MaPLE: A MapReduce Pipeline for Lattice-based Evaluation and Its Application to SNOMED CT

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Abstract—Non-lattice fragments are often indicative of structural anomalies in ontological systems and, as such, represent possible areas of focus for subsequent quality assurance work. However, extracting the non-lattice fragments in large ontological systems is computationally expensive if not prohibitive, using a traditional sequential approach. In this paper we present a general MapReduce pipeline, called MaPLE (MapReduce Pipeline for Lattice-based Evaluation), for extracting non-lattice fragments in large partially ordered sets and demonstrate its applicability in ontology quality assurance. Using MaPLE in a 30-node Hadoop local cloud, we systematically extracted non-lattice fragments in 8 SNOMED CT versions from 2009 to 2014 (each containing over 300k concepts), with an average total computing time of less than 3 hours per version. With dramatically reduced time, MaPLE makes it feasible not only to perform exhaustive structural analysis of large ontological hierarchies, but also to systematically track structural changes between versions. Our change analysis showed that the average change rates on the non-lattice pairs are up to 38.6 times higher than the change rates of the background structure (concept nodes). This demonstrates that fragments around non-lattice pairs exhibit significantly higher rates of change in the process of ontological evolution.

I. Introduction

Ontologies represent not only the concepts, but just as importantly, the relationships between the concepts. Ontologies have become a critical component in informatics and data intensive applications. They are used, for example, to handle terminological heterogeneity, facilitate system interoperability and integration, enable knowledge discovery [1], [2], [3], [4], and manage biomedical big data [5], [6].

However, ontological systems are often incomplete, under-specified, and non-static. New applications call for new ontologies or expansion and enhancement of existing ones. Many additional factors, such as merging or reusing existing ontologies and porting to a common representation framework, may introduce inconsistencies and unintended artifacts. Thus Ontology Quality Assurance (OQA) is an indispensable part of the ontological engineering lifecycle [7].

Due to the increasingly large size and structural complexity of modern ontologies, particularly those from biomedicine, OQA has been hampered by the lack of systematic and scalable methods necessary to keep pace with the evolution and emergence of ontological systems. The state of affairs is that [8]: “given modern tooling and computer power, the barriers for quality assurance can now be overcome, although no well-integrated toolset is yet available.”

One of the generally applicable ontology design principle or pattern is that the subsumption relationship (IS-A hierarchy) should form a lattice [9]. However, extracting non-lattice fragments in large ontological systems is computationally expensive if not prohibitive, using a traditional sequential approach. In previous work [9], we analyzed 34 million pairs of SNOMED CT concepts and identified over 518,000 non-lattice pairs using SPARQL queries over an RDF representation of the ontology. However, the time needed for such an exhaustive analysis – 3 months using standard desktop machines – is incompatible with use in real quality assurance applications.

In this paper we present a general MapReduce pipeline, called MaPLE (MapReduce Pipeline for Lattice-based Evaluation), for extracting non-lattice fragments in large partially ordered sets and demonstrate its applicability in ontology quality assurance. MaPLE consists of a sequence of simple order-theoretic and set-theoretic operations designed for mappers and reducers that collectively capture the non-trivial lattice-theoretic property. We show that the lattice-based analysis of hierarchical relations in SNOMED CT, while quadratic in computational complexity, is tractable using MaPLE with Hadoop. After implementing MaPLE in Cloudera Hadoop 4.3 on a 30-node cluster, we systematically extracted non-lattice fragments in 8 SNOMED CT versions from 2009 to 2014, with an average total compute time of less than 3 hours per version. With dramatically improved turn-around time for analysis, 3 hours instead of 3 months, MaPLE makes it feasible not only to perform exhaustive structural analysis of large ontological hierarchies, but also to systematically track structural changes between versions.

The rest of the paper is organized as follows. In Section II we recall background information on related topics. In Section III we describe our MapReduce algorithm MaPLE for extracting non-lattice fragments in a partially ordered set. In Section IV we describe the implementation of MaPLE in a Hadoop local cloud, and an application for extracting all non-lattice fragments in SNOMED CT. In Section V we present the main statistics and results about non-lattice fragments in SNOMED CT versions and a performance evaluation of MaPLE. The last section contains conclusive remarks.

