, formal, and flexible foundation that can be used to express changes that appear while maintained ontologies evolve. This paper contains a description of the process of constructing a method assessing knowledge increase after an ontology alignment update. Our developed measure estimates how ontology evolution influenced the increase of knowledge for two input ontologies. The developed method has been experimentally verified by simulating random ontology evolutions ad the obtained results have been statistically analyzed. Due to the limitation of this paper, we focus only on the concept level.

## 1 INTRODUCTION

In large and distributed systems the knowledge is dispersed between multiple nodes in a large infrastructure. It is not uncommon that ontologies are used as the underlying knowledge representation. They are usually defined as a formal specification of conceptualization and are one of the foundations of modern semantic applications. To facilitate communication between them, so-called ontology alignment can be used, which informally can be described as creating a bridge between two ontologies. This tool provides the ability to translate the content of one ontology into the content of another one.

However, in such an environment, one cannot expect that business requirements won't change over time. This entails that if some underlying ontology changes, the exchange of information between participating services may become compromised. To remedy this situation, a sound procedure for updating the ontology alignment is required. Such a procedure should start with identifying a situation when changes applied to ontologies are significant enough to potentially invalidate the alignment between ontologies. Then, a sound algorithm for alignment revalidation should be applied. Up until now in our previous research, we have developed and verified several approaches to described tasks ((Kozierkiewicz and Pietranik, 2019), (Kozierkiewicz and Pietranik, 2020)), decomposing them into the level of concepts, relations, and instances. Using them entails that the communication between two knowledge-based systems can be reinstated.

However, there is still an open question. Two aligned ontologies are easy to merge and carry some synergic knowledge potential. Modifications done to such ontologies are frequently followed by modifications of their mappings. So how much both of those modifications influence the aforementioned knowledge potential? Do the applied changes increased or decrease it? In this paper, we present a measure that can be used to estimate how much knowledge about the interoperability of two ontologies has been acquired through the process of updating the ontology alignment. Due to the limited space, we will focus only on a concept level available in ontologies.

The remaining part of this article is organized as follows. In the next section, a summary of related work is given. Section 3 provides the most important definitions that will be used to develop a method for assessing knowledge growth. Section 4 describes the main task we want to solve- a method definition of assessing knowledge increase after ontology alignment update. In Section 5 results of the conducted experiment are provided. Section 6 gives brief summary

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and overviews our upcoming research plans.

## 2 RELATED WORKS

Ontology alignment is a widely discussed topic, frequently investigated in the available literature ((Shvaiko et al., 2018), (Shvaiko and Euzenat, 2011)). The variety of (e.g. (Kolyvakis et al., 2018)) approaches usually define mappings between ontologies as sets of pairs of complementary elements from two ontologies. In other words, pairs of those elements from ontologies describe the same part of the universe of discourse. Those sets are then validated by means of Precision and Recall measures ((Algergawy et al., 2019)) using preprepared mappings treated as a reference.

This approach, despite being perfectly valid, has two downsides. The first one is it measures only the correctness of mappings in relation to the aforementioned references. Using Precision and Recall measures is impossible in practical applications, due to the fact that no reference alignment exists. The second disadvantage is the fact that such assessment takes into account solely mappings, omitting the content of ontologies that are matched.

There some research addressing the raised issues by noticing those flaws and attempted to overcome them (Thiéblin et al., 2020). In (Dragisic et al., 2016) authors provide a survey on involving users in measuring the quality of automated alignment algorithms. Three aspects of human-centric evaluation are especially investigated: the profile of the user, the services of the alignment system, and the user interface while in (Leal et al., 2017) authors attempt to utilize the so-called Ontology of Enterprise Interoperability to assess different aspects of interoperability.

A similar approach can be found in (Ivanova et al., 2017). The article proposes a "human-in-the-loop" approach to overcome the difficulties when reference alignments are unavailable. The main idea is based on a tool called Matrix Cubes, which is used for visualizing dense dynamic networks, this further supports the interactive exploration of multiple ontology alignment in order to assess their quality. The research is further extended in (Li et al., 2019).

The research found in (Solimando et al., 2017) presents detecting and minimizing the violations of the "conservativity principle". This is a situation where novel subsumption entailments between classes from one of the mapped ontologies are marked as unwanted.

