TASK: An Efficient Framework for Instant Error-tolerant Spatial Keyword Queries on Road Networks

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ABSTRACT

Instant spatial keyword queries return the results as soon as users type in some characters instead of a complete keyword, which allow users to query the geo-textual data in a *type-as-you-search* manner. However, the existing methods of instant spatial keyword queries suffer from several limitations. For example, the existing methods do not consider the typographical errors of input keywords, and cannot be applied to the road networks. To overcome these limitations, in this paper, we propose a new query type, i.e., instant error-tolerant spatial keyword queries on road networks. To answer the queries efficiently, we present a framework, termed as TASK, which consists of index component, query component, and update component. In the index component, we design a novel index called reverse 2-hop label based trie, which seamlessly integrates spatial and textual information for each vertex of the road network. Based on our proposed index, we devise efficient algorithms to progressively return and update the query results in the query component and update component, respectively. Finally, we conduct extensive experiments on real-world road networks to evaluate the performance of our presented TASK. Empirical results show that our proposed index and algorithms are up to 1-2 orders of magnitude faster than the baseline.

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1 INTRODUCTION

Geo-textual objects associated with both geographical and textual information are ubiquitous in daily life, such as restaurants, hotels, shopping malls, etc. In the literature, many types of spatial keyword queries have been studied [7, 11], e.g., top-k spatial keyword queries [12, 34], reverse spatial keyword queries [16, 27], why-not spatial keyword queries [6, 45], continuous spatial keyword queries [14, 36], to name but a few. In this paper, we focus on instant spatial keyword queries [19, 32, 47].

Instant queries, a.k.a., *search-as-you-type* or *type-ahead search*, return query results on-the-fly when users type in a query keyword character-by-character [3, 21–23]. They allow users to browse the results during typing characters, which can immensely improve user experience. [19, 32, 47] investigate the instant queries for spatial databases (in this paper, we refer to this type of instant queries as instant spatial keyword queries). Specifically, with every character of keyword being typed in, the instant spatial keyword queries return geo-textual objects that are relevant to the query inputs in terms of text and location. Sometimes, typing a complete keyword is cumbersome and also susceptible to errors. The instant spatial keyword queries save users from typing in complete keywords and thus are helpful for users in real-world applications. As an example, assume that a user (i.e., the red circle in Figure 1) wants to go to a restaurant called "Mama seafood" for dinner, and uses the location based service (LBS) to find the location. As shown in Figure 1, as soon as the user types in "Ma", the queries can return the results containing "Mama seafood" for her/him.

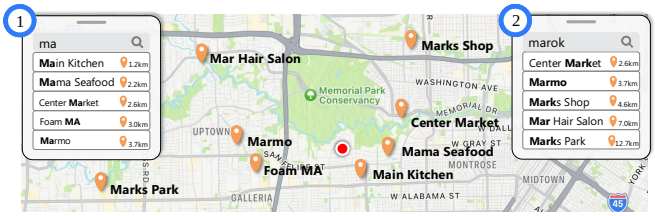

Figure 1: A motivating example

However, the state-of-the-art methods of instant spatial keyword queries [19, 32, 47] suffer from several limitations.

- The existing methods are mainly designed for the Euclidean space. For example, the bound-materialized trie proposed in [32] employs grid to index the space. Both the filtering-effective hybrid index [19] and prefix-region tree [47] leverage R-tree for the space indexing. All those techniques cannot be applied to road networks since they use different metrics to compute the distance between two objects. In real applications, it is straightforward and more practical to query the geo-textual data on road networks [1, 17, 20, 29, 31, 42]. Hence, it is necessary to develop techniques for instant spatial keyword queries on road networks.
- The existing methods do not consider the typographical errors of input keywords. Sometimes, typing accurately is a tedious task, and the users' inputs tend to contain typographical errors, especially for mobile devices. Consequently, it is critical for the instant spatial keyword queries to tolerate typos [30, 33, 35, 37, 48], which can help users query in a friendly way. Thus, it motivates us to consider the error tolerance for the instant spatial keyword queries.
- The traditional instant spatial keyword queries mostly focus on the cases where users type in queries character-by-character. Nevertheless, some common yet important cases

