Randomized Differential Testing of RDF Stores

Rui Yang†, Yingying Zheng†, Lei Tang†, Wensheng Dou†‡, Wei Wang†§, Jun Wei††§
†State Key Lab of Computer Sciences, Institute of Software, Chinese Academy of Sciences
‡University of Chinese Academy of Sciences
§University of Chinese Academy of Sciences Nanjing College
§Nanjing Institute of Software Technology
{yangrui22, zhengyingying14, tanglei20, wsdou, wangwei, wij}@otcaix.iscas.ac.cn

Abstract—As a special kind of graph database systems, RDF stores have been widely used in many applications, e.g., knowledge graphs and semantic web. RDF stores utilize SPARQL as their standardized query language to store and retrieve RDF graphs. Incorrect implementations of RDF stores can introduce logic bugs that cause RDF stores to return incorrect query results. To address this challenge, we develop a randomized differential testing approach of RDF stores, to reveal discrepancies among RDF stores, which indicate potential logic bugs in RDF stores. The core idea of RD2 is to build an equivalent RDF graph for multiple RDF stores, and verify whether they can return the same query result for a given SPARQL query. Guided by the SPARQL syntax and the generated RDF graph, we automatically generate syntactically valid SPARQL queries, which can return non-empty query results with high probability. We further unify the formats of SPARQL query results from different RDF stores and find discrepancies among them. We evaluate RD2 on three popular and widely-used RDF stores. In total, we have detected 5 logic bugs in them. A video demonstration of RD2 is available at https://youtu.be/da7XlsdbRR4.

Index Terms—RDF store, differential testing, SPARQL

I. INTRODUCTION

The Resource Description Framework (RDF) [1] graph model has been regarded as a W3C standard for exchanging graph data. We refer to the graph database systems (GDBs) that are built on the RDF graph model as RDF stores [2]. The representative RDF stores include MarkLogic [3], Apache Jena [4], GraphDB [5], RDF4j [6], etc. They utilize SPARQL [7] as their standardized query language, and play a significant role in knowledge graphs [8], [9] and semantic web [10].

Similar to other GDBs that are built on the labeled property graph model [11]–[13] and relational database systems (RDBMSs) [14]–[18], incorrect implementations of RDF stores can introduce logic bugs that result in an incorrect query result for a given SPARQL query, e.g., omitting a record. Fig. 1 illustrates a real-world logic bug found in MarkLogic. In this example, we first write an RDF triple (Line 2) into MarkLogic, and then retrieve it by a FILTER expression 80596426678+1719307142, which should be evaluated into true (Line 5–7). We expect the RDF triple can be returned (Line 9). However, MarkLogic mistakenly returns an empty result (Line 8) because the expression is evaluated into false due to decimal overflow. But, Apache Jena and RDF4j can correctly return the RDF triple.

Fig. 1. A logic bug in MarkLogic [3].

Logic bugs in RDF stores can easily go unnoticed by developers. Existing GDB testing approaches, e.g., Grand [11], GDsmith [12] and GDBMeter [13], detect logic bugs in Gremlin-based or Cypher-based GDBs, which adopt the labeled property graph model. Existing RDBMS testing approaches [14]–[20] detect bugs in RDBMSs. However, RDF stores adopt totally different graph models and query syntaxes. Existing approaches cannot be directly applied on RDF stores.

In this paper, we propose a randomized differential testing technique RD2, to reveal discrepancies among RDF stores. These discrepancies usually indicate logic bugs in RDF stores. We first randomly build an equivalent RDF graph for multiple RDF stores and write it into multiple target RDF stores. We then generate random SPARQL queries. Finally, we compare the query results returned by these RDF stores to check whether discrepancies exist. To effectively reveal discrepancies among RDF stores, we address two specific challenges. (1) Randomly generated SPARQL queries can return empty query results with high possibility. This can make differential testing inefficient. To address this challenge, we combine the SPARQL syntax and the generated RDF graph to construct syntactically correct and valid SPARQL queries that can return non-empty query results with high possibility. (2) Different RDF stores usually have their own storage and query result formats, which makes the comparison of query results challenging. To address this challenge, we develop a data mapping approach to unify the formats of SPARQL query results in different RDF stores.

To evaluate the effectiveness of RD2, we apply it on the latest versions of three popular and widely-used RDF stores, i.e., MarkLogic [3], Apache Jena [4], and RDF4j [6]. In total, RD2 has detected 5 logic bugs in them. We have made RD2 publicly available at https://github.com/tcse-iscas/RD2.
II. Preliminaries

RDF triples. An RDF [1] triple can be denoted as <subject, predicate, object>. Specifically, subject is an Internationalized Resource Identifier (IRI) or a blank node, predicate is an IRI, and object is an IRI, a literal or a blank node. A literal is a value with a certain data type, e.g., String. A blank node is a node without an IRI.