This paper focuses on a different issue. While approaches described above all focus on evaluating the designated ontology alignments in order to check their correctness, we attempt to address the change factor of ontology alignments. Obviously, when mapped ontologies evolve, it requires that their alignment evolve as well. Therefore, we would like to provide a method for assessing how much knowledge about the interoperability between ontologies has been gained or lost. We claim that such a tool can become very useful in practical applications of ontologies and ontology alignment. Especially, when large-scale ontologies (e.g. in (Kiourtis et al., 2019)) are mapped the knowledge about the degree to which they can cooperate can be invaluable.

## 3 BASIC NOTIONS

Our research focuses on a mathematical model of an ontology. We assume that a real world is defined as a pair $(A,V)$ where: $A$ is a finite set of attributes that can be used to describe objects, $V$ is a set of their valuations (domains) such that $V = \bigcup_{(a\in A)} V_a$, $V_a$ is a domain of a particular attribute $a$. The following quintuple defines an ontology as a $(A,V)$-based ontology:

$$O = (C, H, R^C, I, R^I) \tag{1}$$

where: $C$ is a set of concepts; $H$ is a concepts' hierarchy; $R^C$ is a set of relations between concepts, $R^C = \{r_1^C, r_2^C, ..., r_n^C\}$, $n \in N$, such that $r_i^C \in R^C (i \in [1,n])$ is a subset of $C \times C$; $I$ is a set of instance identifiers; $R^I = \{r_1^I, r_2^I, ..., r_n^I\}$ is a set of relations between concepts' instances.

A concept's$c \in C$ structure from $(A,V)$-based ontology is defined as:

$$c = (id^c, A^c, V^c, I^c) \tag{2}$$

where $id^c$ is an identifier of the concept $c$, $A^c$ is a set of its attributes, such that $A^c \subseteq A$, $V^c$ is a set of attributes domains (formally: $V^c = \bigcup_{(a\in A^c)} V_a$ ), $I^c$ is a set of instances of the concept $c$. We write $a \in c$ to denote that an attribute $a$ belongs to concept $c$ set of attributes $A^C$.

The hierarchy of concepts $H$ is a distinguished relation between concepts. Formally, hierarchy is a set concept pairs ($H \subset C \times C$), where a single pair of concepts $(c_1, c_2) \in H$ represents the fact that $c_1$ is an ancestor of $c_2$. The position of a concept in a hierarchy allows us to deduce how much specific knowledge it carries a concept. Thus, concept $c_2$ is more detailed than $c_1$. This remark will be used for estimating knowledge increase. Based on hierarchy $H$ we can define subtree in the following way:

**Definition 1.** *For given ontology O, and* $c \in C$ *by* $Subtree(O,c)$ *we call a subtree of H such that* $\neg\exists c' \in \{x | (x,x') \in Subtree(O,c)\} : (c',c) \in Subtree(O,c)$.

The subtree definition allows to define the depth properties:

**Definition 2.** *For a given subtree $S = Subtree(O, c_r)$ and the subtree's root classes $c_r \in C$, the depth of class $c \in C$ denoted as $Depth(S, c)$) in the subtree $S$ is the number of subsumption relationships between $c_r$ and $c$.*

We define an auxiliary notion $S_{UNDUP}$ that for a subtree $S = Subtree(O_1, c_1)$, $c_1 \in C_1$ returns this subtree with removed concepts (and their descendants) which have complementary mappings within the alignment $Align(O_1, O_2)$.

$$S_{UNDUP}(S, Align(O_1, O_2)) = S \setminus \bigcup_{(c,c') \in Align(O_1,O_2)} (S \cap Subtree(O_1, c)) \tag{3}$$

As it was mentioned, we assume that ontologies may change over time. Therefore, we need to introduce a formal notion of time. In our work, time is represented as a timeline, which is treated as an ordered set of moments, defined as $\overline{TL} = \{t_n | n \in N\}$. By $TL(O)$ we denote a subset of timeline, with only elements from $\overline{TL}$ during which the ontology $O$ has changed. A superscript $O^{(m)} = (C^{(m)}, H^{(m)}, R^{C(m)}, I^{(m)}, R^{I(m)})$ is used to denote the ontology $O$ in a selected moment in time $t_m \in TL(O)$. A symbol $\prec$ is denotes a fact that $O^{(m-1)}$ is an earlier version of $O$ than $O^{(m)}$ ($O^{(m-1)} \prec O^{(m)}$). A repository of an ontology $O$, is an ordered set of its successive versions, It is defined as $Rep(O) = \left\{ O^{(m)} | \forall m \in TL(O) \right\}$.

