Analysis and Improvement of Optimizer for Query Processing on Graph Store

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Abstract

RDF systems are widely used to store public knowledge bases and process SPARQL queries. A large number of such systems have been proposed in the recent literature to provide low latency and high throughput for concurrent query processing over large RDF data. We perform an in-depth analysis on three key components (cardinality estimation, cost model, and plan enumeration) of the query optimizer to reveal the main issues and challenges on the accuracy and performance for traditional approaches. This calls for a rethink of how to build an accurate and fast query optimizer for modern RDF systems. We introduce a type-centric approach to enhance the accuracy of cardinality estimation prominently, which naturally embeds the lineage of correlated query conditions (triple patterns) into existing type system of RDF data. The preliminary results show that our approach greatly improves the accuracy of query optimization by several orders of magnitude compared to state-of-the-art approaches and provides a better overall performance by reducing execution time or optimization time.

Keywords

Optimizer, Type-centric Estimation, Graph Store, Query Processing

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1 Introduction

Many public knowledge bases [1, 6, 7, 10, 15] are represented and stored as RDF (Resource Description Framework) graphs, where users can issue structured queries on such graphs using SPARQL. Much recent research [8, 16] has been devoted to developing scalable and high performance systems to process SPARQL queries on RDF data by using scan-join or graph-exploration approach.

The query optimization aims to find an optimal query plan such that the execution time is minimized, which is crucial for query performance. While this is one of the most studied problems in the database community, the schema-free nature of RDF data and the emerging graph-exploration scheme for query processing introduce new challenges to generate appropriate statistics, estimate pertinent results, and predict execution time accurately.

In this paper, we first investigate the three main components of the classical query optimizer architecture, as shown in Fig. 1, to reveal the main issues and challenges on the accuracy and performance for existing approaches. For cardinality estimation, the correlation among all of query conditions is crucial to the accuracy, and the statistics and estimation based on two correlated predicates [8, 11, 16] will incur tremendous error on the estimated results. For cost model, the mature model [8, 11] for scan-join approach does not apply to emerging graph-exploration approach, while the initial linear model [16] for graph-exploration approach is not competent for the performance prediction, even just on a single machine. For plan enumeration, with the performance improvement by leveraging advanced software and hardware techniques (e.g., full-history pruning and RDMA [13]),
An RDF dataset is a graph (aka RDF graph) composed by triples, where a triple is formed by (subject, predicate, object). A triple can be regarded as a directed edge (predicate) connecting two vertices (from subject to object). Fig. 2 illustrates a part of the sample graph (G) and the summary of the whole graph. There are three categories of edges linking six types of vertices. SPARQL, a W3C recommendation, is the standard query language for RDF datasets. The major part of SPARQL queries is as follows:

$$Q := \text{SELECT } RD \text{ WHERE } \text{GP}$$

where, GP is a set of triple patterns and RD is a result description. Each triple pattern (TP) is of the form (subject, predicate, object), where each of the subject, predicate and object may denote either a variable (e.g., \( ?X \)) or a constant (e.g., type). The result description contains a subset of variables in GP.

Given an RDF data graph, the SPARQL query searches on the graph for a set of subgraphs, each of which matches all triple patterns by binding pattern variables to values in the graph. For example, the query Q in Fig. 3 asks for all projects (?)Z that were undertaken (ut) by a laboratory which is a sub-organization (so) of an institute. The possible binding over the part of graph G in Fig. 2 is only Pro5. Note that the execution order of triple patterns (i.e., plan) will only impact the performance (much), not the result of the query. Therefore, the RDF system normally relies on the query optimizer to enumerate the valid execution orders to find an optimal query plan (i.e., minimal execution time) from semantically equivalent plan alternatives, such as PL1 and PL2 in Fig. 4. According to different plans, the optimizer estimates the cardinality (e.g., the number of intermediate results) of the plan based on the statistical synopses of RDF data and predicts the execution time of the plan with a cost model (see Fig. 1).
cardinality of a single triple pattern, namely the scan statistics. Second, the number of join partners (i.e., the number of triples for a predicate pair) is used to estimate the cardinality of the join condition on two triple patterns, namely the join statistics. Four cardinalities are precomputed for every predicate pairs joined on subjects or objects. Fig. 5 shows a part of statistics on the sample graph adopted by scan-join systems. For example, so’s scan cardinality is 3000, which can be used to estimate the cardinality of TP2 ((? Y, suborg, ? X)) for Q. As only the objects of so triples and the subjects of tyINS triples may combine together, the so’s join cardinality with tyINS for O = S is 300, and the rest are 0.