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Table 1: Taxonomy of representative related work and our work

Category	Index	Error tolerant	Multiple keywords	Search as you type	Character deletion	Non-tail operations	Road network
Instant spatial keyword queries	Bound-Materialized Trie [32]	✘	✘	✔	✘	✘	✘
	Filtering-effective hybrid index (FEH) [19]	✘	✘	✔	✘	✘	✘
	Prefix-region tree (PR-Tree) [47]	✘	✔	✔	✘	✘	✘
Spatial keywords queries over road networks	Map B-tree and inverted file [31]	✘	✘	✘	✘	✘	✔
	Compact tree [29]	✘	✘	✘	✘	✘	✔
	LB Index and KT Index [20]	✘	✔	✘	✘	✘	✔
	Keyword separated index (K-SPIN) [1]	✘	✔	✘	✘	✘	✔
Instant spatial keywords queries over road networks	**Reverse 2-hop label based trie (Our work)**	✔	✔	✔	✔	✔	✔

are ignored. For instance, users may (i) delete characters during the query, and (ii) add/delete characters anywhere in the query. Considering these cases can greatly enrich the instant spatial keyword queries.

To overcome these limitations, in this paper, we study a new problem, i.e., instant error-tolerant spatial keyword queries on road networks. Specifically, given a road network including geo-textual objects, a query location, and a query string that may have typographical errors, the instant error-tolerant spatial keyword queries return top-k geo-textual objects that are the most relevant to query location and query string. When the query string updates, e.g., the users input new characters to the query string or delete some characters from the query string, the queries should update the top-k geo-textual objects instantly. Our studied problem has wide applications in LBS. For example, in Figure 1, assume that the user wants to query "Marks shop", and starts typing in a string "Ma". Then, five geo-textual objects containing the prefix "Ma" are quickly returned. However, the desired "Marks shop" is not in the results. Next, the user proceeds to type in the string "Marok", where a typo is contained. The queries tolerate the typo, and return new results containing "Marks shop". It is worth mentioning that the traditional instant queries only deal with the cases of typing keywords character-by-character. Our work also considers the deletion of characters, which is beneficial in real applications. As an example, if a user finds a typo in the input string, she/he can delete the typo, and input correct characters for more accurate queries.

In the literature, many indexes have been proposed to handle the instant spatial keyword queries and spatial keyword queries on road networks, as summarized in Table 1. Since those indexes do not take all the requirements of our problem into consideration, they cannot be applied to tackle our problem. To this end, we present a novel index called reverse 2-hop label based trie (R2T) to answer the instant error-tolerant spatial keyword queries on road networks. R2T consists of two parts, i.e., *reverse 2-hop label* and *trie*. Specifically, the reverse 2-hop label is based on 2-hop labeling techniques [10], which enables efficient calculation of the distance between two vertices. With the help of the reverse 2-hop label, R2T is capable of efficient distance computation during the query processing. For the textual information, we employ trie that can efficiently support characters matching. The complete trie is complex and large, which is not efficient for queries since we need to traverse it multiple times. Thus, we design a novel structure called *node array* to store partial trie for each vertex with respect to the reverse 2-hop label. We demonstrate that after getting 2-hop label, R2T can be constructed in $O(\log^2 |V|)$ time, and the size of R2T is bounded by $O(\log |V|)$, where $|V|$ is the road network size. Moreover, we have discussed the index maintenance for dynamic road networks.

