PERFORMANCE EVALUATION OF QUERY TRIMMING STRATEGIES IN SEMANTIC CACHING ENVIRONMENT

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Abstract: The Semantic caching is an efficient caching strategy for client-side processing of queries. This strategy involves comparing user queries with previously cached queries and finding the similarities between these queries. These similarities constitute the partial answer to the user query and therefore they would be extracted from the user query. Then only the remainder of the user query would be sent to the server. Therefore, this can reduce significantly not only the communication between client and server and as a result free network bandwidth, but also improves the speed of query processing in a distributed environment. This paper presents simulations for manipulation of multi-table queries and provides extensive simulations for single-table queries in comparison with previous methods.

1 INTRODUCTION

The semantic model for client side caching was first proposed by Dar et al. (Dar et al., 1996). Their study demonstrated the significant improvements in efficiency of semantic caching over traditional page and tuple caching methods. They also explored several of the most important benefits of semantic caching, including a reduction in network traffic and the ability to partially or fully answer some queries without contacting the server.

Ren et al. (Ren et al., 2003) presented a query splitting method which has direct application of Boolean logic. However, their method is very computationally complex and ineffective for queries with medium to large numbers of predicate clauses in the queries. This inefficiency is due to the use of satisfiability concepts which are necessary to generate the probe and remainder queries.

Guo et al. (Guo et al., 1996) analyzed the question of satisfiability-based methods for database query processing. They demonstrated that a method based on restricted satisfiability concepts is potentially solvable in linear time. Also, the authors in (Hao, et al., 2005) and (Li, et al., 2008) used extensive logical rules to restrict the satisfiability problem to a more manageable size. Although these methods make the actual comparison simpler, the introduction of other logical computations largely obviate the improvements in efficiency that they offer.

Makki et al. (Makki, and Rockey, 2010) presented a novel method for semantic caching which sidestepped the complexity of the satisfiability problem by visualizing the data in the user query and cache data as materialized "layers." This visualization method allows for a direct comparison of the upper and lower bounds of the respective semantic segments and should be much more efficient for query processing. However, they did a very limited experiment to compare their visualization method with the Ren et al.'s method.

2 GENERAL TERMS AND DEFINITIONS

The following terms and definitions are derived from those used by previous works Ren et al. (Ren et al., 2003) and Guo et al. (Guo et al., 1996).

A database D, consists of a set of relations $R_{i,}\ldots,$

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R_n, so that D = {R_i, $1\leq i \leq n$}. Each relation R_i is associated with an attribute set, denoted A_{Ri}, and we may represent the attribute set of the entire database by A, where $A = \cup A_{Ri,}\ 1\leq i \leq n$. A **compare predicate**, P, is defined by P = a op c, where a ∊ A, op ∊ {≤, <, ≥, >, =}, and c is a real constant bound. The authors in (Rosenkrantz and Hunt, 1980) and Guo et al., 1996) have demonstrated that introduction of the comparison operator ≠ makes this problem NP-hard over the integer domain. Since we are primarily interested in comparing the efficiency of two query processing methods, we follow both (Ren et al., 2003) and (Makki and Rockey, 2010) in ignoring ≠ comparison in this simulation.

The primary unit with which semantic caching is concerned is the semantic segment or region. A semantic segment is an earlier (either original or decomposed) query, which is stored together with its result in the cache. Formally, a semantic segment is defined as a tuple $<S_R, S_A, S_P, S_C>$, where $S_R \in D$, $S_A \subseteq A$, $S_C = \pi_{Sa}\sigma_{Sp}S_R$, and $S_P = T_1 \vee T_2 \vee ... \vee T_n$, where each T_j is a disjunctive of predicates, such that $T_j = P_1 \wedge P_2 \wedge ... \wedge P_k$. Each a in P_k, or each predicate term, is such that $a \in A$ of S_R.