To estimate the cardinality of an entire query plan, the optimizer assumes independence among the join of triple patterns and estimates the cardinality of intermediate results gained from the join between two triple patterns recursively, which can be formalized as

$$\text{Card}(TP_{1,2}) = \text{Card}(TP_1) \times \text{Card}(TP_2) \times \text{Sel}(p_1, p_2, JP)$$  \hspace{1cm} (1)

where Card(TP1) and Card(TP2) denote the cardinality of triple pattern TP1 and TP2, respectively. Sel(p1, p2, JP) denotes the join selectivity of the predicate pair (p1, p2) associated with the triple patterns TP1 and TP2, which can be formalized as

$$\text{Sel}(p_1, p_2, JP) = \frac{\text{JoinCard}(p_1, p_2, JP)}{\text{Card}(p_1) \times \text{Card}(p_2)}$$

where JoinCard(p1, p2, JP) denotes p1’s join cardinality with p2 for the way of join partners (p1, p2) (e.g. S = O). For example (see Fig. 6), the cardinality of the first two triple patterns (TP1 and TP2) for PL1 is 300, where the cardinality of TP1 (Card(TP1)) and TP2 (Card(TP2)) are 10 and 3000, and the join selectivity Sel(typeINS, suborg, S = O) is $\frac{300}{10 \times 3000}$.

Based on Equation (1), the cost of an entire plan that is the sum of a specific order of triple patterns ($TP_1, ..., TP_N$). The cardinalities of every scan and join operations are fed into the cost model, which is briefly proportional to the cardinalities with different join operations and the cost of shipping intermediate results. The function parameters need to be measured for a given hardware setting. Finally, a bottom-up dynamic programming (DP) algorithm is used to determine the order of triple patterns that yield the minimal cost. At each DP step, the optimizer calculates the cost of the partial plan considered so far and prunes if the current branch cannot gain the minimal cost any more.

Graph-exploration approach. Instead of joining triple tables, graph exploration on the native graph form is proposed as a new primitive to process the SPARQL queries [4, 12, 13], which starts from a set of vertices and conducts a sequence of graph explorations to generate bindings for each triple pattern. The initial optimizer from Trinity.RDF [12] is inspired by the relational optimizer [11] for the scan-join approach, which models an execution plan as a graph traversal and focuses on the order of directed explorations via predicate (edge). The optimizer uses the size of intermediate results of graph exploration (i.e., the number of paths) as the cardinality and follows the proportional cost model and the DP-based plan enumeration.

The RDF-specific statistical synopses mainly contain two types of statistics associated with predicates for graph exploration. First, the optimizer precomputes the number of distinct subjects ($C_s(p)$), objects ($C_o(p)$), and triples ($C(p)$) for each predicate $p$. Second, the correlation $Cor(p_1, p_2, EP)$ between predicate pairs ($p_1, p_2$) is estimated to denote the number of distinct vertices with both two predicates ($p_1$ and $p_2$) as its incoming/outgoing edges (four combinations selected by $EP$). Fig. 7 illustrates a part of statistics on the sample graph (G) adopted by graph-exploration systems.
The optimizer assumes the cardinality of an entire query plan as the sum of the cardinality of exploring triples with the predicate \( p \), which is estimated as the size of the intermediate results \( R(p) \). Given the binding size of subjects (assume the source vertices) in a triple exploration \( B(s) \), \( R(p) \) and \( B(o) \) (assume the binding size of objects) can be formalized as

\[
R(p) = B(s) \times \frac{C(p)}{C_s(p)}, \quad B(o) = B(s) \times \frac{C_o(p)}{C_s(p)}
\]

Further, the binding size of \( B(s) \) is affected by the last related triple pattern already explored. For exploring triples with the predicate \( p_2 \) from the triples with the predicate \( p_1 \), the correlated binding size \( \hat{B}(v) \) can be predicted by the correlation statistics.

\[
\hat{B}(v) = B(v) \times \frac{\text{Cor}(p_1, p_2, EP)}{C(p_1)}
\]

For example (see Fig. 8), the cardinality of exploring the triple pattern \( (?Y, \text{type}, \text{LAB}) \) in PL1 is 20, where the last binding size \( B(?Y) \) is 300 and the correlation statistic \( \text{Cor}(s_0, t_y \text{LAB}, \text{LAB} \leftarrow \rightarrow) \) is 200. \( C(s_0) \), \( C(t_y \text{LAB}) \), and \( C_s(t_y \text{LAB}) \) are 3000, 200, and 200 respectively.