Based on R2T, we devise efficient algorithms to support instant error-tolerant spatial keyword queries on road networks, including *instant query algorithm* and *instant update algorithm*. The instant query algorithm aims to return the results when users type in characters for the first time. It first traverses the complete trie to get the active nodes, which contains the candidate results, and then, it visits the R2T to progressively find the geo-textual objects that are the most relevant to the query location and query string. The instant update algorithm is to update the query results according to the updated query string. To avoid querying from the scratch, we design *query information inheritance mechanism* to make full use of previous query processing information, which can dramatically improve the query performance. Furthermore, we extend our algorithms to support multiple query strings.

Our key contributions are summarized as follows:

- We identify and formalize the problem of instant error-tolerant spatial keyword queries on road networks, which is rooted in real-world applications. To the best of our knowledge, it is the first attempt to investigate this problem.
- We design a novel index called R2T, which seamlessly integrates the spatial and textual information for each vertex of the road network to facilitate the queries. Efficient algorithms are also proposed to construct and maintain R2T.
- We present efficient algorithms to answer queries using R2T, which can return the results in a progressive way. In particular, the first type of algorithms focus on how to retrieve the results when users type in a query string for the first time. The second type of algorithms handle how to efficiently update the results for the updated query string.
- We conduct extensive experiments on real-world road networks to demonstrate the efficiency of our proposed index and algorithms.

The rest of this paper is organized as follows. Section 2 reviews related work. Section 3 formally defines the problem. Section 4 introduces the framework Task. Section 5 presents the structure, construction, and maintenance of R2T index. Section 6 proposes algorithms for queries. Experimental results are reported in Section 7. Finally, Section 8 concludes the paper.

2 RELATED WORK

Instant spatial keyword queries. Existing studies proposed different indexes to support instant spatial keyword queries [19, 32, 47]. Basu Roy and Chakrabarti [32] first introduced the instant queries to spatial database, and developed the index called materialized trie (MT). MT uses trie as the main index structure, and incorporates spatial information into the node of trie. Ji et al. [19] proposed an R-tree based method so-called Filtering-Effective Hybrid Indexing (FEH) for instant spatial keyword queries. FEH utilizes R-tree as the key index structure. In each R-tree node, FEH incorporates textual filters according to the geo-textual objects contained in this node. Zhong et al. [47] proposed the Prefix-region tree (PR-Tree), which considers spatial information and textual information in a balanced manner. Specifically, PR-Tree first partitions the geo-textual objects of the same prefix into a group, and then, it uses the minimum bounding box to organize the objects within the group. Correspondingly, every node of PR-Tree contains the objects that have the same prefix and meanwhile are within the same minimum bounding box. In addition, as surveyed in [5], many indexes, such as IR-tree [26], have been proposed for spatial keyword queries. Nonetheless, all these indexes are designed for the Euclidean space, and cannot be directly used in our work.

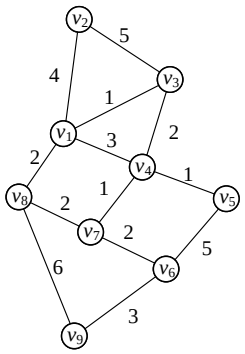
It is worth mentioning that the instant spatial keyword queries are also related to location-aware autocompletion [18, 33]. Specifically, as users type in queries, the location-aware autocompletion returns the possible completion of the queries, which can also help users reduce the amount of typing. However, the location-aware autocompletion also does not consider the road network. Therefore, it cannot be applied to solve our problem.

Spatial keyword queries on road networks. Rocha-Junior and Nørvåg [31] first explored the spatial keyword queries on road networks. An index consisting of map tree and inverted file is proposed to answer the queries. Then, Qiao et al. [29] devised an index structure based on distance oracles and compact trees of keywords. Jiang et al. [20] presented 2-hop label backward index (LB) and keyword-lookup tree index (KT). Abeywickrama et al. [1] designed the keyword separated index (K-SPIN), which inlcudes a set of *on-demand inverted heap* of a keyword. Besides traditional spatial keyword queries on road networks, many variants have also been studied, such as aggregate queries [9], time-aware queries [42], continuous queries [46], why-not queries [43], diversified queries [38], and reverse queries [44]. All these studies need users to type in complete queries and hence cannot be applied in our work.