A user query Q is a semantic segment $<Q_R, Q_A, Q_P, Q_C>$ which is introduced into the cache for comparison. Semantic caching methods split Q into two new, discrete queries: the probe query $Q_{PQ,}$ and the remainder query Q_{RQ}, such that $Q_{PQ} \cup Q_{RQ} = Q_C$ and $Q_{PQ} \cap Q_{RQ} = \emptyset$. Here, Q_C is equivalent to directly querying the server without consulting the cache; while Q_{PQ} retrieves the data which is available in the semantic regions of the cache, since it is the intersection of the data sets of S and Q. And we may define the probe query formally as $Q_{PQ} = Q_P \wedge S_P$. The remainder query requests the data not available in the cache, and can thus be considered $Q_{RQ} = Q_P \wedge \neg S_P$.

3 RELATED WORK

Query trimming, the mechanism of splitting the user query into the probe and remainder queries, is one of the most computationally intensive sections of any semantic caching method. As mentioned above, the method proposed by (Ren, et al., 2003) uses satisfiability concepts. The visualization method of (Makki and Rockey, 2010) on the other hand, seems to adopt a much simpler approach to the issue of query trimming. In this Section, we will outline first the method used by (Ren, et al., 2003) and then the visualization method of (Makki and Rockey, 2010) for query processing, concluding with complexity analysis of the two methods.

3.1 Ren et al.'s Method

The method proposed by (Ren, et al., 2003) for query trimming follows directly from the formal definitions, explained in Section 2, for the probe and remainder query. This method uses Boolean logic to compare the predicate clauses of the user query with those of the semantic regions in order to generate equations of similar form for sending to the cache and server. Recall that we define the probe query as $Q_{PQ} = Q_P \wedge S_P$ and the remainder query as $Q_{RQ} = Q_P \wedge \neg S_P$. By solving these two satisfiability problems, the Ren et al.'s method locates the intersections between the user query (Q_P) and the semantic sections in the cache (S_P). This method is intuitively straightforward and consistently generates an accurate description of Q_{PQ} and Q_{RQ}.

Though the details of implementation differ among the previous proposed algorithms, the general model is consistent in its use of two separate subroutines to compute Q_{PQ} and Q_{RQ}. Further, though different methods of solving the satisfiability problem have been proposed, all of them seek to solve the same definitions of the probe and remainder queries. These overriding similarities enable general analysis of the Ren et al.'s method to proceed without detailed implementation of each individual algorithm.

Let us consider below an example of calculating Q_{PQ} and Q_{RQ} based on S_P and Q_P (Notice the complexity introduced by the negation of S_P in the Q_{RQ} term.)

$S_P = (x \geq 10 \wedge x \leq 15 \wedge y \geq 5 \wedge y \leq 20) \vee (x \geq 5 \wedge x \leq 20 \wedge y \geq 2 \wedge y \leq 10)$

$Q_P = (x \geq 8 \wedge x \leq 17 \wedge y \geq 3 \wedge y \leq 8)$

Probe Query:

$Q_{PQ} = Q_P \wedge S_P = (x \geq 8 \wedge x \leq 17 \wedge y \geq 3 \wedge y \leq 8) \wedge ((x \geq 10 \wedge x \leq 15 \wedge y \geq 5 \wedge y \leq 20) \vee (x \geq 5 \wedge x \leq 20 \wedge y \geq 2 \wedge y \leq 10))$

Remainder Query:

$Q_{RQ} = Q_P \wedge \neg S_P =$

$(x \geq 8 \wedge x \leq 17 \wedge y \geq 3 \wedge y \leq 8) \wedge \neg ((x \geq 10 \wedge x \leq 15 \wedge y \geq 5 \wedge y \leq 20) \vee (x \geq 5 \wedge x \leq 20 \wedge y \geq 2 \wedge y > 10)) \equiv (x \geq 8 \wedge x \leq 17 \wedge y \geq 3 \wedge y \leq 8) \wedge (\neg (x \geq 10) \vee \neg (x \leq 15) \vee \neg (y \geq 5) \vee \neg (y \leq 20)) \wedge (\neg (x \geq 5) \vee \neg(x \leq 20) \vee \neg (y \geq 2) \vee \neg (y > 10)) \equiv (x \geq 8 \wedge x \leq 17 \wedge y \geq 3 \wedge y \leq 8) \wedge (x < 10 \vee x > 15 \vee y < 5 \vee y > 20) \wedge (x < 5 \vee x > 20 \vee y < 2 \vee y \leq 10) \equiv (x \geq 8 \wedge x \leq 17 \wedge y \geq 3 \wedge y \leq 8) \wedge (x < 5 \vee (x < 10 \wedge y < 2) \vee (x < 10 \wedge y < 10) \vee x > 20 \vee (x > 15 \wedge y < 2) \vee (x > 15 \wedge y > 10) \vee (x < 5 \wedge y < 5) \vee (x < 20 \wedge y < 5) \vee y < 2 \vee (x < 5 \wedge y > 20) \vee (x > 20 \wedge y > 20) \vee y > 20)$

Figure 1: A sample query processed using the Ren et al.'s method.

Despite its accuracy, a significant disadvantage is posed by the logical derivation of the Ren et al.'s method from the formal definitions of Q_{PQ} and Q_{RQ}. Because of the negation of S_P involved in generating the remainder query, the calculations that this method requires often become very intense quickly. Since the Boolean negation operations exponentially increase the number of clauses in the problems to which they are applied, the Ren et al.'s method often spends most of its execution time calculating Q_{RQ}. This is particularly the case when there is a large number of compare predicates to begin with in the user query or a large number of semantic sections in the cache. The efficiency of the Ren et al.'s method is thus unfortunately dependent on the complexity involved in solving $Q_{PQ} = Q_P \wedge S_P$ and $Q_{RQ} = Q_P \wedge \neg S_P$. In addition, previous algorithms' consideration of the attributes x and y as coordinates of the semantic regions in a two-dimensional plane is not compatible with the reality of database tables.

3.2 Visualization Method

The visualization method for query trimming proposed by (Makki and Rockey, 2010) was intended to avoid the complexity of the satisfiability problem involved in the Ren et al.'s method. The method's most important difference from previous algorithms rests in its use of relation pointers to represent each compare predicate. In other words, each segment S will be presented by k relation pointers, where k is the number of compare predicates in S. We can call the set of all the relation pointers in the user query Q_{RP} and the set of those in the cache $C_{RP} = k_{S1} \vee k_{S2} \vee ... \vee k_{Sm}$, where $S_1, ..., S_m$ are the semantic segments stored in the cache.

By sorting the compare predicates of both Q_{RP} and C_{RP} by means of these relation pointers, the method is able to process the predicates as individual units and thus directly find areas of intersection between them. The visualization algorithm details a method of comparison of upper and lower bounds to do this comparison; importantly, this operation is identical to the bounds' comparison employed in the final stage of many satisfiability based methods.

Given the formal definitions of Q_{PQ} and Q_{RQ}, we recognize that the visualization method must have a description in the language of satisfiability. In fact, this method essentially reframes the satisfiability problem of the Ren et al.'s method into a much simpler form. By directly comparing the relation pointers, the method implicitly finds the area of intersection between the user query and the cached segments, or $Q_{PQ} \approx Q_{RP} \cap C_{RP} \approx Q_P \wedge S_P$.

Rather than comparing some negation of the pointers to find Q_{RQ}, the visualization method removes this set of relation pointers from the whole set of compare predicates in the original user query: $Q_{RQ} = Q_{RP} - Q_{PQ}$. The real advantage of the use of relation pointers in the visualization method becomes obvious at this point, as this removal operation in linear time would be impossible without the use of relation pointers. With them, the calculation of the remainder query becomes a matter of simple subtraction, and eliminates the need for the complex negations of the Ren et al.'s method. This difference represents a significant improvement in efficiency in visualization method. Finally, this reduced set of pointers remaining in Q_{RP} and the set of overlapping pointers earlier identified between Q_{RP} and C_{RP} can be easily translated back into query form as Q_{RQ} and Q_{PQ}, respectively.

