ABSTRACT

Graph database systems (GDBs) allow efficiently storing and retrieving graph data, and have become the critical component in many applications, e.g., knowledge graphs, social networks, and fraud detection. It is important to ensure that GDBs operate correctly. Logic bugs can occur and make GDBs return an incorrect result for a given query. These bugs are critical and can easily go unnoticed by developers when the graph and queries become complicated. Despite the importance of GDBs, logic bugs in GDBs have received less attention than those in relational database systems.

In this paper, we present Grand, an approach for automatically finding logic bugs in GDBs that adopt Gremlin as their query language. The core idea of Grand is to construct semantically equivalent databases for multiple GDBs, and then compare the results of a Gremlin query on these databases. If the return results of a query on multiple GDBs are different, the likely cause is a logic bug in these GDBs. To effectively test GDBs, we propose a model-based query generation approach to generate valid Gremlin queries that can potentially return non-empty results, and a data mapping approach to unify the format of query results for different GDBs. We evaluate Grand on six widely-used GDBs, e.g., Neo4j and HugeGraph. In total, we have found 21 previously-unknown logic bugs in these GDBs. Among them, developers have confirmed 18 bugs, and fixed 7 bugs.

CCS CONCEPTS
- Information systems → Database query processing; • Software and its engineering → Software testing and debugging.

KEYWORDS
Graph database systems, differential testing, Gremlin

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1 INTRODUCTION
Graph database systems (GDBs) are built on the labeled property graph model [35] or the Resource Description Framework (RDF) graph model [25], and support efficient storage and queries for graph data, which consists of vertices and edges. The popularity of GDBs has increased dramatically recently, and GDBs have played a significant role in many applications, e.g., knowledge graphs [28, 43], social networks [33], and fraud detection [47]. Examples of the most popular GDBs include Neo4j [7], OrientDB [11], JanusGraph [6] (extended from Titan [20]), Nebula [10], HugeGraph [3], TinkerGraph [16], ArcadetoDB [9] and so on.

Similar to relational database systems, GDBs also suffer from logic bugs, in which a query returns an unexpected result without crashing the GDBs. The unexpected results could be incorrect query results (e.g., omitting a vertex in a graph), or unexpected...
We further create a Gremlin to retrieve graph data (also called Gremlin-based GDBs). This approach for automatically finding logic bugs in GDBs that adopt different GDBs can lead to different query results. Thus, we cannot directly apply existing testing tools on different GDBs, we utilize a data mapping approach to obtain uniform query results in different GDBs. Our approach can compare query results with different formats returned by different GDBs.

To the best of our knowledge, Grand is the first approach to detect logic bugs in GDBs. To evaluate the effectiveness of Grand, we apply it on six widely-used GDBs, i.e., Neo4j [7], OrientDB [11], JanusGraph [6], HugeGraph [3], TinkerGraph [16], and ArcadeDB [9]. The experimental results show that Grand is effective in detecting logic bugs in GDBs. Among these bugs, 18 bugs have already been confirmed, and 7 bugs have been fixed. We have made Grand publicly available at https://github.com/tcse-iscas/Grand.

In summary, this paper makes the following contributions.

- We propose Grand, an automated differential testing approach to find logic bugs in Gremlin-based GDBs. We introduce a model-based query generation approach to effectively generate syntactically correct and valid Gremlin queries.
- We implement Grand and evaluate it on six widely-used GDBs and discover 21 previously-unknown bugs.

The remainder of this paper is organized as follows. Section 2 briefly introduces graph models and graph query languages in graph database systems. Section 3 presents the techniques of our approach including the graph database generation, the model-based query generation and differential testing for Gremlin-based GDBs. Section 4 introduces our implementation. The evaluation of Grand is shown in Section 5, followed by the threats and limitations of our approach in Section 6. Section 7 presents related work and Section 8 concludes this paper.

## 2 PRELIMINARIES

In this section, we introduce graph models and query languages used in graph database systems.

### 2.1 Graph Models in Graph Database Systems

Graph database systems (GDBs) adopt graph data structure to store and query data [55]. To explicitly lay out the associated relationships between vertices of data, GDBs use several graph models, which mainly include labeled property graph model and Resource Description Framework (RDF) graph model.

**Labeled property graph model.** The labeled property graph describes the relationship between entities, and consists of a set of vertices, a set of edges (i.e., the relationships of these vertices), and properties on these vertices and edges.
labels (i.e., the groups of vertices or edges), and properties (i.e., attributes). Specially, each vertex or edge has a set of properties associated with it, and can be divided into different groups by its label. For example, as shown in Figure 2, two vertices with label person (i.e., vertex1 and vertex3) have name and gender properties, while a vertex with label book has title and wordCount properties. Two edges labeled by write and read, associate person and book vertices, and have publish and since properties, respectively. Edges in a labeled property graph are directed. For example, the edge labeled by write points from vertex1 to vertex2, while the edge labeled by read points from vertex3 to vertex2.

RDF graph model. The RDF graph model is a W3C standard for data exchange and uses triples (i.e., subject, object and predicate) to represent resources in the Web. Different from labeled property graph model, vertices and edges play absolutely the same role in RDF [12]. In RDF triple structure, subject can be a vertex or an edge, object is another vertex, edge or a literal value, and predicate describes the relationship between them. For example, a triple (Nancy person name) means that Nancy is a person name.

These two graph models provide different ways to describe connected data, and can be used in different applications with their own strength. For example, in knowledge graph, RDF is widely used for its highly structured information. However, in graph database systems, the labeled property graph model is more popular [22]. Specifically, almost all GDBs support the labeled property graph model, e.g., Neo4j [7], JanusGraph [6], and TigerGraph [1], while less than half of GDBs, e.g., Virtuoso [34], support the RDF graph model. Thus, we focus on the labeled property graph model in our research.