3 PROBLEM FORMULATION

In this section, we formalize the problem of instant error-tolerant spatial keyword queries on road networks.

The road network is denoted as a connected undirected weighted graph $G = (V, E)$. V and E are the sets of vertices and edges of G, which represent the road junctions and segments, respectively. The weight of an edge $e = (u, v)$, denoted by $\mathsf{w}(e)$ or $\mathsf{w}(u, v)$, is a positive integer, which denotes a metric, such as distance or travel time, between u and v. A path p is a sequence of vertices $p = (v_1, v_2, ..., v_j)$, where $\forall 1 \le i \le j$, $(v_i, v_{i+1}) \in E$. The length of a path is the sum of weights of edges along the path. Given two vertices u and v of a road network G, the distance between u and v, denoted by $\mathsf{dis}(u, v)$, is the shortest path between u and v in G. For example, in Figure 2, the length of path $p = (v_5, v_6, v_7)$ is $\mathsf{w}(v_5, v_6) + \mathsf{w}(v_6, v_7) = 5 + 2 = 7$; and the distance between v_5 and v_7 is $\mathsf{dis}(v_5, v_7) = \mathsf{w}(v_5, v_4) + \mathsf{w}(v_4, v_7) = 2$.



(a) Road network

Vertex	Keywords
v_1	baber shop
v_2	starbucks
v_3	stadium
v_4	book store
v_5	starline club
v_6	cloud school
v_7	bus station
v_8	cinema
v_9	baby center

(b) Textual information

Figure 2: A running example

The geo-textual objects and query location may appear on any point of the road network G. Given a geo-textual object and a query location on G, we can compute the distance between them by mapping each of them to an adjacent vertex with an offset. To make exposition simpler, we assume that the geo-textual objects and query location all appear on vertices, which follows previous studies such as [1, 20]. Under this assumption, in the road network G, a vertex v contains a set of keywords, which is denoted by $\mathsf{doc}(v)$. We use the notation $kw \in \mathsf{doc}(v)$ to denote that the vertex v includes the keyword kw. If a string str is the prefix of a keyword kw, we denote it by $str \preceq kw$. For instance, in Figure 2, "bus" $\in \mathsf{doc}(v_7)$ and "bu" $\preceq$ "bus". Next, we introduce the concepts of edit distance and prefix edit distance to measure the textual similarity.

Definition 3.1. **(Edit Distance, Prefix Edit Distance)** *Given a keyword kw, two strings str_1 and str_2.*

(1) *The edit distance between str_1 and str_2, denoted by $\mathsf{ED}(str_1, str_2)$, is the minimum number of single-character edit operations, including insertion, deletion, and substitution, needed to transform str_1 to str_2.*

(2) *The prefix edit distance between kw and str_1, denoted by $\mathsf{PED}(kw, str_1)$, is the minimum edit distance between kw's prefix and str_1, i.e., $\mathsf{PED}(kw, str_1) = \min_{\forall str' \preceq kw} \mathsf{ED}(str', str_1)$.*

For example, ED("school", "scholar") = 3, PED("school", "sco") = ED("sch", "sco") = ED("sc", "sco") = ED("scho", "sco") = 1. Based on the metric of textual similarity presented above, we formally define the error-tolerant spatial keyword queries on road networks.