A set of RDF triples corresponds to an RDF graph. Fig. 2 shows an RDF graph with ten RDF triples. In Fig. 2, an ellipse represents an IRI or a blank node in subject or object, a rectangle represents a literal, and a directed edge represents an IRI in predicate. For example, we can use <$http://John>, foaf:age, 20> to describe a person with name John who is 20 years old. We can use a blank node to connect the IRI of Peter Green (i.e., <$http://PeterGreen$>) and his given name (i.e., Peter) and family name (i.e., Green).

SPARQL queries. SPARQL [7] is a standardized query language for RDF stores. Fig. 3 shows a SPARQL query on the RDF graph in Fig. 2 which retrieves the given names and ages of persons whose age is not 20. A SPARQL query generally consists of four components, i.e., a prologue, a SELECT clause, a WHERE clause and an optional solution modifier. Specifically, the prologue declares prefix names, e.g., declaring a prefix name <$http://xmlns.com/foaf/0.1$> as foaf (Line 1). The SELECT clause specifies the variables to return (Line 2). The WHERE clause specifies the graph pattern to be queried with triple patterns, FILTER, etc. A triple pattern is similar to an RDF triple except that the subject, predicate and object may be a variable. In Fig. 3, the WHERE clause contains three triple patterns and a FILTER expression (Line 3-8). For example, {?person, foaf:name, ?name} (Line 4) matches the RDF triples with predicate foaf:name, and binds the values of subjects and objects in RDF triples to ?person and ?name. The FILTER expression filters persons whose age is not 20. The solution modifier processes the query results by sorting, limiting the number of returned results, etc, e.g., ORDER BY sorts results by ?givenName (Line 9).

III. RD²

RD² first randomly generates an RDF graph and writes it into multiple target RDF stores (Section III-A). Then, RD² randomly generates SPARQL queries (Section III-B). Finally, RD² runs a SPARQL query on multiple target RDF stores, gets the query result (Res for short in Fig. 4) of each target RDF store, and reveals discrepancies among these query results (Section III-C).

A. RDF Graph Generation

An RDF graph consists of a prefix declaration and a set of RDF triples. The prefix declaration is used to simplify IRIs in each RDF triple, and we generate it by randomly generating a prefix name and its corresponding IRI. Here, the IRI is retrieved from the Python library Faker [21]. An RDF triple consists of a subject (i.e., an IRI or a blank node), a predicate (i.e., an IRI), and an object (i.e., an IRI, a literal, or a blank node). To generate an RDF triple, we first randomly generate a set of IRIs and literals, and then randomly select corresponding data for subject, predicate, and object, respectively. Specifically, we generate IRIs with the Python library Faker [21]. To generate literals, we first randomly choose a data type (e.g., String), and then generate a random value for this data type. After that, we construct an RDF triple by randomly selecting a generated IRI or a blank node for subject, randomly selecting an IRI for predicate, and randomly selecting an IRI, a literal or a blank node for object. Finally, we write the generated RDF graph into target RDF stores.

For example, in Fig. 2 we first generate a prefix name foaf for <$http://xmlns.com/foaf/0.1$>. Then, we generate RDF data to construct ten RDF triples. For the first RDF triple, we select an IRI <$http://John$>, an IRI foaf:age, and a literal 20 from the previously generated data to construct an RDF triple <$http://John$, foaf:age, 20$. For the second RDF triple, we select an IRI <$http://PeterGreen$>, an IRI foaf:name and a blank node to construct an RDF triple <$http://PeterGreen$, foaf:name, [ ]>.
B. SPARQL Query Generation

To generate syntactically correct and valid SPARQL queries, we build Abstract Syntax Trees (ASTs) to generate SPARQL queries, and choose values for parameters in a SPARQL query from the generated RDF graph to increase the probability of returning non-empty query results.

Generating SPARQL queries. We randomly build a SPARQL query’s Abstract Syntax Tree (AST) based on the SPARQL syntax. A SPARQL query consists of a prologue, a SELECT clause, a WHERE clause, and an optional solution modifier. The prologue is used to simplify IRIs in each RDF triple, and we generate it with “PREFIX”, a prefix name and its corresponding IRI generated in Section III-A (e.g., Line 1 in Fig. 2). Then we generate the WHERE clause with triple patterns (e.g., Line 4–6 in Fig. 3) and FILTER expressions (e.g., Line 7 in Fig. 3). To generate a triple pattern, we first randomly generate a set of variables, and then randomly select variables to bind to subject, predicate or object, respectively. We generate a FILTER expression by building an expression tree, which will be explained in the next paragraph. After that, we generate the SELECT clause by randomly selecting several variables (e.g., ?givenName and ?age in Line 2 of Fig. 3) existing in the triple patterns of WHERE clause. Finally, we optionally generate a solution modifier with ORDER BY and a variable randomly selected from the triple patterns of WHERE clause (e.g., Line 9 in Fig. 3).