2.2 Graph Query Languages
Different from relational database systems, which use SQL as a universal way to create, access, and modify data, there is no standardized way in GDBs to query a labeled property graph. To efficiently and conveniently access the data stored in the labeled property graph, some graph query languages are developed [40]. According to their design principles, we can divide these query languages into two categories.

Category 1: SQL-like graph query language. Different SQL-like graph query languages are developed for different GDBs, which focus on individual GDBs’ requirements. (1) The Cypher graph query language [36] is designed for Neo4j [2] and has been extracted as an open source project openCypher [21]. It uses MATCH (a pattern matching clause), WHERE (a filter clause) and RETURN (a transformation clause) as its query syntax. For example, we can use the query in Figure 3 to access the writer whose book is read by Nancy in Figure 2. (2) Nebula [10] uses nSQL which uses FETCH to query the labeled property graph. (3) TigerGraph [15] proposes GSQL [32], which uses SELECT, FROM and WHERE to obtain data. A GSQL query usually contains one or more SELECT statements. Most SQL-like declarative query languages are implemented for specific GDBs, and cannot be supported by other GDBs.

Category 2: Functional graph query language. Gremlin [51] is a functional, data-flow query language for traversing labeled property graphs and enables users to express complex traversals by composing a sequence of Gremlin steps (i.e., Gremlin API calls). Gremlin is introduced by Apache TinkerPop framework [54], and has been widely used in most popular GDBs, e.g., Neo4j [7], JanusGraph [6], TinkerGraph [16], and HugGraph [3].

We can use the query in Figure 4 to get the same result as the Cypher query in Figure 3. Specifically, we can first get all vertices using g.V(). Then we filter the person whose name is Nancy using where() API. The book that Nancy has read can be accessed by outE('read').inV(). Finally, the writer can be obtained by inE('write').outV().values('name'). In this case, a nested query exists in where() API, in which is() is used to judge whether a property value matches the predicate, i.e., eq('Nancy').

Besides query APIs, Gremlin provides a set of update APIs to build a graph database. For example, for an empty TinkerGraph can be built using the query tinkergraph = TinkerGraph.open(), and then, the Gremlin traversal source g can be obtained with the query g = traversal().withEmbedded(tinkergraph). After that, we can use some Gremlin APIs to update the created tinkergraph, e.g., addV() (adding a vertex to the graph), addE() (adding an edge to the graph), and drop() (removing elements or properties from the graph).

Note that, SQL-like declarative graph query languages are usually designed for specific GDBs, while the Gremlin query language is widely used in most popular GDBs. In the DB-Engine Ranking of Graph DBMSs [22], 66% (23/35) GDBs support Gremlin APIs. Specially, for the top ten GDBs, eight GDBs support Gremlin APIs. Therefore, we mainly focus on the Gremlin query language and the GDBs using Gremlin to retrieve graph data (also called Gremlin-based GDBs) in this paper. We will discuss how to extend Grand to other graph query languages in Section 6.1.

3 APPROACH
In this paper, we propose Grand, a randomized differential testing approach for automatically finding logic bugs in Gremlin-based GDBs. Figure 5 shows the overview of Grand. Grand includes three
In the phase of graph database generation, Grand first randomly generates the graph schema to define the types of vertices and edges, including labels and properties of vertexes and edges in the graph database (1). Then, the detailed vertices and edges can be randomly generated according to the generated graph schema (2). The generated database will be written into target GDBs (3).

In the phase of Gremlin query generation, we use a model-based query generation approach to generate syntactically correct and valid Gremlin queries. Specifically, we first construct a traversal model for Gremlin APIs (4), and then generate Gremlin queries based on the constructed traversal model and the generated graph database (5).

Finally, Grand executes the generated Gremlin queries (6) and validates the query results by differential testing. In details, for each target GDB, the result for each query will be recorded and then transformed as a unified query result with the help of the mapping information (7). Then, Grand checks these unified results to identify whether there exist discrepancies (5). If some GDBs exhibit different outputs, then a potential bug is found.

### 3.1 Graph Database Generation

Grand generates random database states for target GDBs, i.e., graph schema and graph data, which are used to construct Gremlin queries.

**Graph schema generation.** A graph schema defines the vertex types and edge types in a labeled property graph. A vertex contains a label and a set of properties. Let \( \text{vertex} = \{\text{label}, \text{property}\} \) denote a vertex type, in which \text{label} and \text{property} denote its label name and property types, respectively. An edge contains an input vertex, an output vertex, a label and a set of properties. Let \( \text{edge} = \{\text{in vertex}, \text{out vertex}, \text{label}, \text{property}\} \) denote an edge type, in which \text{in vertex} and \text{out vertex} denote the types of incoming and outgoing vertices, and \text{label} and \text{property} denote the label name and property types, respectively. Each property contains a property name and its value type. Let \( \text{property} = \{\text{name}, \text{type}\} \) denote a property type, in which \text{name} and \text{type} denote the property name and its data type, respectively.

Take the graph in Figure 2 as an example. The type of \text{vertex} 1 is presented as \{\text{person}, \{\text{name}, \text{String}\}, \{\text{gender}, \text{String}\}\}. Its label name is \text{person}. It has two property types with name and gender, and their data types are both \text{String}. The type of \text{vertex} 2 is presented as \{\text{book}, \{\text{title}, \text{String}\}, \{\text{wordCount}, \text{Integer}\}\}. Its label name is \text{book}. It has two property types with \text{title} and \text{wordCount}, and their data types are \text{String} and \text{Integer} respectively. The type for the first edge (from \text{vertex} 1 to \text{vertex} 2) is presented as \{\text{person}, \text{book}, \text{write}, \{\text{publish}, \text{Integer}\}\}. Its incoming vertex type is \text{person}, and outgoing vertex type is \text{book}. Its label name is \text{write}, which has a property type \text{publish} with data type \text{Integer}.