3.3 Complexity Analysis

Analysis of the algorithm presented by Ren et al. suggests that their method should be of order $O(n^k)$, where $k \geq 2$, since the computation of Q_{RQ} is alone of order $O(n^2)$ in many cases. Simulations of Ren et al.'s method by (Ren, et al., 2003), (Guo, et al., 1996), (Hao, et al., 2005) have all produced results that can be best matched to exponential curves.

Analysis of the algorithm presented by (Makki and Rockey, 2010) suggests that the visualization method should be of order $O(n)$, since the comparisons involved occur individually to each set of relation pointers. Previous simulations have not included a large enough sample set to allow curve matching.

4 SIMULATION

The previous simulations of the methods of (Ren, Dunham, et al., 2003) and (Makki and Rockey, 2010) have been limited to queries requesting data from only one table (Ren, et al., 2003), (Guo, et al., 1996), (Makki and Rockey, 2010). We extended our simulation to model join queries, where users may request data from two or more tables joined by the specification of a join condition. This section provides the simulation result not only for join queries but also for single table selection query.

4.1 Join Queries

This section provides an overview of the setup, test cases, and results of our join queries simulation.

In order to make the comparison between the two methods as clear and fair as possible, we began our simulation setup by identifying points of similarity in the Ren et al. and visualization algorithms. We developed an efficient method for modelling a small cache and reading in user queries and implemented the two query processing algorithms with two programs based on this modelling method. By using the same data structure in both programs to contain our simulated cache, user queries, temporary remainder query (after processing each individual semantic region), and so on. We were able to produce two streamlined programs that worked in much the same way, except for the specific methods of query trimming. This approach allowed us to test the efficiency of the query processing trimming methods directly. Both programs were based on the use of an original object class, `RelationPredicate()`, which contained the table name, primary keys, attributes, and compare predicates for each query. Each program was written in Java and ran on a Pentium processor running Windows Vista with 2 GB of RAM.

4.1.1 Test Cases

Following similar simulations conducted in (Ren, et al., 2003), (Guo, et al., 1996), (Hao, et al., 2005) and (Li, et al., 2008), we chose to compare the two programs on the basis of execution time. We modelled growing query complexity by gradually increasing the number of semantic regions to be processed. Since this method of measuring time sometimes produces wildly varying results because of other operations running on the system, we ran each simulation 15 times and computed the mean of the middle 10 results, allowing us to discard obviously exotic times. We selected a variety of test cases (Table 1 lists the test queries), ranging from full containment (no remainder query generated) to no intersection between the user query and the semantic region (no probe query generated).

4.1.2 Results for Join Queries

Over the 10 cases that we tested, a consistent pattern of differing efficiencies between the Ren et al. and visualization methods clearly emerged. The visualization method's execution time increases linearly, as we predicted, while the Ren et al. method's execution time increases exponentially in some cases.

Table 1: Test queries for Case 1 through 5.