Between two independent $(A, V)$-based ontologies $O_1$ and $O_2$ there may exist some correspondences called alignment. Of course, for each ontology level like concepts, instances and relations it is possible to determine separate set of correspondences. However in this paper we will focus only on concept level, so we formally define a set $Align(O_1, O_2)$ containing tuples of the form $(c_1, c_2, \lambda_C(c_1, c_2), r)$ where: $c_1, c_2$ are concepts from $O_1$ and $O_2$ respectively, $\lambda_C(c_1, c_2)$ is a real value representing a degree to which concept $c_1$ can be aligned into the concept $c_2$, $r$ is a relation's type connecting $c_1$ and $c_2$ (equivalency, generalization). $\lambda_C(c_1, c_2)$ can be designated using one of the matching methods described in i.e.(Shvaiko et al., 2018). A vast majority of alignments between two ontologies include only mappings of concepts that are equivalent with 100% certainty. Therefore, for simplicity, we can reduce the definition of $Align(O_1, O_2)$ to only pairs of concepts:

$$Align(O_1, O_2) = \{(c_1, c_2) | (c_1, c_2) \in C_1 \times C_2 \wedge \lambda_C(c_1, c_2) = 1\} \tag{4}$$

The above notation can be easily extended to include the notion of time, by analogously usage of superscripts. For example, $Align(O_1^{(m)}, O_2^{(n)})$ represents an alignment of the two ontologies $O_1$ and $O_2$ in their states in moments $m$ and $n$ respectively, where $m, n \in \overline{TL}$.

# 4 A METHOD FOR ESTIMATING THE POTENTIAL KNOWLEDGE INCREASE

In our research, we have noticed that the value of depth for a given concept is related to the detailed knowledge stored in this concept. These remarks have been used for developing a measure for estimating the potential knowledge increase. For a given concept $c_r \in C_1$ of some ontology $O_1$ its knowledge potential is calculated as:

$$\lambda(O_1, c_r) = \sum_{c_s \in C_1} Depth(S_{UNDUP}(S, Align(O_1, O_2)), c_s) \tag{5}$$

where: $S = Subtree(O_1, c_r)$. Figure 1 represents two examples of the same ontology however for different alignments. The mapped concepts are marked in yellow color. The value of $\lambda$ for particulars concepts are assigned to each of them:

Equation 5 allows us to calculate the knowledge potential of complementary mappings in the alignment $Align(O_1, O_2)$:

$$\sigma(c_{r1}, c_{r2}) = \lambda(O_1, c_{r1}) + \lambda(O_2, c_{r2}) \tag{6}$$

where: $c_{r1} \in C1$, $c_{r2} \in C2$, $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$. Thus, for estimating the knowledge potential of the whole alignment $Align(O_1, O_2)$ we should repeat the calculation for each pair mapped concepts:

$$\gamma(O_1, O_2) = \sum_{(c,c') \in Align(O_1,O_2)} \sigma(c, c') \tag{7}$$

By $Root(O)$ let's denote a set of classes in ontology $O$ which are direct children of the abstract class *Thing*. In other words- this is a set of concepts that are in the highest level of the taxonomy. Then, let us introduce an auxiliary notion:

$$\eta(O_1) = \sum_{c_d \in Root(O_1)} \lambda(O_1, c_d) \tag{8}$$

Lets denote by $\mu(O_1, O_2)$ a knowledge potential of two mapped ontologies $O_1$ and $O_2$. It needs to fulfill the following postulates:

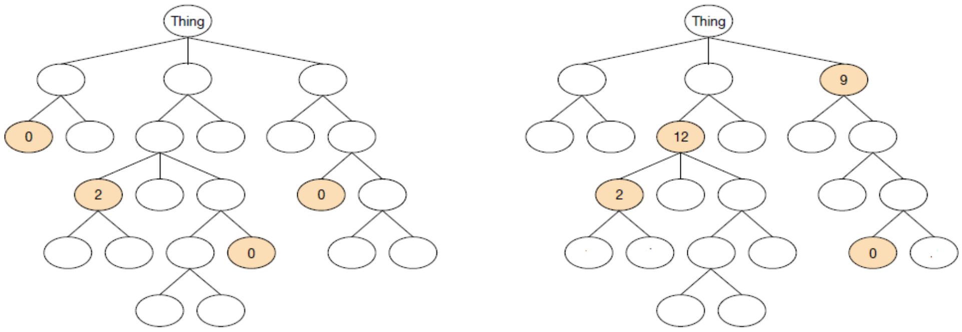


Figure 1: The example of calculating $\lambda$.