We generate a set of vertex types \( \text{VTSet} \) by the following algorithm. For each vertex type, we first randomly generate its label name, and then generate a set of property types. For each property type, we assign a random data type from \{\text{Integer}, \text{String}, \text{Double}, \text{Boolean}, \text{Float}, \text{Long}\}. Note that, we require that all vertex types have different label names, and all property types in an vertex type have different property names, but different vertex types may contain same property types.

We then generate a set of edge types \( \text{ETSet} \) by the following algorithm. To generate an edge type, we first randomly select two vertex types from \( \text{VTSet} \) as its incoming vertex and outgoing vertex, respectively. Then we use the same way to generate its label name and property types as the vertex type generation. Note that, we require that all edge types have different label names, and all property types in an edge type have different property names, but different edge types may contain same property types.

**Graph data generation.** According to the generated graph schema, Grand further generates the graph data that can be stored in GDBs. Basically, we randomly generate some vertices and edges that conform the graph schema. Then, these generated vertices and edges are written into GDBs. Algorithm 1 illustrates how a vertex and an edge can be generated.

For the vertex generation (Line 1-8), we first randomly get a vertex type \text{vertexType} from vertex types \text{VTSet} generated above. We generate a vertex \text{vertex} according to the vertex type \text{vertexType}. Note that, we randomly select a subset of \text{vertexType}'s properties types, and generate \text{vertex}'s properties (Line 5-6). In this way, we can create vertices that lack some properties. For each selected property, we randomly generate its value according to its data type (Line 23).

For the edge generation (Line 9-18), we first randomly get an edge type \text{edgeType} from edge types \text{ETSet} generated above. We generate an edge \text{edge} according to the edge type \text{edgeType}. The properties for edge generation is the same as that in vertex generation. For the incoming/outgoing vertex of edge \text{edge}, we randomly
select one vertex that conform edge’s incoming/outgoing vertex type (Line 15-16). Note that, for any two vertices, we only add one edge with the same type.

Note that, the maximal numbers of vertex types, edge types, property types, vertices, edges in a graph database, can be specified by GDB testers. In our experiment, we generate at most 10 vertex types, 20 edge types, 20 property types, 100 vertices, and 200 edges for a graph database.

3.2 Model-Based Query Generation

Random query generation is a commonly-used approach for testing databases [13, 14, 52]. However, the effectiveness of GDB testing heavily relies on the quality of query generation. Gremlin has flexible programming interfaces, which consists of a sequence of (potentially nested) Gremlin API calls acting on a graph traversal source $g$. Although we can extract grammar constraints among Gremlin APIs with automated tools (e.g., JCrasher [30]), a completely random Gremlin query generation based on the grammar for Gremlin APIs can cause two issues. First, we can easily generate grammatically correct but meaningless queries, e.g., $g.V().V()$. Second, from the Gremlin grammar, we cannot know the semantics of Gremlin APIs and their parameters. For example, in $g.V().outE('read')$, we cannot know that the parameter of $outE()$ should be a label. Without these semantics, almost all generated Gremlin queries return empty results, which cannot be used to compare return results in differential testing. These two issues can greatly affect the effectiveness of GDB testing.

To address the above two issues, we first construct a traversal model in Gremlin that can exactly understand Gremlin APIs and their semantics. Based on this traversal model, Grand can link Gremlin APIs correctly and generate syntactically correct and meaningful queries. Further, Grand can utilize these semantics and design various strategies to generate valid Gremlin queries, which can return non-empty query results with a high probability. Note that, we only focus on Gremlin query APIs for query generation, and ignore update APIs that are used to build and update graph databases.

3.2.1 Traversal Model in Gremlin

In this section, we explain the traversal model in general, and then explain Gremlin APIs.

A Gremlin query consists of a sequence of Gremlin API calls, which are correctly linked together. However, there exist constraints about how to link Gremlin APIs. Generally, the input type of a Gremlin API in a query should match the output type of its previous Gremlin API. Otherwise, the Gremlin query will be illegal. For example, for Gremlin API $outE()$ (moving to the outgoing edges), its input should be a vertex set, and its output is an edge set. As such, we can construct a query $g.V().outE()$, but cannot construct $g.E().outE()$, because the output of API $g.E()$ is an edge set not a vertex set.

To construct a syntactically correct and meaningful Gremlin query, we need to build a precise traversal model for Gremlin APIs. By carefully studying Gremlin APIs [18, 19, 51], we build a traversal model to represent the legal transformations among Gremlin query APIs, as shown in Figure 6. Our traversal model contains three types of entities (i.e., $Vertex$, $Edge$, and $Value$), three types of operations (i.e., $Filter$, $Predicate$, and $Aggregate$), and $Constant$. Figure 6 formally expresses the transformation of entities and the detailed Gremlin APIs. Based on this traversal model, the legal transformation between adjacent Gremlin APIs can be easily followed. For example, $g.V()$ is used to retrieve all $vertices$ in a graph. We can get $Edges$ with the expression $Vertex$.outE().inE().bothE(), in which, outE(), inE(), and bothE() can be linked after $Vertex$ to obtain an edge set. In addition, our traversal model can present recursion relations among Gremlin APIs in a concise way. For example, $Vertex$ can be followed by $Filter$, and $Filter$ can use $Vertex$ as parameter.