II. Background

A. SNOMED CT

Developed by the International Health Terminology Standard Development Organization (IHTSDO), SNOMED CT is the world’s largest clinical terminology and provides broad coverage of clinical medicine, including findings, diseases, and procedures for use in electronic medical records. The international release of SNOMED CT is produced twice a year, in January and in July, reflecting both changes to medical
knowledge (e.g., new drugs) and changes to the editorial process (e.g., changes to the representation of anatomical entities). In addition, the member countries of the IHTSDO also create extensions of SNOMED CT, with additional concepts specific to the needs of a particular country. For example, the U.S. extension of SNOMED CT is now packaged together with the international release and released in March and September.

From a structural perspective, SNOMED CT can be seen as a series of large directed acyclic graphs, one for each of its 19 “sub-hierarchies.” A non-lattice fragment in SNOMED CT. 1: Tissue specimen from breast; 2: Tissue specimen from heart; 3: Specimen from heart; 4: Specimen from breast; 5: Specimen from mediastinum; 6: Tissue specimen; 7: Specimen from trunk; 8: Specimen.

B. Lattice and Formal Concept Analysis

We recall some basic definitions and notations in partial orders and lattice theory [10, 11].

In a partially ordered set (poset) \( L \), an element \( u \) is called an upper bound of a subset \( X \subseteq L \), if for each \( x \in X \) we have \( x \leq u \). An element \( m \) is called a minimal upper bound of a subset \( X \subseteq L \), if \( m \) is an upper bound of \( X \), and for any \( n \leq m \) such that \( x \leq n \) for each \( x \in X \), we have \( m = n \). We write \( \text{mub}(X) \) for the set of minimal upper bounds of \( X \). When \( \text{mub}(X) \) is a singleton, the unique minimal upper bound is called the least upper bound of \( X \). The notions of lower bound, maximal lower bound, greatest lower bound, and least upper bound are defined dually. Specifically, \( \text{mlb}(X) \) represents the set of maximal lower bounds of \( X \).

A poset \( L \) is a lattice if every two elements of \( L \) have a least upper bound (join) and greatest lower bound (meet). The meet and join of binary sets are often written in infix notation: \( \{x, y\} \) and \( x \wedge y \). A poset \( L \) is a complete lattice if every subset \( S \subseteq L \) has a least upper bound \( \bigvee S \) (join) and a greatest lower bound \( \bigwedge S \) (meet).

In connection with ontology, one can think of concepts as elements of a poset, and the ordering relation as the subsumption relation [13]. If \( x, y \) are concepts, we write \( x \leq y \) to mean \( x \text{ IS-A } y \), or \( y \) subsumes \( x \). The join \( x \lor y \) of two concepts \( x, y \) is the least common ancestor of \( x \) and \( y \), and the meet \( x \land y \) are their greatest common descendant.

Formal Concept Analysis (FCA) [14] is a general lattice-based method for extracting higher-level organizational information from lower-level classification of objects according to their attributes. The primary notion in FCA is a formal context \( (O, A, R) \), where \( O \) is a collection of objects, \( A \) a collection of attributes, and \( R \) is a relation \( R \subseteq O \times A \). A fundamental theorem of FCA is that every formal context determines a complete lattice, and reversely, every complete lattice can be derived from a formal context.

C. Lattice-based Ontology Auditing

Well-formed ontologies often have a lattice structure [9]. The deeper philosophical and mathematical reason for lattice to be a desirable structural property for the taxonomy relation (e.g., IS-A) in ontologies can be elucidated with FCA [12]. Starting from two very basic types, objects and attributes, with the assumption that intension and extension are fundamental adjoining facets of the notion of concept, one obtains a complete lattice automatically using FCA [14].

The upshot of this is that if we encounter a non-lattice fragment in a taxonomic hierarchy, then somewhere upstream, the notion of intension and extension may not have been crystalized. This may reveal gaps in conceptual modeling.

Though desirable, the lattice property of ontologies is not always found in most biomedical ontologies. Fig. 1 is a non-lattice fragment [9] from SNOMED CT. “Tissue specimen from heart” is not a concept in SNOMED CT. Including it appropriately makes this fragment lattice conforming.

D. MapReduce

MapReduce [15] is a distributed programming environment to process large amounts of data in a scalable way. A MapReduce job consists of a mapper and a reducer function, specified by the user to process data in the form of key-value pairs. Such a job is automatically broken into tasks executed in parallel across a cluster of machines called compute nodes. Designing efficient algorithms in MapReduce requires a different mentality than the transitional approach, with more attention paid to data locality, job break-down, and a trade-off between parallelism and communication latency.