Q1	Select t1.x, t1.y, t2.x, t2.y from t1, t2 where t1.x>=3& t1.x<=8& t1.y>=8&t1.y<=12&t2.x>=4&t2.x<=11&t2.y>=4 & t2.y<=10;
Q2	Select t1.x, t1.y, t2.x, t2.y from t1, t2 where t1.id=t2.id& t1.x>=0&t1.x<=2&t1.y>=0&t1.y<=2&t2.x>=0&t2.x<=2& t2.y>=0& t2.y<=2;
Q3	Select t1.x, t1.y, t2.x, t2.y from t1, t2 where t1.id>=t2.id& t1.x>=5&t1.x<=8&t1.y>=6&t1.y<=8&t2.x>=6&t2.x<=7& t2.y>=5&t2.y<=7;
Q4	Select t1.x, t1.y, t2.x, t2.y from t1, t2 where t1.id>=t2.id& t1.x>=1&t1.x<=2&t1.y>=6&t1.y<=8&t2.x>=2&t2.x<=15& t2.y>=2&t2.y<=7;
Q5	Select t1.x, t1.y, t2.x, t2.y from t1, t2 where t1.id=t2.id& t1.x>=0&t1.x<=10&t1.y>=0&t1.y<=20&t2.x>=5&t2.x<=10 &t2.y>=2&t2.y<=7;
Q6	Select t1.x, t1.y, t2.x, t2.y from t1, t2 where t1.id=t2.id& 1.x>=3& t1.x<=11&t1.y>=9&t1.y<=14&t2.x>=8&t2.x<=13 & t2.y>=9 & t2.y<=13
Q7	Select t1.x, t1.y, t2.x, t2.y from t1, t2 where t1=t2.id& t1.x>=3&t1.x<=8&t1.y>=8&t1.y<=12&t2.x>=4&t2.x<=11 & t2.y>=4&t2.y<=10;
Q8	Select t1.x,t1.y,t2.x,t2.y from t1,t2 where t1.id=t2.id& t1.x>=0& t1.x <=2&t1.y>=0&t1.y<=2& t2.x>=0&t2.x<=2& t2.y>=0&t2.y<=2;
Q9	Select t1.x,t1.y,t2.x,t2.y from t1,t2 where t1.id>=t2.id& t1.x>=5 &t1.x<=8&t1.y>=6&t1.y<=8&t2.x>=6&t2.x<=7& t2.y>=5&t2.y<=7;

Case 1: No Intersection

Figure 2 models the performance of the two methods for two test queries that represent the case where there is no probe query generated (Q_{PQ} = Ø). For both examples (Query2 and Query4), the visualization method is clearly more efficient than the Ren et al.'s method as the number of semantic regions increases (Note: Query 2 and Query 4 of visualization have completely overlapped in the Figure 2).

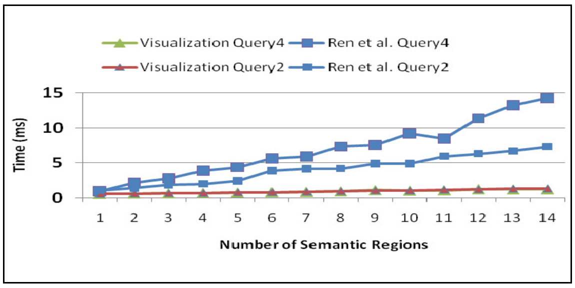


Figure 2: No Containment.

Case 2: Full Containment

Figure 3 models performance for our other base case, where there is no remainder query because the user query is fully contained within a semantic region in cache ($Q_{RQ} = \varnothing$). Because both algorithms exit the query trimming process as soon as a null remainder query is returned, which happens after semantic region 5, both methods remain consistent as further new semantic regions are added.

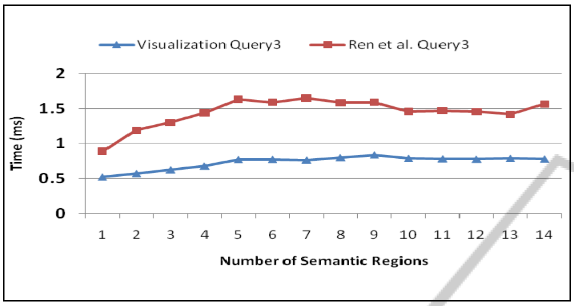


Figure 3: Full Containement.

Case 3: Hybrid Query Trimming I

Figure 4 models performance for two relatively small user queries that require hybrid query trimming over both tables.

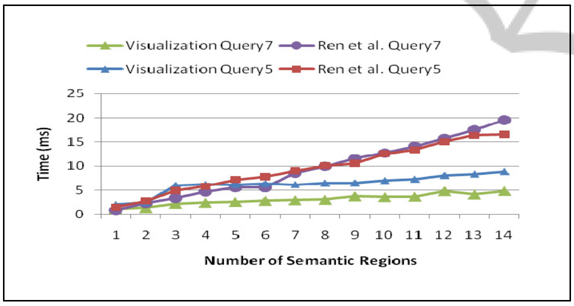


Figure 4: Hybrid Trimming I.