- $\mu(O_1, O_2) = 0 \iff \forall_{(c_{r1}, c_{r2}) \in Align(O_1, O_2)} \sigma((c_{r1}, c_{r2}) = 0$ (in other words: concept $c_{r1}$ and $c_{r2}$ has empty set $Subtree(O, c_{r1})$ and $Subtree(O, c_{r2})$, respectively)
- $\mu(O_1, O_2) = 0 \iff Align(O_1, O_2) = \emptyset$ (in other words, the alignment of $O_1$ and $O_2$ is empty)
- $\mu(O_1, O_2) = 1 \iff \forall_{(c_{r1}, c_{r2}) \in Align(O_1, O_2)} (c_{r1} \in Root(O_1) \wedge c_{r2} \in Root(O_2))$ (in other words - all of the alignments connect only top level concepts in both ontologies)

Therefore, the knowledge potential of two mapped ontologies is normalized to set $[0, 1]$, and calculated as according to the equation below:

$$\mu(O_1, O_2) = \frac{\gamma(O_1, O_2)}{\eta(O_1) + \eta(O_2)} \tag{9}$$

Example ontologies with a minimal value of $\mu$ are presented in Figure 2, while ontologies with the maximal value of $\mu$ are presented in Figure 3.

Equation 9 can be used to assess the knowledge potential for two mapped ontologies assuming that they are constant and unchanging in time. However, in the real world, changes applied in ontologies and alignments between could be more or less significant.

In our work, we would like to know how the changes applied to two ontologies which entail updating the alignment between them influence their knowledge potential. In other words, for ontologies $O_1^{(n)}$ $O_2^{(n)}$ and the alignment between them in moment of time $n$ and two ontologies after changes and updated alignment between them in the moment of time $m$ such that $O_1^{(n)} \prec O_1^{(m)}$ and $O_2^{(n)} \prec O_2^{(m)}$. The potential knowledge increase after updating ontology mappings is calculated as follows:

$$\delta(O_1^{(m)}, O_2^{(m)}, O_1^{(n)}, O_2^{(n)}) = \left(\frac{\mu(O_1^{(m)}, O_2^{(m)})}{\mu(O_1^{(n)}, O_2^{(n)})} - 1\right) * 100\% \tag{10}$$

We assume that $\mu(O_1^{(n)}, O_2^{(n)}) \neq 0$ because if the knowledge increase in the initial state of the ontology is equal to 0 then we have no reference value to refer to. $\delta \in [-100\%, \infty)$ and values greater than 0 will symbolize the growth of knowledge in comparison to the earlier state. Values lower than 0 means the decrease of knowledge stored in two ontologies.

## 5 THE RESULTS OF EXPERIMENTS

For our experiment, we used ontologies provided by OAEI (Ontology Alignment Evaluation Initiative) (oae, 2020). It is an organization that annually organizes a campaign aiming at assessing the strengths and weaknesses of ontology matching systems and comparing their performances. To determine alignments, we used a widely known tool LogMap (log, 2020), which is a highly scalable ontology matching solution with integrated reasoning and inconsistency repair capabilities. More importantly, LogMap earned high positions in subsequent OAEI campaigns.

The main aim of our experiment was to verify the developed measure of $\delta$ and its applicability in the case of evolving ontology. From the benchmark set of ontologies, we have chosen pairs of ontologies presented in Table 1.

For each pair, the first ontology has been modified by randomly adding or deleting some concepts. Such an approach allows us to simulate the ontology evolution process. We formulated nine different scenarios of such evolution:

1. Adding about 20% random new concepts, all satisfying the following condition: for each new concept $c_{new}$ added to ontology $O_1$ $\exists c_{r1} \in C_1$ and $c_{r2} \in C_2$, where $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$ and $(c_{r1}, c_{new}) \in Subtree(O_1, c_{r1})$ and $Depth(S, c_{new} = 1)$ for a given subtree $S = Subtree(O, c_{r1})$
2. Adding about 20% new random concepts, all satisfying the following condition: for