III. The MapLE Algorithm

In this section, we introduce the algorithmic aspect of MapLE, our MapReduce Pipeline for Lattice-based Evaluation. It takes a partially ordered set (poset) as input, and generates the collection of all non-lattice pairs in the poset.

A. Non-lattice Pairs

A pair of elements \( a, b \) in a poset \( (L, \leq) \) is a non-lattice pair if \(| \text{mub}(a, b) | > 1 \), i.e. the pair \( a, b \) has at least two minimal upper bounds. For example, in the poset given in Fig. 1, we have \( \text{mub}(1, 2) = \{6, 7\} \), so the size of \( \text{mub}(1, 2) \) is 2, making \( (1, 2) \) a non-lattice pair in this poset. On the other hand, we have \( \text{mub}(1, 3) = \{7\} \), and so \( (1, 3) \) is a lattice pair.
Thus, finding non-lattice pairs reduces to computing the minimal upper bounds, achieved through a sequence of set-theoretic operations using closures as explained next.

B. Computing Minimal Upper Bounds

Given a set $X$ of elements in a poset $L$, we use $\mathcal{X}$ to denote the set of all common ancestors of $X$, i.e., $\mathcal{X} := \{a \mid \forall x \in X, x < a\}$. Note that $X \cap \mathcal{X}$ is always empty. When $X$ is a singleton, i.e., $X = \{x\}$, we write $\mathcal{X}$ for $\mathcal{X}_x$. Similarly, we define $\mathcal{X} := \{a \mid \exists x \in X, x < a\}$. Thus, $\mathcal{X}$ represents its strict upper closure. It is straightforward to check that for any set $X, Y \subseteq L$,

$$\mathcal{X} = \bigcap_{x \in X} \mathcal{Y}_x, \text{ and } \mathcal{Y} = \bigcup_{y \in Y} \mathcal{Y}.$$

For singletons, we have $\mathcal{X} = \{x\}$. Two elements $x, y$ are called incomparable if neither $x \leq y$, nor $y \leq x$.

The correctness of our algorithm for computing minimal upper bounds rests on the following simple result (Theorem 1). Before introducing this result, the following lemma should be helpful (whose proof is omitted):

**Lemma 1:** Let $x, y$ be elements in a poset $L$. If $y \leq x$ but $x \not\leq y$, then $x = y$.

**Theorem 1:** Let $X$ be a set of pairwise incomparable elements of a poset $L$, with the size of $X$ at least two. We have

$$\text{mub}(X) = \mathcal{Y} - \mathcal{X}.$$

**Proof:** Let $m \in \mathcal{Y} - \mathcal{X}$. Since $m \in \mathcal{Y}, m$ is an upper bound of $X$. Since $m \not\in \mathcal{X}$, we have $m \not\in \mathcal{Y}$ for each $t \in X$.

For any upper bound $u$ of $X$ (i.e., $x \leq u$ for each $x \in X$) with $u \leq m$, we need to show that $u = m$. Since $u$ is an upper bound of $X$, which contains at least two incomparable elements, we have $u \not\in \mathcal{X}$. Also, because $m \not\in \mathcal{Y}$ for each $t \in \mathcal{X}$, we have $m \not\in \mathcal{Y}$. Hence, $m$ is a minimal upper bound of $X$.

A special case for Theorem 1 is a pair of incomparable elements $x$ and $y$, which is stated as:

$$\text{mub}((x, y)) = (\mathcal{X} \cap \mathcal{Y}) - \bigcup_{t \in \mathcal{X} \cap \mathcal{Y}} \mathcal{Y}_t. \quad (1)$$

Fig. 2 displays a general algorithm to detect non-lattice pairs in a poset. The input (line 1) is a poset $L$, represented by its associated set of pairs $x, y$ with $x \leq y$. The output (line 2) is a set of detected non-lattice pairs and their minimal upper bounds. Lines 3-5 collect ancestors for each element of $L$. Lines 6-17 detect non-lattice pairs by computing minimal upper bounds using Equation (1) for each candidate pair, and output pairs with more than one minimal upper bound.

IV. MAPE Implementation for SNOMED CT

The algorithm (Fig. 2) to detect non-lattice fragments is implemented using two MapReduce jobs (Fig. 3 and Fig. 4), for exhaustive, structural analysis of SNOMED CT.