Three entities in the traversal model are used to retrieve detailed graph data in a graph. In detail, $Vertex$ represents how to obtain vertices using Gremlin APIs. To retrieve vertices, we can use a start Gremlin API (i.e., $g.V()$), append $Filter$ operations on $Vertex$, append obtaining vertices operations on $Vertex$ (e.g., $out()$), and append obtaining vertices operations on $Edge$ (e.g., $outV()$). Similarly, $Edge$ represents how to obtain edges using Gremlin APIs. We can use a start Gremlin API (i.e., $g.E()$), append $Filter$ operations to $Edge$, or append obtaining edge operations on $Vertex$ (e.g., $inE()$). The $Value$ expresses property values in the labeled property graphs. We can get all property values belonging to $Vertex$ or $Edge$ using Gremlin API $values()$, or get a specific property value by adding property name in $values()$ (e.g., $values('name')$). Besides, we can
get the property value of a specified vertex or edge through the combined Gremlin APIs \( \text{properties().values()} \).

Three operations are used to operate graph data in our traversal model. Specially, \( \text{Filter} \) operation can be used to map entities that satisfy certain filter conditions. We can use \( \text{has()} \), \( \text{where()} \) or \( \text{hasLabel()} \) API to filter vertices or edges that we require. Specially, we can add some parameters to these APIs. For example, \( \text{has(key, value)} \) can be used to select those vertices or edges whose value of property \( \text{key} \) is equal to \( \text{value} \). Another example, we can use \( \text{where(\text{Value.is(Predicate)})} \) to construct a nested sub-query, in which a sequence of Gremlin API calls act as a parameter in \( \text{where()} \).

The \( \text{Predicate} \) is used to express predicates, e.g., \( \text{eq(number)} \) is used to judge whether the incoming object is equal to \( \text{number} \). Besides basic APIs like \( \text{eq()} \) and \( \text{inside()} \), we can also use \( \text{not()} \), \( \text{and()} \), or \( \text{or()} \) APIs to connect one or more \( \text{Predicate} \) operations. The \( \text{Aggregate} \) represents a series of operations aggregating vertices, edges, or properties. For instance, \( \text{count()} \) can be used to count the number of vertices or edges, and \( \text{sum()} \) is usually used to compute a sum of property values (e.g., \( \text{values(‘age’).sum()} \)). Finally, \( \text{Constant} \) acts as API arguments and is used for type definition.

Note that some special cases are not described in the above traversal model for clear presentation. First, the parameters in some Gremlin APIs have been ignored in the traversal model. For example, in \( \text{hasNot()} \) API, a property name should be used as a parameter, and in \( \text{hasLabel()} \) API, a label name is required. Second, some extra constraints are required for \( \text{Aggregate} \). For example, although we use \( \text{Value.sum()} \) and \( \text{min()} \) APIs can follow a \( \text{Value} \), we need to make sure that \( \text{sum()} \) can only be used when \( \text{Value} \) has the Number type.

### 3.2.2 Query Generation

Based on the above traversal model, we first generate syntactically correct Gremlin queries, and then generate the parameter values in the generated Gremlin queries.

**Query statement construction.** Guided by the traversal model in Section 3.2.1, we iteratively generate syntactically correct Gremlin queries step by step. Algorithm 2 outlines this generation process. Initially, \( \text{query} \) is set to a Gremlin graph traversal source \( g \) (Line 1) and the previous traversal step \( \text{preStep} \) is initialized as \( \text{Start} \), i.e., the traversal source \( g \) (Line 2). Grand randomly selects a next Gremlin step, until the maximum query length \( \text{MaxLength} \) is reached or \( \text{Exit} \) condition (e.g., the step type is a Constant value) is satisfied (Line 4-21). Note that, the selected next step must be compatible with \( \text{preStep} \) according to our traversal model. The newly generated step is appended into the end of current \( \text{query} \).

![Figure 6: Traversal model in Gremlin.](image)

**Algorithm 2: Gremlin Query Generation**

```plaintext
1. query ← ‘g’;
2. preStep ← Start;
3. length ← 0;
4. while length ++ < MaxLength do
   5. switch getRandomStep(preStep) do
      6. case Map do
      7.       step ← CreateMap(preStep.type);
5.       case Filter do
      9.       step ← CreateFilter(preStep.type);
5.       case Property do
      11.      step ← CreateProperty(preStep.type);
5.       case Aggregate do
      13.      step ← CreateAggregate(preStep.type);
      14.      end
5.       case Exit do
      15.      break;
      16.      end
   18. end
   19. query ← query + ‘.’ + step.toString();
   20. preStep ← step;
21. return query;
```

Specifically, Grand randomly chooses the next step type based on our traversal model and passes the previous step \( \text{preStep} \) as an argument (Line 5). The Map step mainly contains the APIs that are followed by \( \text{Vertex} \) and \( \text{Edge} \) in Figure 6, e.g., \( \text{out()} \), \( \text{outV()} \) and \( \text{outE()} \). In Filter step, function \( \text{createFilter()} \) can create the detailed operations depicted in Figure 6, including the \( \text{has(Predicate)} \) API, \( \text{hasLabel()} \) API, etc. The \( \text{Property} \) step constructs the \( \text{Value} \) entity, e.g., \( \text{values()} \). The \( \text{Aggregate} \) step constructs \( \text{Aggregate} \) operations, e.g., \( \text{count()} \) and \( \text{sum()} \).

We further use Algorithm 3 to introduce the generation of a \( \text{Filter} \) step. Grand can create various \( \text{Filter} \) operations in Figure 6. We first randomly select one \( \text{Filter} \) operation in our traversal model (Line 2). In this algorithm, we only use \( \text{HasPredicate} \) to explain how we generate a \( \text{HasPredicate} \) filter step (Line 3-11). Other \( \text{Filter} \) steps can be generated similarly. If the input \( \text{type} \) is \( \text{Vertex} \), then a vertex property is randomly selected from the generated...
vertex properties (Line 4-5). Otherwise, an edge property is randomly selected (Line 6-7). According to the data type of the selected property, we create a `CreatePredicate` operation (Line 9) `predicate`. Now, we can create a `HasPredicate` step based on the property name `p.name` and `predicate` (Line 10). Finally, we set the filter’s type as its previous step’ type (Line 11). Thus, Algorithm 2 can further generate the following step according to this filter’s type.