Definition 3.2. **(Error-tolerant Spatial Keyword Queries on Road Networks)** *Given a road network $G = (V, E)$, a parameter k, an error threshold τ, a query $q = (q.loc, q.str)$, where $q.loc \in V$ and $q.str$ are the query location and query string, respectively. The error-tolerant spatial keyword queries on road networks return a set $\mathcal{R} \subseteq V$ such that:*

(1) $|\mathcal{R}| = k$;

(2) $\forall v \in \mathcal{R}$, $\exists kw \in \mathsf{doc}(v)$, $\mathsf{PED}(kw, q.str) \le \tau$;

(3) $\forall v \in \mathcal{R}$ *and* $\forall v' \in V - \mathcal{R}$, $\mathsf{score}(q, v) \le \mathsf{score}(q, v')$, *in which $\mathsf{score}(q, v)$ computes the spatial and textual similarity between q and v. Specifically,*

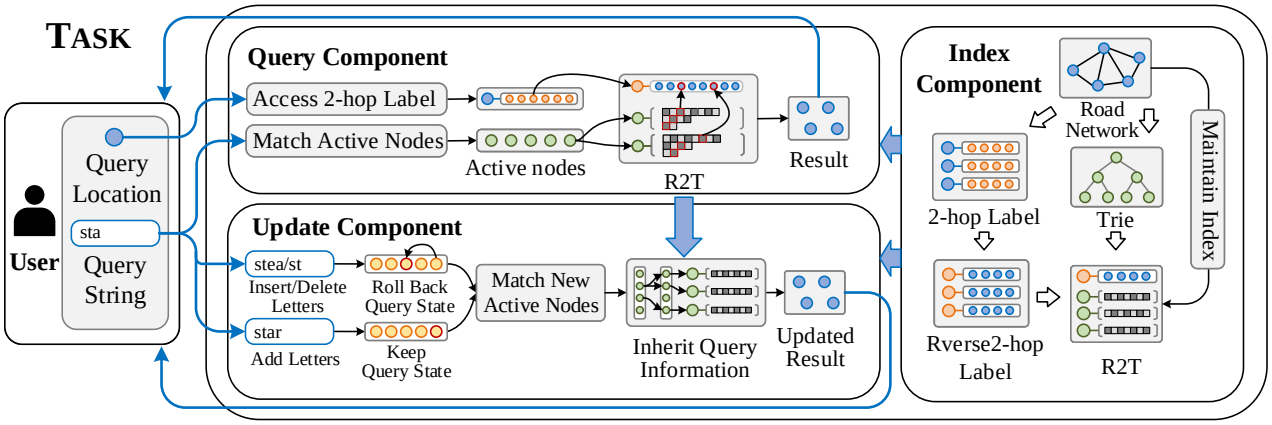


Figure 3: The workflow of TASK

$$\text{score}(q,v) = \alpha \cdot \frac{\text{dis}(q.loc, v)}{\max_{\forall u,u' \in V} \text{dis}(u,u')} + (1-\alpha) \cdot \frac{\min_{\forall kw \in \text{doc}(v)} \text{PED}(kw, q.str)}{\tau} \quad (1)$$

Here, $\alpha \in [0,1]$ is a parameter to tune the weights of spatial and textual similarity, and we assume that the smaller score is better.

In Definition 3.2, (1) the first condition ensures that the returned results have at most k geo-textual objects; (2) the second condition gives the upper bound of the typographical error for the query string such that the keywords of each returned geo-textual object can match the query string; and (3) the third condition employs the normalized aggregated score of spatial similarity and textual similarity to rank the geo-textual objects such that the returned k geo-textual objects are optimal. In brief, the error-tolerant spatial keyword queries on road networks tolerate the input error, and return the most relevant geo-textual objects for users. Based on this, we formalize our studied problem below.