Finally, a proportional cost model is adopted to predict the execution time, which is a linear combination of the cardinalities for computation cost and the size of bindings for communication cost. Besides, the dynamic programming algorithm is also used in plan enumeration.

3 Analysis of Query Optimization

This section presents an in-depth analysis on the accuracy and performance issues of query optimization.

Cardinality estimation. The main weakness of existing approaches is that they simply assume the independence among triple patterns and only consider at most two correlated predicates. However, we observe that the correlation among all of triple patterns is crucial to the accuracy of cardinality estimation. For example, consider two plans PL1 and PL2 in Fig. 4, the cardinalities in both scan-join and graph-exploration estimation are incorrect and reverses the relative result. The true cardinality of PL2 should be better.

According to the statistical synopses, given 3000 vertices have the predicate \( \text{so} \), only 200 of them also have the predicate \( \text{tyLAB} \). Consequently, given 300 vertices (?Y), the intermediate results becomes 20. But, the possibility of being a LAB is \( \frac{200}{3000} \), for the sub-organization of INS. Fig. 9 shows the true and estimated cardinality for different plans of a single query (L1) on LUBM-2560. The deviation in both two state-of-the-art systems, TriAD [8] (scan-join) and Trinity.RDF [8] (graph-exploration), is extremely high. More importantly, this is a fundamental problem of approaches that estimate the cardinality based on the correlated predicates. A straightforward solution is to keep more statistics for three or more correlated predicates. However, the size of statistics would rapidly increase beyond the memory capability, and it is impossible to precompute all the dependencies between multiple predicates due to the schema-free nature of RDF data.

Cost model. The cost model for the scan-join approach has been well-studied, which thoroughly considers different join operations and the cost of data transferring. Unfortunately, it is quite difficult or impossible to attach scan-join’s cost model to the graph-exploration approach directly. The initial cost model [12] for graph-exploration briefly uses a linear combination of the cardinalities for computation cost and the size of bindings for communication cost. To reveal the importance and necessity of an appropriate cost model, Fig. 10(a) compares the true cardinality and the execution time for the same plan. For brevity, we run the query (L1) on LUBM-2560 using a single machine to eliminate the communication cost. It is obvious that the cardinality alone is not sufficient to predict the execution time exactly. Fig. 10(b) further illustrate several cases with the same cardinality but different computation cost.

Plan enumeration. The optimization time (PLAN) has not received much attention since it is negligible compared to the execution time (EXE) in traditional systems like TriAD (see Table 1). However, with the dramatical performance

![Fig. 9: A comparison btw. estimated and true cardinality for (a) TriAD and (b) Trinity.RDF using L1 on LUBM-2560.](image)

![Fig. 10: (a) A comparison btw. true cardinality and execution time. (b) The different cases with the same cardinality.](image)
improvement by leveraging advanced software and hardware techniques, the optimization time may occupy a notable fraction of the overall query time for selective (light) queries (e.g., L4 in Table 1). Moreover, we observe that the optimization time has nothing to do with the execution time but with the complexity (i.e., the number of triple patterns) of the query. This is a typical dilemma that the heavy query demands an optimal plan by thorough optimizing but the light query demands an acceptable plan by efficient optimizing. Besides, the execution time is not known in advance.

4 Type-centric Estimation

Observations. To overcome the fundamental problem of approaches that estimate the cardinality based on the correlated predicates, the query optimizer needs to find an efficient way to embed the lineage of correlated triple patterns explored so far and pass it on to the next graph exploration. Fortunately, the predicate type is a perfect candidate. W3C has provided a set of unified vocabularies (as part of the RDF standard) to encode the rich semantics, where the predicate type (short for rdfs:type) provides a classification of vertices of an RDF graph into different groups. We observe that the same type of vertices commonly has a similar combination of predicates. For example, in Fig. 2, the instance of LAB has three predicates: so, ut, and tyLAB. Therefore, the combination of predicates in triple patterns can be used to deduce the type of bindings, which may have multiple candidates with different probabilities. On the other hand, the combination of the type of bindings and the predicate in next triple pattern can also be used to deduce the number and the type of next bindings. Moreover, if the predicate type appears in the triple pattern of a given query, which is common (e.g., Q in Fig. 3), it will directly improve the overall accuracy of the estimation.