For the FILTER expression in a WHERE clause, we randomly generate it by building an expression tree with a specified maximum depth. The data types of the expression’s returning value can be Boolean, String or Numeric. Therefore, we randomly select one of these data types for the root node of the expression tree, and then recursively generate the nodes of the expression tree until the maximum depth is reached. Specially, each generated node must satisfy its required data type. To generate a node, we randomly select an operator or a value that matches its given data type. Leaf nodes can be randomly generated as constants or variables that appear in the query. For the expression !(?age = 20) in Fig. 3, we first randomly choose an operator !, and then randomly create an operator = as its operand. To create the operator =, we first select a data type (e.g., Integer), and then generate a variable ?age and an Integer value 20 as its operands.

Generating parameter values. Without any guidance, the IRIs and literals in a SPARQL query can be generated randomly. This can cause almost all generated SPARQL queries to return empty results. To tackle this problem, we select IRIs or literals from the generated RDF graphs. Specifically, for the IRI in a triple, we randomly select an IRI from the existing IRIs in the RDF graph. For the constants in a FILTER expression, we randomly select an existing value from the RDF graph, or randomly generate a constant value.

C. Differentially Testing RDF Stores

We adopt differential testing to find discrepancies among multiple target RDF stores. We write the same RDF graph into multiple target RDF stores, and then execute the same SPARQL queries on them. We compare the query results returned by different RDF stores, and find discrepancies among them. The query results can be a list of IRIs, literals or blank node IDs. However, different RDF stores adopt different strategies for generating blank node IDs. Thus, we need to handle this special situation when comparing query results.

Unifying formats of blank node IDs. Since the formats of blank node IDs are different in multiple RDF stores, we need to convert the blank node IDs returned by multiple RDF stores into a unified format. To achieve it, we generate a unique ID bNodeId for each blank node when generating RDF graph data. After writing a blank node to an RDF store, we extract its actual ID actualID in the RDF store. Then we build a mapping table to record the mapping relationship between bNodeId and actualID in all target RDF stores. After obtaining the query results, we convert different formats of blank node IDs returned by multiple target RDF stores into IDs in a unified format through this mapping table. For example, the same blank node has different actualIDs _bnode7293854958399345579 and b0 in MarkLogic and Apache Jena, respectively. We map them into the same bNodeId 1.

IV. IMPLEMENTATION AND USAGE

We implement RD2 with around 2,300 lines of Java codes. RD2 first establishes connections to target RDF stores. For MarkLogic, RD2 uses MarkLogic APIs to connect the remote MarkLogic Server. For Apache Jena and RDF4j, RD2 uses Model and Repository APIs to create and visit a local graph database, respectively. Then, RD2 invokes corresponding APIs provided by each target RDF store to write the generated RDF graph data into target RDF stores, executes the generated SPARQL queries and obtains their returned results.

RD2 is implemented as a command line tool. After installing target RDF stores, two main steps are needed for running RD2.

1) Run RD2. We can execute the command “java -jar RD2.jar --dbname --host --port --username --password --db-num --query-num” to run RD2.

   • --dbname: The RDF graph database name to test.
   • --host: The IP address.
   • --port: The port.
   • --username: The username to login.
   • --password: The password to login.
   • --db-num: The number of testing round.
   • --query-num: The number of queries in each testing round.

Note that only MarkLogic needs the first five parameters, since Apache Jena and RDF4j use local graph databases. For example, to test MarkLogic with built-in Apache Jena and RDF4j, we can execute the command “java -jar RD2.jar --dbname tmpRDFGraph --host 127.0.0.1 --port 8000 --username root --password 123 --db-num 10 --query-num 100”. Then, RD2 will execute queries on the three RDF stores and report discrepancies among them.
TABLE I
TARGET RDF STORES

<table>
<thead>
<tr>
<th>RDF Store</th>
<th>DB-Engines Ranking</th>
<th>GitHub Stars</th>
<th>Initial Release</th>
</tr>
</thead>
<tbody>
<tr>
<td>MarkLogic</td>
<td>1</td>
<td>-</td>
<td>2001</td>
</tr>
<tr>
<td>Apache Jena</td>
<td>3</td>
<td>890</td>
<td>2000</td>
</tr>
<tr>
<td>RDF4j</td>
<td>9</td>
<td>308</td>
<td>2000</td>
</tr>
</tbody>
</table>

2) Check reports. A discrepancy report contains the RDF graph, the executed SPARQL queries, and their query results returned by each target RDF store.