Hybrid trimming means that a semantic region shares some columns and rows of those columns with the query (see Figure 5). For both examples (Query6 and Query7), the visualization method is more efficient than the Ren et al.'s method as the number of semantic regions increases.

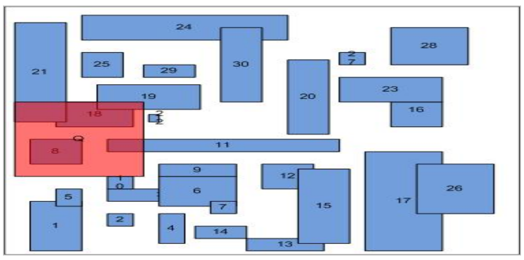


Figure 5: This box models a user query (red box) that requires hybrid trimming of the semantic regions (blue boxes), since it needs both "vertical" and "horizontal" trimming.

Case 4: Hybrid Query Trimming II

Figure 6 models performance for a user query that requires the hybrid query trimming over a larger area of the cache. It places upper and lower bounds on every attribute selected. This increase in the complexity of the probe and remainder query has noticeable effects in the efficiency of the Ren et al.'s method, which grows in execution time sharply, while the visualization method grows consistently.

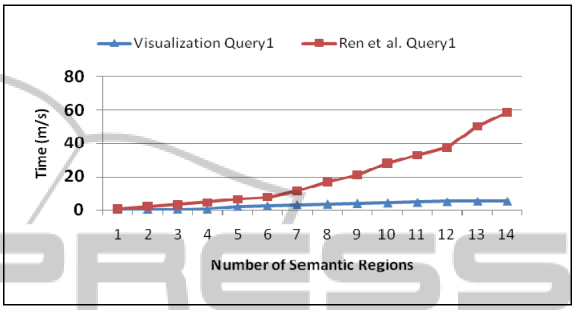


Figure 6: Hybrid Trimming II.

Case 5: Hybrid Query Trimming III

Figure 7 models performance for two user queries that require more complex hybrid query trimming over a larger area of cache.

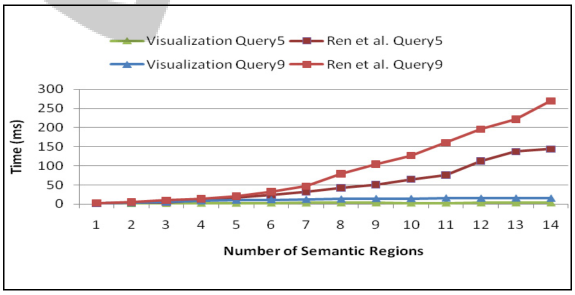


Figure 7: Hybrid Trimming III.

These queries were specifically written to model a situation in which a query intersects with many different semantic regions. The differences in efficiency between the Ren et al. and visualization methods are extremely pronounced in these cases, as the graph of the Ren et al.'s method begins to assume an exponential shape. To offer perspective on this figure, the Ren et al.'s method took (on average) 17 times as long as the visualization method to generate the probe and remainder queries over 15 regions for Query9, and 47 times as long for Query5, demonstrating the increased efficiency of the visualization method for multiple-table joins.

4.2 Simple Select Queries

In this section we extended (Makki and Rockey, 2010)'s simulation of single-table queries by enlarging the number of semantic regions used, which allowed us to obtain a better comparison of the Ren et al. and Makki et al.'s methods. We again made use of the `RelationPredicate()` object class for both programs. This object contains the attributes, compare predicates, table names, and primary keys for each query submitted by the user or stored in cache, making comparisons on the basis of the attributes or primary keys simple. Each program was written in Java and ran on a Pentium processor running Windows Vista with 2 GB of RAM.