Type-based statistical synopses. Based on above observation, it makes sense that the type-centric approach uses the correlation statistics of type and predicates as the statistical synopses. Two kinds of type-based statistics are pre-computed during loading RDF data: Type-formation statistics: for each predicate p, Wukong+P precomputes the type-formation array for the subjects/objects, namely C_{i}(p)/C_{o}(p), which returns the type composition and the number of subjects/objects. In Fig. 11, C_{i}(so) returns an array of the type composition and the number of subjects. The total number of subjects is 3000, where ty_{DEF} has 2700, ty_{LAB} has 200, and ty_{INS} has 100. These statistics are usually used to explore the first triple pattern of the plan. Type-derivation statistics: for each correlated predicate p and type, Wukong+P precomputes the type-derivation array for the subjects/objects, namely C_{i}(type,p)/C_{o}(type,p), which returns the type composition and the number of subjects/objects, when exploring the vertex (object/subject) with a deduced type along with a given predicate p. In Fig. 11, C_{i}(ty_{INS},so) returns an array of the type composition and the number of subjects. The total number of subjects is 300, where ty_{INS} has 100 and ty_{LAB} has 200. These statistics are used to explore a triple pattern with a given predicate p from vertices with a deduced type.

Type-centric cardinality estimation. Wukong+P still uses the size of intermediate results of graph exploration (i.e., the number of paths) as the cardinality and estimate the cardinality for each exploration along with triple patterns of the plan, which can be formalized as

\[
\text{Card}_{\text{res}}(\text{TP}_k) = \sum_{i=1}^{n} |C_{i}(p_{k})(\text{ty}_{k-1})| \times \sum_{j=1}^{n} C_{o}(\text{ty}_{k-1})(p_{k})[j] \]  

\[
= \sum_{i=1}^{n} \text{Card}_{i}(\text{ty}_{k})(i) \]  

\[
\text{Card}_{\text{res}}(\text{start}) = \left\{ \frac{\sum_{i=1}^{n} C_{i}(p_1)[i]}{\sum_{i=1}^{n} C_{o}(p_1)[i]} \right\} \quad \text{start} = s_1 \]  

\[
\quad \left\{ \frac{\sum_{i=1}^{n} C_{i}(p_1)[i]}{\sum_{i=1}^{n} C_{o}(p_1)[i]} \right\} \quad \text{start} = s_1 \]  

\[
\quad \left\{ \frac{\sum_{i=1}^{n} C_{i}(p_1)[i]}{\sum_{i=1}^{n} C_{o}(p_1)[i]} \right\} \quad \text{start} = \text{const} \]  

where Card_{res}(TP_k) denotes the result cardinality of the kth triple pattern, and Card_{i}(ty_{k})(i) denotes the cardinality of the ith type in the result of the kth exploration. C_{i}(ty_{k-1}) denotes the number of vertices having such type from statistics.

For the first triple pattern of the plan, there exist two kinds of start points we can choose. For starting from a variable, the cardinality is estimated using Equation (4) by looking up the type-formation statistics (C_{i}(p) or C_{o}(p)). For starting from a constant, the type of the constant is required for

<table>
<thead>
<tr>
<th>#TP</th>
<th>PLAN</th>
<th>TriAD</th>
<th>EXE</th>
<th>PLAN</th>
<th>Wukong</th>
<th>EXE</th>
<th>PLAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>6</td>
<td>2496</td>
<td>621</td>
<td>0.46</td>
<td>429</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>L2</td>
<td>2</td>
<td>4</td>
<td>128</td>
<td>0.18</td>
<td>182</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>L3</td>
<td>6</td>
<td>2496</td>
<td>413</td>
<td>0.44</td>
<td>629</td>
<td>0.31</td>
<td></td>
</tr>
<tr>
<td>L4</td>
<td>5</td>
<td>480</td>
<td>19.9</td>
<td>0.36</td>
<td>0.06</td>
<td>0.09</td>
<td></td>
</tr>
<tr>
<td>L5</td>
<td>2</td>
<td>2</td>
<td>2.6</td>
<td>0.17</td>
<td>8.04</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>L6</td>
<td>4</td>
<td>28</td>
<td>30.8</td>
<td>0.30</td>
<td>0.33</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>L7</td>
<td>6</td>
<td>2496</td>
<td>2654</td>
<td>0.48</td>
<td>555</td>
<td>0.37</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 11: A part of statistics used by Wukong+P.
the total number of (see Equation (2)).