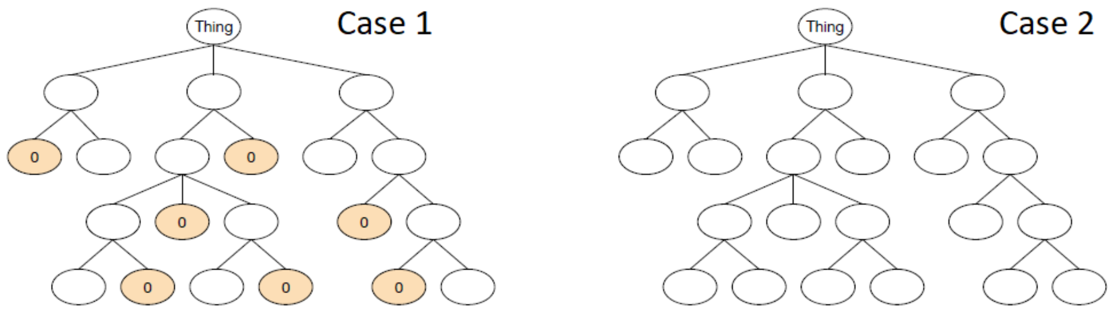


Figure 2: The ontologies with the minimal value of $\mu$.

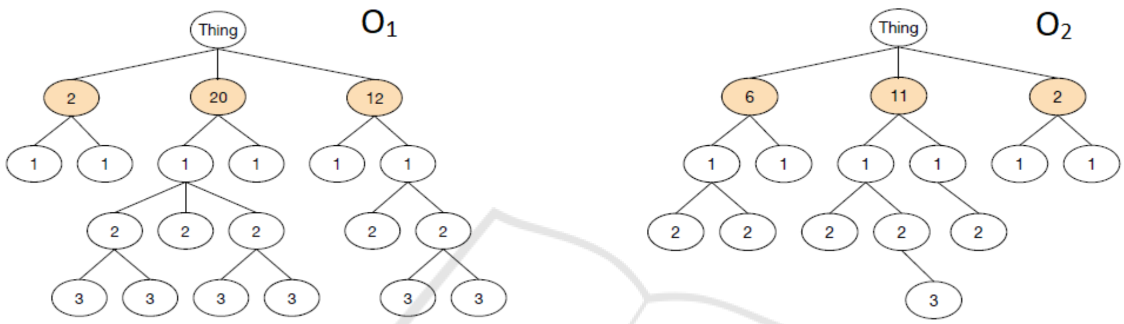


Figure 3: The ontologies with maximal value of $\mu$.

Table 1: The pair of ontologies used in experiment.

| No. | Name of ontologies | Number of Concepts | No. | Name of ontologies | Number of concepts |
|---|---|---|---|---|---|
| 1 | Cocus/Iasted | 55/ 140 | 2 | ConfTool/Sofsem | 38/ 60 |
| 3 | Ekaw/Sigkdd | 74/ 49 | 4 | Cmt/Paperdyne | 36/ 47 |
| 5 | Edas/Iasted | 104/ 140 | 6 | Sofsem/Confious | 60/ 57 |
| 7 | OpenConf/Ekaw | 62/ 74 | 8 | Edas/Sofsem | 104/ 60 |
| 9 | openConf/Cocus | 62/ 55 | 10 | Edas/Conftool | 104/ 38 |
| 11 | Cosus/Pcs | 55/ 23 | 12 | Ekaw/MyRieview | 74/ 39 |
| 13 | Confios/Sigkdd | 57/ 49 | 14 | Iasted/OpenConf | 140/ 62 |
| 15 | Ekaw/Paperdyne | 74/ 47 | 16 | Paperdyne/Sofsem | 47/ 60 |

each new concept $c_{new}$ added to ontology $O_1$ $\exists c_{r1} \in C_1$ and $c_{r2} \in C_2$ where $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$, and $(c_{r1}, c_{new}) \in Subtree(O_1, c_{r1})$ and $Depth(S, c_{new} = 1$ or $Depth(S, c_{new} = 2$ for a given subtree $S = Subtree(O, c_{r1})$

3. Adding about 20% random new concepts, all satisfying the following condition: for each new concept $c_{new}$ added to ontology $O_1$ $\exists c_{r1} \in C_1$ and $c_{r2} \in C_2$ where $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$, and $(c_{r1}, c_{new}) \in Subtree(O_1, c_{r1})$

4. Adding about 20% random new concepts, all satisfying the following condition: for each new concept $c_{new}$ added to ontology $O_1$ $\neg\exists c_{r1} \in C_1$ and $\neg\exists c_{r2} \in C_2$ such that $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$ and $(c_{new}, c_{r1}) \in Subtree(O_1, c_{r1})$

5. Adding about 10% random new concepts, all satisfying the following condition: for each new concept $c_{new}$ added to ontology $O_1$ $\exists c' \in C_1$ where $(c_{new} = c')$.