Generating parameter values for Gremlin APIs. Some Gremlin APIs need certain parameters, e.g., a property name `title` used in `values('title')`, and a constant value 234000 used in `eq(234000)`. Without any guidance, these parameters can be generated randomly, resulting in returning empty query results for almost all generated Gremlin queries. To address this issue, we adopt two strategies for generating these parameter values. First, we randomly choose values based on graph database content, i.e., the graph schema and graph data generated in Section 3.1, to increase the probability of returning a non-empty result. For example, for the parameter that needs a property name, we randomly select a property name (e.g., `title`) from the graph schema. Second, we use a random function to generate parameter values according to the constant type. For example, for `eq(Long)` API, we randomly generate a long value 234000 for its parameter. We randomly use these two strategies to increase the probability of returning a non-empty result and avoid overlooking some bugs.

An example for Gremlin query generation. Take the query `g.V().where(values('name').is(eq('Nancy'))).values('gender')` for Figure 2 as an example. As shown in Figure 7, three traversal steps are randomly generated by Algorithm 2, e.g., a Map step (5) in (3), a Filter step (where() in (2)), and a Property step (values() in (6)). Specially, the Filter step includes a nested sub-query, which consists of a Property API (values() in (3)) and a Filter API (is() in (4)). Since the output of the Map step (1) is Vertex, the property name (i.e., name) in the nested sub-query of the Filter step (2) is randomly selected from the generated vertex properties or randomly created with our random function. Besides, the property value of the Predicate API (eq() in (5)) and the property name of the Property API (values() in (6)) can be generated following the same way.

3.3 Differential Testing for GDBs

We use differential testing [45] to detect logic bugs in GDBs. In detail, we first write the same graph data to a group of target GDBs, and then execute the same Gremlin queries on them. By comparing the return results from different GDBs, we identify a discrepancy as a potential bug in these GDBs.

The returned result of a Gremlin query could be a value or a list of vertices, edges or properties. The returned results from different GDBs, we identify a discrepancy as a potential bug in these GDBs. When the query result is a list of vertices or edges, the format of the returned results from different GDBs may be different. That is because different ID generation strategies are used in different GDBs. For example, JanusGraph creates an edge `e[7eo-2kg-iz9-268]` to describe an edge, while Neo4j creates an edge `e[2]` to present the same edge. Thus, we need to convert them to a unified format to make the comparison feasible.

To achieve this, we first generate a unique ID `uID` for each vertex and edge generated in Section 3.1. After we write a vertex or an edge into a target GDB, we retrieve its actual ID `actualID` stored in the target GDB. We use a mapping table to record the mapping relations between `uID` and `actualID` in all GDBs for each vertex and edge. For example, as shown in Figure 8, the vertex with ID 1, has different actual IDs 4152, 1605 and 495992707018129408 in JanusGraph, Neo4j and HugeGraph, respectively. By using the mapping table, we can conveniently convert the list of returned vertices or edges from different GDBs into a unified format.

Specifically, for the returned vertices and edges, five steps are needed in our differential testing as shown in Figure 8. For a generated Gremlin query `Q`, Grand first executes it in the target GDBs (1), and obtains the query results. Then for each GDB, Grand extracts the ID of each vertex or edge in the query results to obtain a list of actual vertex IDs or edge IDs to represent the query result (2). The vertex with ID 1, has different actual IDs 4152, 1605 and 495992707018129408 in JanusGraph, Neo4j and HugeGraph, respectively. By using the mapping table, we can conveniently convert the list of returned vertices or edges from different GDBs into a unified format.

Finally, Grand checks whether the unified query results of the target GDBs are the same (3). A `True` value will be returned showing that all results for `Q` are the same, otherwise, a `False` value will be returned to indicate a potential bug.
4 IMPLEMENTATION

Grand establishes connections to target GDBs before writing the graph into them. For Neo4j, OrientDB, JanusGraph, TinkerGraph and ArcadeDB, Grand uses GraphTraversalSource to connect GDB servers remotely, invokes APIs provided by GraphTraversalSource to directly write each vertex and edge into GDBs (e.g., `g.addV()` and appends properties (e.g., `g.V(vertex).property(k, v)`). After that, Grand uses the Gremlin client to submit the generated queries and obtain query results (e.g., `gremlinclient.submit('g.V()')`).

Additional efforts need to be made to write graph data in HugeGraph, as GraphTraversalSource is not available in HugeGraph’s Java Client. Instead, HugeClient [4] is used to connect HugeGraph Server by sending HTTP requests. The major difference and effort lie on graph schema creation. Instead of writing the graph directly into GDBs, HugeGraph requires setting up graph schema first. Some extra constraints are explicitly introduced in HugeGraph to standardize graph schema. For instance, the frequency of `EdgeLabel` should be set to `multiple`, otherwise only a single edge of each label is allowed between two vertices, which may lead to data overwritten. Beyond that, Grand needs to invoke the specific APIs provided by HugeClient to write data (e.g., `hugeclient.graph().addVertex()`), submit queries (e.g., `hugeclient.gremlin().gremlin('g.V()')`), and obtain query results.