4.2.1 Test Cases

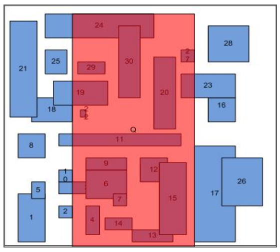
As in our multiple-table query simulation, we modelled an increase in query complexity by gradually increasing the number of semantic regions to be processed, beginning with 2 and progressing up to 30 regions stored in the model cache. We again chose a variety of test cases, from full containment of the user query to no intersection between the query and the semantic regions stored in cache (Table 2 lists the five test queries). Since we were interested in observing the change in efficiency of the respective methods as the complexity of the query increased, several of these cases represented overlaps and expansions of each other. Again, this large sample set allowed us to create graphs to evaluate our complexity analysis.

Table 2: Test queries for Case1 through 5.

Q1	Select x, y from t where x>60&x<70& y>87&y<97;
Q2	Select x, y from t where x>70&x<78&y>8&y<18;
Q3	Select x, y from t where x>2&x<27&y>35&y<65;
Q4	Select x, y from t where x>22&x<52&y>2&y<77;
Q5	Select x, y from t where x>25&x<70&y>3&y<100;

4.2.2 Results for Simple Select Queries

Over the 10 cases that we tested, a consistent pattern of differing efficiencies between the two methods of Ren et al. and Makki et al. quickly emerged. The following is a sample of five specific cases that illustrate in detail the differences between the two methods, and serves as a fair representation of the whole test set in general. These queries can be modelled in the cache as shown in Figures 8a, 8b.



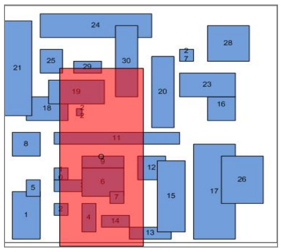


Figure 8a: Models Query4. Figure 8b: Models Query5.

Case 1: No Intersection

Figure 9 models the performance of the two methods for one of our two base cases (Query1), where there is no probe query. Visualization is clearly more efficient than Ren et al. as the number of semantic region increases.

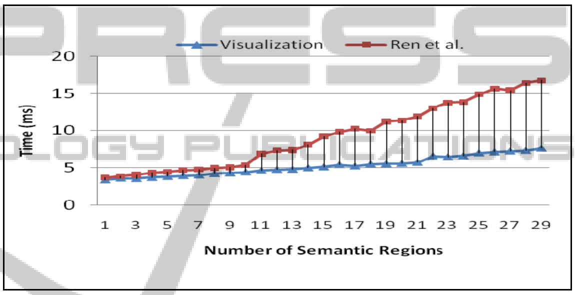


Figure 9: No Intersection.

Case 2: Full Containment

Figure 10 models the performance for our other base case, where there is no remainder query because the user query is fully contained within a semantic region in cache (Query2). Again, visualization remains consistent as the Ren et al.'s method execution time continues to rapidly grow.

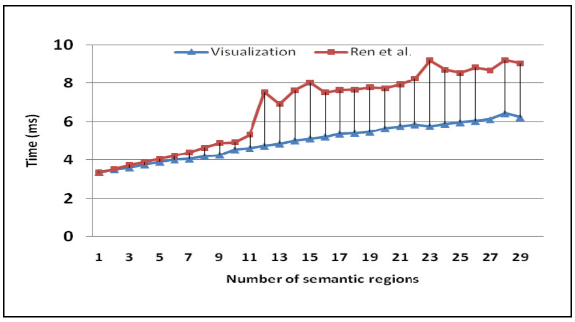


Figure 10: Full Containment.

Case 3: Hybrid Query Trimming I

Figure 11 models performance for a user query that requires hybrid query trimming over a relatively small area in a single table (Query3).

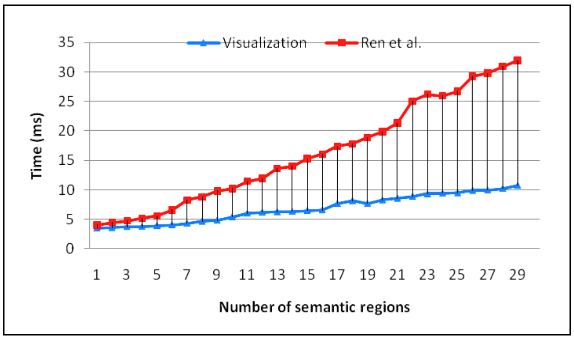


Figure 11: Hybrid Trimming I.