Since finding the ancestors of a concept is a basic operation repeatedly performed throughout the MAPE algorithm, we assume that the transitive closure of the SNOMED CT concepts hierarchy has been precomputed, to save overall time.

```java
1: Input: A poset $L$
2: Output: A set $R$ of non-lattice pairs and their minimal upper bounds
3: for each element $x \in L$ do
4:   Find the set of its ancestors $\mathcal{X}_x$
5: end for
6: Initialize $R = \emptyset$
7: for each pair of elements $(x, y)$ do
8:   Calculate $\mathcal{X}_x \cap \mathcal{Y}_y$
9: end for
10: for each $t \in [x, y]$ do
11:   $U \leftarrow U \cup \mathcal{Y}_t$
12: end for
13: if $x$ and $y$ are incomparable and $|\mathcal{X}_x \cap \mathcal{Y}_y - U| > 1$ then
14:   $R \leftarrow R \cup ((x, y), (\mathcal{X}_x \cap \mathcal{Y}_y - U))$
15: end if
16: end for
17: return $R$
```

Fig. 2. Algorithm for detecting non-lattice pairs in a poset.

A. MapReduce Jobs

Given a set of transitive closure pairs of SNOMED CT concepts, the first MapReduce job described in Fig. 3 simply collects ancestors for each concept. In the mapping phase (lines 3-5), each mapper reads in a set of transitive closure concept pairs and emits key-value pairs $(c, a)$ where $c$ is a concept and $a$ is a concept identifier. In the reduce stage (lines 6-8), each reducer collects all the ancestors $\mathcal{X}_c = \{a_1, a_2, \ldots\}$ of a concept $c$ and emits concept-ancestors pairs $(c, \mathcal{X}_c)$.

```java
1: Input: Transitive closure concept pairs
2: Output: Concept-ancestors pairs
3: class Mapper
4:   method Map((concept c, ancestor a))
5:     Emit(c, a)
6:   class Reducer
7:     method Reduce((c, $\mathcal{X}_c$))
8:     Emit(c, $\mathcal{X}_c$)
```

Fig. 3. MapReduce Job 1: collecting ancestors for each concept.

Fig. 4 gives the description of the second MapReduce job. The input is a set of concept-ancestors pairs $(c, \mathcal{X}_c)$ resulting from MapReduce Job 1. In implementation, such input concept-ancestors pairs are not only split and fed into multiple mappers, but also read by all the mappers and reducers as DistributedCache in Hadoop.

In the map stage, each mapper first loads all concept-ancestors pairs $(c, \mathcal{X}_c)$ into a hash map $\text{CA}$ to facilitate the generation of candidate pairs (lines 4-7). Then each mapper generates candidate pairs for each concept $c_1$ (lines 8-13) by iterating through each concept $c_2$ in $\text{CA}$, checking if $c_1$’s concept identifier is less than $c_2$’s concept identifier to ensure uniqueness of the pair. A concept pair $(c_1, c_2)$ is then emitted as a key and their ancestors $(\mathcal{X}_1, \mathcal{X}_2)$ where $\mathcal{X}_1 = \{a_{11}, a_{12}, \ldots\}, \mathcal{X}_2 = \{a_{21}, a_{22}, \ldots\}$, respectively, as a value. The requirement that $c_1$’s concept identifier is less than $c_2$’s concept identifier avoids the situation that the same concept pair generates two different keys.

In the reduce stage, each reducer first loads all concept-ancestors pairs $(c, \mathcal{X}_c)$ into a hash map $\text{CA}$ (lines 15-18). Then each reducer checks if $c_1$ and $c_2$ in a concept pair

```java
1: Input: Concept-ancestors pairs
2: Output: Candidate pairs
3: class Mapper
4:   method Map((concept c, concept ancestry $\mathcal{X}_c$))
5:     Emit($\mathcal{X}_1$, $\mathcal{X}_2$)
6:   class Reducer
7:     method Reduce(($\mathcal{X}_1$, $\mathcal{X}_2$))
8:     Emit($\mathcal{X}_1$, $\mathcal{X}_2$)
```

Fig. 4. MapReduce Job 2: generating candidate pairs from concept pairs.
are incomparable (lines 20-21), calculates their minimal upper bounds (lines 22-27), and emits pairs with more than one minimal upper bound as keys and their minimal upper bounds as values (lines 28-30).

Fig. 5 illustrates the two MapReduce jobs in the MaPLE pipeline using the poset example given in Fig. 1.