6. Adding about 10% random new concepts, all satisfying the following condition: for each new concept $c_{new}$ added to ontology $O_1$ $\exists c_{r1} \in C_1$ and $\exists c_{r2} \in C_2$ such that $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$, and $(c_{r1}, c_{new}) \in Subtree(O_1, c_{r1})$ and $\exists c' \in C_2$ where

$(c_{new} = c')$.

7. Randomly removing about 5% of concepts, such that each removed concept $c_{rem}$ from ontology $O_1$ satisfies the following condition: $\exists c_{r1} \in C_1$ and $\exists c_{r2} \in C_2$ such that $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$, and $(c_{r1}, c_{rem}) \in Subtree(O_1, c_{r1})$
8. Randomly removing about 5% of concepts, such that each removed concept $c_{rem}$ from ontology $O_1$ satisfies the following condition: $\exists c_{r1} \in C_1$ and $\exists c_{r2} \in C_2$ such that $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$ and $\lambda(O_1, c_{r1})$ is maximal.
9. Removing only 2 concepts and their subtrees which satisfy the following condition: for each removed concept $c_{rem}$ from ontology $O_1$ $\exists c_{r1} \in C_1$ and $\exists c_{r2} \in C_2$ where $(c_{r1}, c_{r2}) \in Align(O_1, O_2)$, for which $\lambda(O_1, c_{r1})$ is maximal.

For all modified ontologies (according to the evolution scenarios described above), values of δ have been designated. The results, shown in Table 2, demonstrate that the developed measure δ returns intuitive values. The evolution scenarios have been designed such that in the case of Scenario 1, 2, 3, and 5 we expected the growth of knowledge. Scenarios 7, 8, and 9 are based on removing concepts- it is related to knowledge decrease. Knowledge increase in Scenarios 4 and 6 is not expected. On the one hand, we add concepts. On the other hand, in Scenario 4 we added concepts in such a place in an ontology that there is no effect on the growth of knowledge. In Scenario 6, new concepts are copied from one ontology to another, therefore, one ontology becomes similar to the other. This entails that the level of knowledge stored in ontologies does not increase. Most of the values of δ are in line with our expectations. However, δ measures evaluate knowledge increase from the perspective of entire ontologies. Single or not significant changes do not influence the δ values, and results are invalid in terms of the direction of change (an increase or a decrease).

The results of the experiments have been statistically analyzed. We accepted a significance level $\alpha = 0.05$. We decided to verify a correlation between δ values and the percentages of changes applied in ontologies. We assumed, that the changes have been calculated as the number of added/removed concepts divided by the number of all concepts in the initial state of an ontology. In the case of adding concepts, the obtained score is multiplied by 100%, and in the case of removing concepts by -100%.

In the first step, we have checked the normal distribution of the analyzed samples. We rejected the hypothesis about the normal distribution of the sample, so we have calculated Spearman's rank correlation coefficient, and we obtain a value equal to 0.603969 and $p$-value equals $1.13e^{-15}$. It allows us to conclude that there exists a moderate positive correlation between δ value and the percentage number of changes applied in ontologies. It proved the correctness of our assumption and allows us to conclude that changes in ontologies and their mappings influence the assessment of knowledge increase.

The results allow us to decide which alignment is the most valuable. If we need need to choose for example for EDAS ontology the most important mappings we need to analyze pairs: 8, 10, and 5. As we can see, the biggest value of $\mu = 0.6$ is for the pair: Edas-Sofsem. The alignment for this pair of ontologies should be maintained and frequently validated.

# 6 FUTURE WORKS AND SUMMARY

Two ontologies that can be aligned by a set describing mappings of their elements can be easily merged into one unified knowledge structure. Therefore, they both carry some synergic knowledge potential. However, in modern days it is impossible to expect that ontologies will not change in time. Their evolution influences their mappings and in consequence their synergic knowledge. In this paper, we presented a measure that can be used to estimate how much knowledge about interoperability of two ontologies has been acquired or lost through the process of updating ontologies and their alignment.