V. EVALUATION

A. Methodology

The Target RDF stores. We evaluate RD² on three widely-used RDF stores, i.e., MarkLogic [3], Apache Jena [4] and RDF4j [6]. Table I shows their DB-Engines ranking of RDF stores [22], GitHub stars and initial releases. We can see that, our experimental subjects are popular and widely-used RDF stores. Among these RDF stores, two of them (i.e., Apache Jena and RDF4j) only support the RDF graph model, while MarkLogic supports multiple models, e.g., RDF and document. We test their latest versions when we started this work, i.e., MarkLogic 10, Apache Jena 3.3.0, and RDF4j 3.6.0.

Testing methodology. We run RD² on these three RDF stores for 10 testing rounds. In each testing round, we first randomly generate an RDF graph database with 50 RDF triples, and then randomly generate 1000 SPARQL queries. For each query, we execute it on the three target RDF stores, and verify whether their query results are the same. Any discrepancy can be reported by RD². For the reported discrepancies, we manually simplify and analyze them to figure out which RDF store performs unexpectedly and whether it can be identified as a potential bug. After filtering out duplicated bugs, we submit a bug report for each bug to the corresponding community on GitHub or Stack Overflow.

B. Detection Results

RD² takes about 94.5 seconds to run each testing round. In each testing round, 30% of SPARQL queries return non-empty results on average. For 10 testing rounds, RD² reports 445 discrepancies in total. After filtering out duplicated discrepancies, we finally find 6 discrepancies among the three RDF stores. After analyzing these discrepancies, we identify 5 logic bugs from 5 discrepancies, and the remaining one discrepancy is caused by different SPARQL versions that these RDF stores support. We have submitted these bugs to corresponding developers. At the time of writing this paper, 2 bugs have been confirmed, and the remaining 3 bugs have been considered as intended behaviors due to different implementations of RDF stores. The root causes of these bugs mainly relate to automatic type conversion, numeric representation, and handling the same values with different data types.

MarkLogic. We find four logic bugs in MarkLogic. In the first bug, MarkLogic cannot convert a value with Integer type to Double type automatically, which leads to decimal overflow in FILTER expressions. In the second bug, MarkLogic omits equal values with different data types. In the third bug, MarkLogic treats the same value with different data types as equivalent, which does not follow the RDF specification. In the fourth bug, MarkLogic returns literals with different numeric representative format from the other two RDF stores. For example, MarkLogic returns 1589301716 while Apache Jena and RDF4j return 1.589301716E9 for the same literal. MarkLogic developers explain that the scientific notation appears to be lost for Double in JSON.

RDF4j. We find one logic bug in RDF4j. RDF4j cannot automatically perform type conversion between Integer and its derived types, e.g., Int and Long. This prevents users from retrieving data with derived types of Integer using the equal values with Integer type. RDF4j developers have prepared a feature proposal to fix this bug.

VI. RELATED WORK

Testing of graph database systems (GDBs). Some approaches [11]–[13], [23] are proposed to test GDBs. Grand [11] and GDSmith [12] apply differential testing [24] to detect logic bugs in Gremlin-based and Cypher-based GDBs, respectively. GDBMeter [13] adopts metamorphic testing by partitioning a given query into three derived sub-queries to test GDBs. However, all of these works cannot detect bugs in RDF stores due to different graph models and query syntaxes.

Testing of relational database systems (RDBMSs). Many approaches [14]–[20], [25]–[33] are proposed to find bugs in RDBMSs that use SQL as a standardized query language. RAGS [14], APOLLO [31] and TAQO [32] utilize differential testing for detecting bugs in RDBMSs. SQLsmith [33] is used to detect bugs causing exceptions or crashes in RDBMSs. TLP [15], NoREC [16], PQS [17] and DQE [18] develop various test oracles to detect logic bugs and optimization bugs, and have found many bugs in popular RDBMSs. DT2 [19] and Troc [20] detect transaction bugs in RDBMSs. However, these tools cannot be directly applied to test RDF stores because SPARQL has different data models and query syntaxes from SQL.

VII. CONCLUSION

We present RD², an automated testing technique for revealing discrepancies among RDF stores and detecting logic bugs in RDF stores. RD² randomly generates an equivalent RDF graph for multiple RDF stores, and checks whether these RDF stores can return the same query result for a given SPARQL query. Our experiment shows that RD² has detected 5 logic bugs in three widely-used RDF stores, and 2 bugs have been confirmed by developers.

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