B. Optimization Strategies

To reduce the total number of input and resulting pairs yet without missing any non-lattice fragments, we incorporate two optimization strategies in MaPLE implementation, which were first introduced in [12].

1) Leveraging Duality and Reversing Order: After obtaining the transitive closure of a set of SNOMED CT pairs \( \{(c, a) \} \), we reverse the pairs and take the pairs \( \{(a, c)\} \) as input for MaPLE. Ontological hierarchies have a “fan-out” shape: they tend to have fewer upper level concepts representing more general entities, while having lower level concepts representing more specific entities. Since lattices can be viewed either top-down or bottom-up, only one direction needs to be tested for lattice property. The effect of this is that instead of computing minimal upper bounds, we compute the maximal lower bounds in the original hierarchy.

2) Concepts with a Unique Parent: The second optimization strategy is skipping concepts with a unique parent in the map stage of MapReduce Job 2. The rationale for considering concepts with a single parent is that whenever such a concept is involved in a non-lattice pair, there must be an ancestor of this concept already involved in a non-lattice fragment [12], [9]. In implementation, all concepts with a unique parent are extracted and loaded as a DistributedCache in the map stage of MapReduce Job 2 (Fig. 4).

C. Experimental Environment

We ran MaPLE on a private cloud using Cloudera Hadoop 4.3 (Hadoop 2.0.0-cdh4.3.0) with 1 master node and 30 slave nodes. The master node uses a dual quad-core Intel Xeon 5150 2.66GHz, while the compute nodes are machines with dual quad-core Intel Xeon 5450 3.0GHz processors, all running RedHat Enterprise Linux 6.4. Each node has a local 146GB SAS hard drive. Each server has 16GB of RAM. The compute nodes are interconnected using a low-latency 10 Gigabit Ethernet network based on Arista switches and Intel NetEffects Ethernet adapters.

V. RESULTS

A. Basic SNOMED CT Statistics and Non-lattice Pairs

We ran MaPLE on 8 versions of SNOMED CT from 2009 to 2014, dated 07/2009 (i.e., July 2009), 01/2010, 01/2011, 01/2012, 07/2012, 01/2013, 07/2013, and 03/2014. Table I summarizes the basic results about each version of SNOMED CT. The 07/2009 version contained a total of 306,627 concepts, with 445,549 direct IS-A relationship connecting concepts. Among all possible concept pairs, 559,182 were found to be non-lattice pairs. The MaPLE processing of all 07/2009 SNOMED CT hierarchies in the 30-node Cloudera Hadoop environment took a total 10,168 seconds, roughly 2.8 hours.

Table II summarizes the results for the 10 largest sub-hierarchies in the most recent (03/2014) version. For the
For example, processing “Clinical Finding,” the largest sub-hierarchy, took about 2 hours. The total computing time for the 03/2014 version was 11,166 seconds, around 3 hours.

### B. Comparison of SNOMED CT Versions

MaPLE allows us to track the changes of non-lattice pairs between different versions. Fig. 6 shows the summary of the differences between SNOMED CT versions using the percentage of non-lattice pair changes. We use |N-O|/|N| and |O-N|/|O| to show the difference. Here |X| stands for the size of the set X. Therefore, |N-O|/|N| is the percentage of non-lattice pairs which is newly added to the later version. |O-N|/|O| is the percentage of non-lattice pairs which is removed from the previous version. It is important to note that |N-O|≠|N|-|O| in general – we can have two equal-sized sets that have nothing in common, and so in the extreme, |N-O|=|N| but |N|-|O|=0.