For every test round, Grand stores all the graph information in the log files, including graph schema, graph data and ID mapping tables. The executed queries and the results obtained from target GDBs will be stored as well if exceptions or diverse results are detected. Grand provides the method to restore the graph into target GDBs, HugeGraph requires setting up graph schema first. Some extra constraints are explicitly introduced in HugeGraph to standardize graph schema. For instance, the frequency of `EdgeLabel` should be set to `multiple`, otherwise only a single edge of each label is allowed between two vertices, which may lead to data overwritten. Beyond that, Grand needs to invoke the specific APIs provided by HugeClient to write data (e.g., `hugeclient.graph().addVertex()`), submit queries (e.g., `hugeclient.gremlin().gremlin('g.V()')`), and obtain query results.

Table 1: The GDBs we tested are popular and widely-used

<table>
<thead>
<tr>
<th>GDB</th>
<th>Rank</th>
<th>GitHub Stars</th>
<th>Initial Release</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neo4j</td>
<td>1</td>
<td>9.2k</td>
<td>2007</td>
</tr>
<tr>
<td>OrientDB</td>
<td>5</td>
<td>4.4k</td>
<td>2010</td>
</tr>
<tr>
<td>JanusGraph</td>
<td>8</td>
<td>4.1k</td>
<td>2017</td>
</tr>
<tr>
<td>HugeGraph</td>
<td>26</td>
<td>1.7k</td>
<td>2018</td>
</tr>
<tr>
<td>TinkerGraph</td>
<td>29</td>
<td>1.4k</td>
<td>2009</td>
</tr>
<tr>
<td>ArcadeDB</td>
<td>31</td>
<td>119</td>
<td>2021</td>
</tr>
</tbody>
</table>

Table 5: Evaluation methodology. We use a script to configure testing related parameters, e.g., the number of generated queries (1,000 in our experiment), and the graph database generating related parameters, i.e., the max length of each query (10 in our experiment), the max number of vertex types, edge types, vertices and edges (10, 20, 100, 200 in our experiment, respectively).

We configure Grand to run 15 rounds and generate 1,000 random Gremlin queries in each round. At the beginning of each round, Grand first randomly constructs a testing graph database to the target GDBs (Section 3.1), and then applies 1,000 randomly generated Gremlin queries (Section 3.2.2) on the target GDBs to perform a differential testing (Section 3.3). Each reported discrepancy is logged as a potential logic bug. For each bug reported by Grand, we manually reproduce and analyze it, to verify whether it is a real logic bug. Specifically, three steps are needed as follows. First, Grand may generate a complex query to reveal a discrepancy, which makes it challenging to identify its root cause. So, we manually simplify the query to a simple one, which can trigger the same discrepancy.

5 EVALUATION

To demonstrate the effectiveness of Grand, we evaluate Grand on six widely-used GDBs, and detect real-world logic bugs in them.

5.1 Methodology

Target GDBs. We evaluate Grand on six GDBs, i.e., Neo4j [7], OrientDB [11], JanusGraph [6], HugeGraph [3], TinkerGraph [16], and ArcadeDB [9]. Table 1 shows their DB-Engine Ranking of Graph DBMS [22], GitHub starts, and initial release date. We can see that they are among the most popular and widely-used GDBs. Specifically, TinkerGraph was developed by TinkerPop and natively uses Gremlin as its query language. JanusGraph, HugeGraph and ArcadeDB encapsulate Gremlin Server in their own servers, apply some special optimizations, and also natively use Gremlin to query graph data. OrientDB implements its own TinkerPop3 interfaces, and offers OrientDB-TinkerPop3 distribution. We access Neo4j through the Neo4j-Gremlin plugin [8], which is provided by TinkerPop. For all GDBs, we test their latest release versions when we start this work, i.e., Neo4j 3.2.3 (with Neo4j-Gremlin 3.4.10, not the latest version), OrientDB 3.2.4, JanusGraph 0.5.3, HugeGraph 0.11.2, TinkerGraph 3.4.10, and ArcadeDB 21.12.1. Note that, we use the latest version of Neo4j-Gremlin, but it does not support the latest Neo4j at that time.

Testing methodology. We use a script to configure testing related parameters, e.g., the number of generated queries (1,000 in our experiment), and the graph database generating related parameters, i.e., the max length of each query (10 in our experiment), the max number of vertex types, edge types, vertices and edges (10, 20, 100, 200 in our experiment, respectively).

We configure Grand to run 15 rounds and generate 1,000 random Gremlin queries in each round. At the beginning of each round, Grand first randomly constructs a testing graph database to the target GDBs (Section 3.1), and then applies 1,000 randomly generated Gremlin queries (Section 3.2.2) on the target GDBs to perform a differential testing (Section 3.3). Each reported discrepancy is logged as a potential logic bug. For each bug reported by Grand, we manually reproduce and analyze it, to verify whether it is a real logic bug. Specifically, three steps are needed as follows. First, Grand may generate a complex query to reveal a discrepancy, which makes it challenging to identify its root cause. So, we manually simplify the query to a simple one, which can trigger the same discrepancy.
Second, a discrepancy in Grand cannot tell which GDBs are buggy. So, we manually investigate the expected result of the query in the discrepancy, and then identify which GDBs are buggy. Third, Grand may report different discrepancies for the same bug. We need to understand the root causes of observed discrepancies, and identify whether some discrepancies are caused by the same bug. After filtering out duplicated bugs, we submit an issue for each logic bug to the corresponding community on GitHub.

All experiments were conducted on a cluster with 7 high-performance servers, each equipped with a 64-bit CentOS Linux release 8.0.1905 system, a 125GB RAM, and one 20-core 2.50GHz Intel Xeon Gold 5215 CPU. Specifically, each target GDB was installed in one server.

5.2 Overall Bug Detection Results

Grand takes around 160 seconds on average to perform each testing round. For total 15,000 randomly generated Gremlin queries, 6,046 Gremlin queries (40.3%) return non-empty results. We obtain 709 (47 per round) discrepancies, which may be potential bugs. We carefully reproduce and analyze these 709 discrepancies, and find that all of them are true discrepancies. However, after deep analysis, we find that some discrepancies are caused by the same bug.