The paper contains both formal, mathematical definitions, and verification of the developed measure. The experiment involved simulating ontology evolution according to the predefined scenarios. It has been conducted using widely accepted benchmark ontologies provided by Ontology Alignment Evaluation Initiative. Collected results have been statistically analyzed, which proved the correctness of our ideas and intuitiveness of the developed measure.

In the future, we plan to extend the proposed methods to other levels of ontologies, namely relations and instances. We will also perform more extensive experiments that will involve larger ontologies, possibly from a medical domain.

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Table 2: The results of experiment.

| **No. of evolution scenario** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| No changes $\mu = (O_1^{(0)}, O_2^{(0)})$ | 0.3451 | 0.5205 | 0.4612 | 0.278 | 0.272 | 0.1524 | 0.2648 | 0.6001 | 0.2545 | 0.4371 | 0.1705 | 0.3516 | 0.043 | 0.125 | 0.3523 | 0.5347 |
| $\delta(O_1^{(1)}, O_2^{(1)}, O_1^{(0)}, O_2^{(0)})$ | 12.88 | 1.23 | -0.2 | -1.74 | 20.99 | 64 | 13.66 | -3.44 | 17.68 | 6.97 | 77.92 | 34.29 | 297.36 | 50.88 | 16.05 | 6.4 |
| $\delta(O_1^{(2)}, O_2^{(2)}, O_1^{(0)}, O_2^{(0)})$ | 21.24 | 56.55 | 47.95 | 28.57 | 36.45 | 29.41 | 32.8 | 60.52 | 33.62 | 50 | 36.92 | 50 | 22.35 | 22.27 | 43.88 | 59.46 |
| $\delta(O_1^{(3)}, O_2^{(3)}, O_1^{(0)}, O_2^{(0)})$ | 29.79 | 7.92 | 11.04 | 20.81 | 50.44 | 120.68 | 33.37 | 4.01 | 47.12 | 21.44 | 253.24 | 49.3 | 552.13 | 109.18 | 32.22 | 17.92 |
| $\delta(O_1^{(4)}, O_2^{(4)}, O_1^{(0)}, O_2^{(0)})$ | -8.87 | -10.98 | -13.08 | -12.7 | -16.07 | -21.53 | -20.44 | -12.18 | -28.88 | -21.84 | -21.43 | -18.39 | -33.9 | -22.31 | -1.97 | -22.99 |
| $\delta(O_1^{(5)}, O_2^{(5)}, O_1^{(0)}, O_2^{(0)})$ | -2.06 | 17.33 | 6.36 | 2.65 | 65.1 | 24 | 105.03 | 34.02 | 28.65 | 10.35 | 140 | 19.25 | 647.23 | 301.02 | 36.92 | 3.9 |
| $\delta(O_1^{(6)}, O_2^{(6)}, O_1^{(0)}, O_2^{(0)})$ | 4.05 | -9.52 | 9.43 | -23.79 | 39.28 | -3.53 | 87.4 | 23.75 | 0.35 | -3.06 | 107.78 | 9.49 | 489.47 | 332.85 | 22.22 | -20.93 |
| $\delta(O_1^{(7)}, O_2^{(7)}, O_1^{(0)}, O_2^{(0)})$ | -0.14 | -9.32 | 21.15 | -35.6 | -22.57 | -100 | -13.73 | -9.23 | -49.24 | -13.23 | -20.56 | -11.8 | -100 | 50.38 | -14.16 | -27.69 |
| $\delta(O_1^{(8)}, O_2^{(8)}, O_1^{(0)}, O_2^{(0)})$ | -3.72 | 8.06 | -6.55 | -28.15 | -13.45 | -36.1 | -4.05 | -4.45 | -4.91 | -5.63 | -28.46 | 2.51 | -100 | -33.14 | 7.19 | 1.13 |
| $\delta(O_1^{(9)}, O_2^{(9)}, O_1^{(0)}, O_2^{(0)})$ | -65.12 | -8.9 | -5.13 | -32.22 | -36.15 | -81.65 | -46.9 | -16.79 | -88.02 | -50.68 | 22.79 | -14.85 | -59.66 | -74.76 | -1.03 | -41.02 |

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