In the last exploration, the predicate \( ut \) was used to estimate the result cardinality of the next bindings. In this exploration, all results were pruned due to not matching the triple pattern. Therefore, the result cardinality in this exploration is able to estimate using Equation (2) based on type-derivation statistics from Fig. 11. The total number of \( ty_{INS} \) is 10. The type-derivation statistics show that the total number of \( ty_{RG} \) and \( ty_{LAB} \) derived from \( ty_{INS} \) along with so edge is 300. Thus, each \( ty_{INS} \) has 100 vertices with the type \( ty_{RG} \) and 200 vertices with the type \( ty_{LAB} \). Therefore, the result cardinality in this exploration is 300 using Equation (3) to combine the type cardinalities. In the third exploration, all \( ty_{RG} \) is pruned due to not matching the triple pattern. In the last exploration, the predicate \( ut \) is explored and the final result cardinality is pruned to 20.

As we can see, the third exploration in PL1 drops the 100 of 300 results, which matches with the case in real query processing. But both scan-join and graph-exploration systems severe under-estimate the prune ratio as \( \frac{200}{300} \). This is because Wukong+P embed the dependencies into the predicate type, while existing systems only consider two correlated predicates.

No type and multiple types. In rare cases, some vertices may have no type. Wukong+P will assign a new virtual type to them according to the combination of their predicates. On the other hand, some vertices may have multiple types.

![Fig. 12: The estimated and true results of two plans in Wukong+P.](image)

### Table 2: A summary of RDF datasets.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#Triples</th>
<th>#Subjects</th>
<th>#Objects</th>
<th>#Predicates</th>
</tr>
</thead>
<tbody>
<tr>
<td>LUBM-2560</td>
<td>352 M</td>
<td>55 M</td>
<td>41 M</td>
<td>17</td>
</tr>
<tr>
<td>LUBM-10240</td>
<td>1,410 M</td>
<td>222 M</td>
<td>165 M</td>
<td>17</td>
</tr>
</tbody>
</table>

Wukong+P will also assign a new virtual type to them according to the combination of their types. The virtual type will be calculated separately, except that the type cardinality of this virtual type will not be pruned if the given type in the triple pattern belongs to the virtual type.

### 5 Future Work

Wukong+P is still an ongoing project, we plan to solve the following issues in future:

**Cost model.** We need a new cost model for graph-exploration systems to consider new features [13], including key-value lookups, full-history pruning, in-place and fork-join execution mode. Inspired by symbolic execution, we plan to feed the complete history of estimated cardinalities and other information (e.g., path pruning) as the history table (intermediate results) into a mimic graph exploration, which provides the detailed behavior of query processing. Furthermore, unlike prior work [12], Wukong+P expects to predict an absolute execution time instead of a relative number. Thus, we will make a tool to measure (only once) the parameters of the cost model for a given hardware and benchmark setting.

**Plan enumeration.** As shown in Table 1, the optimization time may become the bottleneck for light queries (e.g., L4). Currently, Wukong+P will try to estimate one plan selected by some heuristics (e.g., start from the constant of a triple pattern) first and then use a fixed threshold to classify the query into two kinds, heavy or light. Wukong+P will enumerate all of the plans to find the optimal one for heavy queries and directly choose the first plan for light queries. We plan to use a budget-based mechanism for plan enumeration. The optimization budget is the user-defined rate of the least execution time predicted so far. Wukong+P will enumerate and predict plans till the budget runs out or the optimal plan has been found.

### 6 Preliminary Results

**Experimental Setup.** All evaluations were conducted on a 24-core Intel machine, which has two 12-core Xeon E5-2650 v4 processors and 128GB DRAM. We dedicate one processor to run up to 10 worker threads, and use a single thread to generate requests and perform query optimization. We use 2 datasets of Lehigh University Benchmark (LUBM) [2] (see Table 2) and the queries were widely used by many RDF systems [5, 8, 13, 14, 16, 17]. We compare the accuracy and
Wukong+P, we compare the selected and optimal execution thanks to the type-centric approach. The max L1 on LUBM-2560. Wukong+P can achieve negligible errors of cardinality estimation across different systems, we use query optimizer on Wukong [13]. To measure the accuracy performance of Wukong+P against two state-of-the-art approaches, TriAD [8] and Trinity.RDF [12]. Since the source code of Trinity.RDF is not available, we implemented its approaches, TriAD [8] and Trinity.RDF [12]. Since the source code of Trinity.RDF is not available, we implemented its approaches, TriAD [8] and Trinity.RDF [12].