After carefully analyzing 709 discrepancies, we obtain 21 logic bugs in the six tested Gremlin-based GDBs. Table 2 shows the statistics of logic bugs that we find. We have submitted these bugs to the corresponding community on GitHub. At the time of writing this paper, 18 bugs have been confirmed by developers, and all of them are previously-unknown bugs. Seven bugs have already been fixed by developers.

The 21 bugs have caused severe consequences for these GDBs. Among them, 18 bugs return an unexpected exception for a valid query, whereas they should not. In this case, users cannot get their expected results correctly. Note that, all these bugs return commonly-used exceptions, e.g., IllegalArgumentExeption, NumberFormatException, NoIndexException and IllegalStateException which can also be returned by invalid queries. The remaining 3 bugs can lead to incorrect query results. In the following, we explain these bugs found in each GDB.

**HugeGraph.** We found nine logic bugs in HugeGraph. Among them, all nine bugs have been confirmed, and three bugs have been fixed. Specifically, seven bugs were caused due to that HugeGraph cannot support some Gremlin APIs correctly, including `between()`, `outside()`, `not()`, or(), `has()`, `hasLabel()` and `order()`. One bug was caused due to that HugeGraph omits boundary values, including infinity value and NaN value. Another one bug was caused by the search constraint of Gremlin APIs that needs to scan the whole table. Even though developers thought users can use alternative queries to avoid the constraint, they still confirmed that they will enhance the usage experience for users after we reported the bug.

**JanusGraph.** We found three logic bugs in JanusGraph. Among them, all three bugs have been confirmed, two bugs have been fixed by developers, and one of the fixed bugs has been added into their milestone version. In detail, two bugs are related to type coercion. For example, JanusGraph cannot correctly handle numeric comparisons when it comes to the infinity value and NaN value. Unless the data type has been explicitly set in the query, JanusGraph will throw a number format exception. Another bug is related to the unique Query Normal Form (QNF) check, in which JanusGraph cannot necessarily generate a QNF in some cases.

**TinkerGraph.** We found three logic bugs in TinkerGraph and all of them were confirmed by developers. In one bug, TinkerGraph cannot perform any type coercion with the property values, which means you cannot query the float or double value stored before. This bug has already been fixed. The second bug was caused due to that TinkerGraph cannot compare BigDecimal with Double/Float infinite value, which means you cannot query the float or double value stored before. Another one bug was caused by the unique QNF check, in which JanusGraph cannot necessarily generate a QNF in some cases.

**Neo4j.** We found three bugs in Neo4j, and all of them were similar to the bugs previously mentioned in TinkerGraph. Actually, this result is not surprising, because the Neo4j-Gremlin we used to query Neo4j is also implemented by TinkerGraph developers. This explains why two different databases meet similar issues.

**ArcadeDB.** We found two bugs in ArcadeDB, which are similar to the second and third bugs in TinkerGraph.

**OrientDB.** We found one bug in OrientDB, which is similar to the second bug in TinkerGraph.

5.3 Bug Analysis

We summarize the 21 logic bugs found by Grand into four categories according to their root causes.

- **Non-robust handling on special values.** Five logic bugs are caused by non-robust handling with special values, e.g., Infinity and NaN. For example, HugeGraph cannot process Infinity or NaN value for Double and Float type. In Figure 9, we assign the value

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**Table 2: Logic bugs that we found in the tested GDBs**

<table>
<thead>
<tr>
<th>GDB</th>
<th>Detected</th>
<th>Confirmed</th>
<th>Fixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neo4j</td>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>OrientDB</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>JanusGraph</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>HugeGraph</td>
<td>9</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>TinkerGraph</td>
<td>3</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>ArcadeDB</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>21</td>
<td>18</td>
<td>7</td>
</tr>
</tbody>
</table>

---

Figure 9: HugeGraph cannot process infinity value for Double type.
Four logic bugs are caused by incorrect logical implementation in tested GDBs. For instance, HugeGraph does not remove duplicate elements when performing range queries using Gremlin APIs like not() and or(). Figure 1 shows such an example. HugeGraph developers stated that HugeGraph has not implemented deduplication for overlapping OR operation for now, and they have added this issue into their TODO list to optimize for OR operation.

5.4 Coverage

All the GDBs we tested are implemented in Java. Thus, we utilize JaCoCo [5] to collect instruction coverage for these GDBs, and ran Grand for 24 hours. The detailed instruction coverage is shown in Figure 12. We can see that Grand can achieve instruction coverage from 16% to 42% for these GDBs, and from 32% to 61% for their query engines, which appears to be low. However, this is expected because we mainly focused on testing Gremlin-specific graph queries. We summarize the main reasons as follows. (1) Some GDBs, e.g., ArcadeDB and OrientDB, are multi-model DBMS, and they also support other data models, e.g., document, key/value, time-series, and full-text. We currently did not test these data models. (2) Some GDBs also support various query languages, e.g., ArcadeDB supports SQL, Cypher, and GraphQL. We cannot test the implementation related to these query languages yet. (3) Some GDBs provide features such as user management, replication, transaction and graph analysis, which we did not test.

6 DISCUSSION

In this section, we first discuss how to generalize Grand, the threats to validity, and the limitations of our approach.

6.1 Generalizing Grand to more GDBs

As the first approach to detecting logic bugs in GDBs, Grand can only be applicable to GDBs that support Gremlin APIs. The core philosophy in Gremlin queries is to construct a subgraph through a traversal model, which is used to query GDBs. Grand’s design mainly depends on this philosophy. Fortunately, many other query languages also adopt this philosophy to query GDBs. Figure 3 shows such an example for Cypher in Neo4j. Therefore, although some GDBs adopt totally different query languages, we believe, the idea of Grand, e.g., traversal model, model-based query generation and differential testing, can be generalizable to these GDBs.