<table>
<thead>
<tr>
<th>Sub-Hierarchy (SNOMED Identifier)</th>
<th>N</th>
<th>TC</th>
<th>NL</th>
<th>PP</th>
<th>NC%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Body Structure (123073004)</td>
<td>30,624</td>
<td>927,549</td>
<td>90,465</td>
<td>468,686,753</td>
<td>0.019%</td>
</tr>
<tr>
<td>Clinical Finding (404684003)</td>
<td>100,652</td>
<td>1,937,520</td>
<td>277,071</td>
<td>5,065,362,226</td>
<td>0.0054%</td>
</tr>
<tr>
<td>Observable Entity (363787002)</td>
<td>8,314</td>
<td>49,006</td>
<td>613</td>
<td>34,557,141</td>
<td>0.0017%</td>
</tr>
<tr>
<td>Organism (410807006)</td>
<td>35,175</td>
<td>380,364</td>
<td>1,530</td>
<td>550,273,725</td>
<td>0.0028%</td>
</tr>
<tr>
<td>Pharmaceutical/Biological Product (375870005)</td>
<td>16,797</td>
<td>123,940</td>
<td>6,819</td>
<td>141,061,206</td>
<td>0.0088%</td>
</tr>
<tr>
<td>Physical Object (260780044)</td>
<td>4,518</td>
<td>31,897</td>
<td>364</td>
<td>10,294,453</td>
<td>0.0035%</td>
</tr>
<tr>
<td>Procedure (713880049)</td>
<td>54,091</td>
<td>997,984</td>
<td>189,110</td>
<td>1,462,891,095</td>
<td>0.0129%</td>
</tr>
<tr>
<td>Qualifier Value (362981000)</td>
<td>8,978</td>
<td>39,863</td>
<td>380</td>
<td>40,297,753</td>
<td>0.0094%</td>
</tr>
<tr>
<td>Social Context (48176007)</td>
<td>4,824</td>
<td>33,122</td>
<td>804</td>
<td>11,633,076</td>
<td>0.0089%</td>
</tr>
<tr>
<td>Substance (105590001)</td>
<td>23,964</td>
<td>281,550</td>
<td>18,019</td>
<td>287,076,741</td>
<td>0.0096%</td>
</tr>
</tbody>
</table>

Fig. 4. MapReduce Job 2: detecting non-lattice fragments.
of non-lattice pairs in the 01/2010 version. On the other hand, 8,525 non-lattice pairs were found in the 07/2009 version but not 01/2010 (O-N), which amounted to 1.52% of the non-lattice pairs in the 07/2009 version. Similarly, for the 01/2011 version, 13,210 (2.33%) non-lattice pairs were excluded from the earlier 01/2010 version and 23,659 (4.10%) non-lattice pairs were included. One can see that the largest percentage change took place in the most recent (03/2014) version, which contained 41,103 new non-lattice pairs.

Our results show that the change rates in non-lattice pairs are significantly higher than the change rates of the corresponding underlying structure (nodes and IS-A edges) between the 8 SNOMED CT versions. With respect to concept nodes, the average percentage change rate in non-lattice pairs is 38.6 times higher for “in old but not in new” (O-N) and 8.4 times higher for “in new not in old” (N-O). With respect to IS-A edges, the average percentage change rate in non-lattice pairs is 4.4 times higher for (O-N) and 3.5 times higher for (N-O). This suggests that fragments around non-lattice pairs exhibit significantly higher rates of change in ontological evolution.

Scalability is one of the most important features of cloud computing. We performed an experiment on the number of reducer tasks in MapReduce Job 2 for MaPLE, a more computationally intensive step. We found a linear decrease of the computing time when the number of reducer tasks ranged from 1 to 10. However, for 15 to 60 reducer tasks, we see a diminishing return in saved time. This may be due to the fact that when splitting intermediate results from mapper into a large number of smaller file fragments for reducer, the task setup and scheduling time may become a more significant contributor in total time. For the computing time reported in Table I, 9 reducer tasks were involved.

VI. Conclusion

In this paper we introduced a general MapReduce pipeline, called MaPLE for extracting non-lattice fragments in large partially ordered sets and demonstrate its applicability in ontology quality assurance. Our contributions include: a general MapReduce lattice-checking algorithm for posets; an application of MaPLE for exhaustive analysis of 8 SNOMED CT versions since 2009; and a global change analysis of such SNOMED CT versions with respect to the underlying concepts, relationships, and non-lattice pairs. Our change analysis indicated that fragments around non-lattice pairs exhibit significantly higher rates of change in the process of ontological evolution.

One limitation of this approach is that it does not take into account the editorial guidelines of the IHTSDO for the development of SNOMED CT, which are used to prevent the creation of unnecessary concepts (from the perspective of clinical utility). If such guidelines were formalized in machine-readable form, we could integrate them into our analysis, in order to prevent certain non-lattice pairs from being seen as errors. In the future, we plan to work with the IHTSDO to tailor our analysis to their quality assurance processes.

Our approach sets the foundation for structural auditing of ontologies in a couple of new directions. One is to mine the large collection of non-lattice fragments to extract clinically interpretable insights in the ontological evolution. The second is to perform large-scale MapReduce analysis of biomedical ontologies taking advantage of the combination of linguistic and structural information conveyed by the ontological systems, along the lines of work reported in [16], [17], [18].

VII. Acknowledgments

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