Cardinality estimation. We first compare the estimated cardinality between Trinity.RDF and Wukong+P using all plans (2496) of L1 on LUBM-2560 and LUBM-10240. The sum of the intermediate results in each graph exploration is recorded as the true cardinality. As shown in Fig. 13, the estimated cardinalities in Trinity.RDF extremely deviate from the ideal line, where the estimated and true cardinality are equal. The estimated cardinalities of Wukong+P are very close to the ideal result on both two datasets, which confirms the benefits of the type-centric approach. Table 3 shows the median (50th), 90th, 95th and max (100th) percentiles of the q-error for the cardinality estimation using all plans of L1 on LUBM-2560. Wukong+P can achieve negligible errors thanks to the type-centric approach. The max q-error is still quite close to the optimal value. For TriAD and Trinity.RDF, both of them produce very high q-error (up to 474X deviation).

Query performance. To further study the effectiveness of Wukong+P, we compare the selected and optimal execution time using LUBM-2560. For Wukong, we execute all possible plans for all queries to find the optimal plan (OPT) with the least execution time. Note that we can not achieve the optimal plan for TriAD since it is not very stable for repeated execution. As shown in Table 4, Wukong+P can choose the optimal or near-optimal plan in most cases. For L3 and L7, Wukong+P outperforms Trinity.RDF due to the accurate cardinality estimation. For L1, Trinity.RDF can also choose the near-optimal plan even using a very inaccurate estimator, since the minimal cost plan coincidentally has low execution time. However, the second minimal cost plan has nearly 3X slowdown performance. For light queries (L4, L5 and L6), Wukong+P can also provide comparable performance with near-optimal plans even only enumerate a single plan, thanks to the heuristic mechanism. As expected, the plan time is much smaller than that of Trinity.RDF. Therefore, the overall performance in Wukong+P is still better than Trinity.RDF.

Comparing with the number in original Wukong paper [13] (OSDI16), which uses a heuristic method to choose the plan manually, Wukong+P can still outperform it, especially for heavy queries (e.g., L1 and L7), which have large plan space. Hence, the statistic-based optimizer is critical to improve the performance for RDF systems.

7 Conclusion

This paper proposes a novel type-centric approach for the cardinality estimation, which embeds the lineage of correlated query conditions into the predicate type. The preliminary results show that Wukong+P can improve the accuracy of query optimization by several orders of magnitude compared to state-of-the-art approaches.

Acknowledgments

We sincerely thank the anonymous reviewers for their insightful suggestions and Kai Zeng for sharing his experience to design and implement optimizer for Trinity.RDF. This work is supported in part by the National Natural Science Foundation of China (No. 61772335), the National Key Research & Development Program (No. 2016YFB1000500).

<table>
<thead>
<tr>
<th>Table 4: A comparison of optimal and selected performance (msec) on LUBM-2560. OPT</th>
<th>PLAN</th>
<th>Trinity.RDF</th>
<th>Wukong+P</th>
</tr>
</thead>
<tbody>
<tr>
<td>TriAD</td>
<td>OPT</td>
<td>OSDI16</td>
<td>Trinity.RDF</td>
</tr>
<tr>
<td>L1</td>
<td>621</td>
<td>0.46</td>
<td>427</td>
</tr>
<tr>
<td>L2</td>
<td>128</td>
<td>0.18</td>
<td>102</td>
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<td>GM</td>
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<td>8.01</td>
</tr>
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</table>

Fig. 13: A comparison of cardinality estimation between Wukong+P and Trinity.RDF using L1 on (a) LUBM-2560 and (b) LUBM-10240.

Table 3: Q-error for cardinality estimation.

<table>
<thead>
<tr>
<th>LUBM-2560</th>
<th>TriAD</th>
<th>Median</th>
<th>90th</th>
<th>95th</th>
<th>MAX</th>
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<td>Wukong+P</td>
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<td>1.002</td>
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Wukong+P uses a statistic-based method to choose the plan manually, Wukong+P can still outperform it, especially for heavy queries (e.g., L1 and L7), which have large plan space. Hence, the statistic-based optimizer is critical to improve the performance for RDF systems.
References