Case 4: Hybrid Query Trimming II

Figure 12 models the performance for a user query that requires hybrid query trimming over a larger area of cache (Query4; see Figure 8a). This increase of complexity has noticeable effects in the efficiency of the Ren et al.'s method, which grows in execution time sharply.

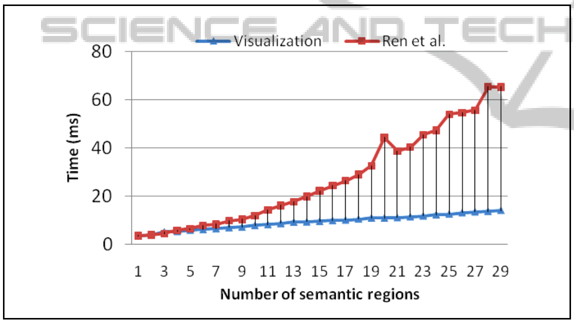


Figure 12: Hybrid Trimming II.

Case 5: Hybrid Query Trimming III

Figure 13 models performance for a user query that requires hybrid query trimming over a still larger area of cache (Query5; see Figure 8b).

The differences in efficiency between the Ren et al. and visualization methods are even more pronounced in this case, as the graph for Ren et al.'s method assumes a definitively exponential shape while the visualization grows very slowly.

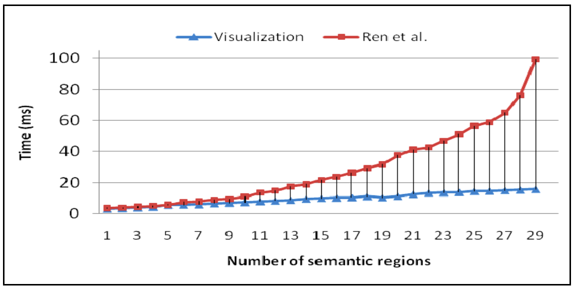


Figure 13: Hybrid Trimming III.

Figure 14 overlays the graphs of the five previous cases over each other in order that a scalar comparison can be made.

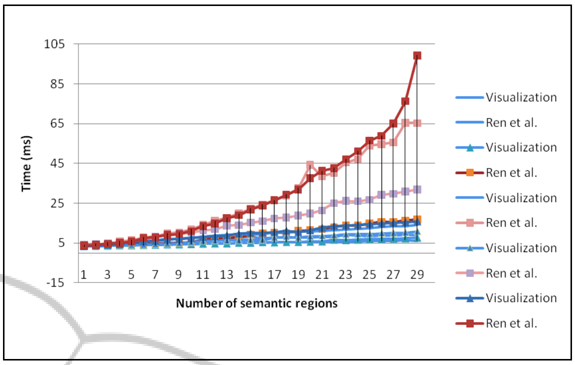


Figure 14: Overlay of 5 Cases.

It is immediately obvious from this figure that the efficiency of the Ren et al.'s method varies drastically depending on the particular query being processed, while the visualization method is of nearly identical efficiency and grows linearly no matter what query is being processed. While this variation means that in some cases (such as full containment) Ren et al.'s method may be only slightly less efficient than the visualization method, visualization is consistently a much more efficient algorithm than Ren et al. Further, it is clear that the more complex the user query is, the more closely the Ren et al.'s method follows an exponential growth pattern, while visualization remains linear, confirming our previous analysis.

5 CONCLUSIONS

This paper compared a new technique for semantic caching, visualization, with the previous Ren et al.'s method with regards to complexity and efficiency. Both methods were explained and their relationships to the problem of satisfiability were explored. Our initial complexity analysis of the Ren et al. and visualization algorithms was supported by our two simulation studies of the two methods, where the visualization method proved consistently more efficient--O(n)--than the Ren et al.'s method as the complexity of the query increased for both single and multiple table queries. This finding demonstrates that the visualization method is a faster and simpler method for query optimization and processing and it represents a significant improvement over previous methods.

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