GDBs that utilize the RDF graph model usually adopt SparQL as their query language. SparQL also needs to construct a subgraph similar to Gremlin. As such, Grand’s design philosophy can potentially be adapted to the RDF graph model and SparQL, too.

6.2 Threats to Validity

The main threats to our evaluation are related to the representativeness of our selected GDBs. These six subjects are the most popular open source GDBs that support the Gremlin query language. Neo4j, OrientDB, and TinkerGraph have been developed for more than 10 years, while JanusGraph and HugeGraph are developed actively in the last four years. All of them are well maintained for now. Thus, we think our studied GDBs are representative.
Another threat lies in the manual validation process of logic bugs found in GDBs. We manually reproduce, analyze and deduplicate discrepancies reported by Grand, which may introduce errors due to human error. To make the validation as accurate as possible, three authors analyze all reported discrepancies, and reach consensus for all discrepancies.

6.3 Limitations
Grand has some limitations on finding bugs in Gremlin-based GDBs.

First, Grand mainly focuses on commonly-used Gremlin query APIs. For update APIs (e.g., insert, update and delete graph data), we mainly use them to create databases, and Grand cannot test them systematically. Therefore, logic bugs related to these APIs cannot be found through Grand by now. Actually, we believe Grand can find more bugs when we add more Gremlin APIs in our traversal model.

Second, Grand may miss some bugs due to characteristics of differential testing. Grand cannot detect bugs when the tested GDBs all suffer from the same bug and return the same wrong results.

Finally, although we can automatically find bugs by repeatedly generating and executing Gremlin queries as well as validating the returned results, we still have to manually find and remove duplicated bugs. In the future, we will investigate how to efficiently filter duplicated bugs reported by Grand.

7 RELATED WORK
In this section, we discuss related works that are close to ours.

7.1 Testing of DBMS
Differential testing of DBMS. Differential testing [45] is commonly used in different domains [29, 31, 38, 52] to find bugs. Its key idea relies on passing the same input to the different testing objects and comparing the output. A difference indicates a potential bug. Slutz first presents RAGS [32] to find bugs in DBMS by differential testing. APOLLO [37] uses differential testing to find performance regression bugs in DBMS. CYNTHIA [53] uses differential testing for testing Object-Relational Mapping systems. Since GDBs adopt different storage structures and query languages, these approaches cannot be easily adopted into GDB testing.

Metamorphic testing of DBMS. Metamorphic testing [44] tests software systems by mutating test cases via metamorphic relations. Rigger et al. provide two metamorphic testing approaches [48, 49], namely Ternary Logic Partitioning (TLP) and Non-optimizing Reference Engine Construction (NoREC), to test DBMS. TLP [49] partitions a query into three sub-queries, and detects bugs by comparing the combination of results of three sub-queries with the result of the original query. NoREC [48] compares the execution results of a given optimized query with its non-optimized version, to detect optimization bugs in DBMS. All the above approaches target relational database systems, and can potentially be applicable on GDBs.

Other testing of DBMS. SQLSmith [14] is a fuzzing tool for testing DBMS. It can randomly generate SQL queries as inputs. SQLancer offers Pivoted Query Synthesis (PQS) [50] approach to find logic bugs by randomly selecting a pivot row as oracle and generating random queries containing the selected row to test DBMS. ADUSA [39] translates SQL query to Alloy specification, generates Alloy instance satisfying query conditions in Alloy specification, and further obtains the expected result from Alloy instance. All the above tools target relational database systems, and cannot be applied on GDBs.

7.2 Performance Testing of GDB
Performance benchmarks for GDB. Angles et al. launch the Linked Data Benchmark Council (LDBC) [26] project to develop benchmarks for graph and RDF data management systems. In the project, LDBC social network benchmark (LDBC SNB) [33] consists of a synthetic social network dataset and three workloads with complex graph dependencies. Pacaci et al. [46] further integrates Kafka into LDBC SNB to simulate real-time graph data. Besides, some benchmarks with simple atomic queries are developed. Angles et al. [27] develop a benchmark consisting of social graphs and atomic queries for social network applications. Lissandini et al. [42] develop a larger set of queries and operators, and evaluate the performance of GDBs on both synthetic and real graphs. Kovács et al. [41] develop a benchmark to evaluate different GDBs with Wikidata. All these benchmarks are used to measure performance of GDBs, and cannot be used to detect logic bugs in GDBs.

Performance evaluations for GDB. Fernandes et al. [35] analyze five popular GDBs and evaluate flexible graph schemas, query languages, and scalability of GDBs. Abdelaziz et al. [24] perform an evaluation for representative distributed SPARQL graph databases. Wang et al. [55] evaluate the performance of different queries on LDBC SNB benchmark. Besides, TigerGraph also evaluates its own performance using the LDBC SNB benchmark [1]. These works focus on evaluating the performance of GDBs, and do not consider logic bugs in GDBs.

8 CONCLUSION
In this paper, we propose Grand, an automated differential testing approach, for detecting logic bugs in Gremlin-based graph database systems. Specifically, we design a model-based Gremlin query generation approach to generate syntactically correct and valid test cases, and utilize a data mapping approach to obtain uniform query results in different graph database systems. Our experimental results on real-world graph database systems show that Grand is effective in finding logic bugs. Grand finds 21 previously-unknown logic bugs on six widely-used graph database systems. In particular, 18 bugs have been confirmed and 7 bugs have been fixed by developers.

9 DATA AVAILABILITY
The source code of Grand is available at Zenodo [23].

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