PROBLEM 1. *Given a road network $G = (V, E)$, a parameter k, an error threshold τ, and a query $q = (q.loc, q.str)$, the problem of instant error-tolerant spatial keyword queries on road networks should* (1) *return the set $\mathcal{R}$ satisfying the three conditions in Definition 3.2; and* (2) *update $\mathcal{R}$ whenever the query string $q.str$ changes.*

In a word, the goal of Problem 1 is two-folded. First, when a user types in a string, we should return the top-k geo-textual objects that best match user's location and the typed string. Second, when the typed string changes, e.g., a new character is inserted into the string or a character is deleted from the string, we should update the results instantly. For instance, in Figure 2, assume that $q.loc = v_1$, $k = 3$, $\tau = 1$, and $\alpha = 0.5$. When a user types in a query string "st", the results $\{v_3, v_4, v_2\}$ are returned. When the user proceeds to type in "a" after "st", i.e., the current query string is "sta", the results are updated to $\{v_3, v_2, v_5\}$ immediately.

4 FRAMEWORK OVERVIEW

Problem 1 returns k geo-textual objects with the minimum score, and the typo should be not larger than τ. A naive method is to traverse the road network from $q.loc$ in a breadth first manner. For the visited vertex, we check whether the prefix edit distance of the vertex's keywords is no larger than τ. If yes, we compute its score using Equation 1, and add it to the candidate set. Finally, k vertices with the minimum score are returned. When the query string changes, we can use the above naive method to compute the results from the scratch. Obviously, the simple combination of road network traversal and text examination leads to poor performance of the naive method. First, at the worst, it may traverse the whole road network with time complexity $O(|E| + |V|)$, which is costly for online search. Second, when the query string changes, it is time consuming to query from the scratch.

Motivated by this, we propose an efficient framework, termed as TASK, to tackle the instant error-tolerant spatial keyword queries on road networks. As illustrated in Figure 3, TASK consists of an index component, a query component, and an update component. The index component is responsible for (1) constructing the R2T index for the road network and (2) maintaining R2T when the road network changes, e.g., the insertion/deletion of vertices/keywords and the change of edge's weight. The index component provides support for queries, and is the cornerstone of the framework. When a user types in a query string at the first time (i.e., when the current query string is empty), TASK uses the query component to return the results to user. Whenever the user makes change for the query string, TASK calls the update component, which employs the information of previous query processing to quickly update the results for user. The user proceeds to type in the query string until the desirable results are found. In the following two sections, we will detail these three components. Note that, due to the space limitation, some details and proofs are moved to Appendix.

5 R2T INDEX

In this section, we propose a novel index called reverse 2-hop label based trie (R2T for short) for Problem 1. We first introduce the structure of R2T, and then present the construction and maintenance algorithms of R2T.

5.1 R2T Structure

R2T integrates both road network information and textual information. Specifically, we employ the reverse 2-hop label and trie techniques to store spatial and textual information, respectively. First, we introduce the concept of 2-hop label [2, 8, 10, 15, 28].

Table 2: 2-hop label and reverse 2-hop label of the road network in Figure 2

Vertex	2-hop label	Reverse 2-hop label
v_1	$(v_1, 0)$	$(v_1, 0), (v_3, 1), (v_8, 2), (v_4, 3), (v_2, 4), (v_5, 4), (v_7, 4), (v_6, 6), (v_9, 8)$
v_2	$(v_2, 0), (v_1, 4)$	$(v_2, 0)$
v_3	$(v_3, 0), (v_1, 1), (v_4, 2)$	$(v_3, 0)$
v_4	$(v_4, 0), (v_1, 3)$	$(v_4, 0), (v_5, 1), (v_7, 1), (v_3, 2), (v_6, 3), (v_8, 3), (v_9, 6)$
v_5	$(v_5, 0), (v_4, 1), (v_1, 4)$	$(v_5, 0)$
v_6	$(v_6, 0), (v_4, 3), (v_1, 6)$	$(v_6, 0), (v_7, 2), (v_9, 3), (v_8, 4)$
v_7	$(v_7, 0), (v_4, 1), (v_6, 2), (v_1, 4)$	$(v_7, 0), (v_8, 2)$
v_8	$(v_8, 0), (v_1, 2), (v_7, 2), (v_4, 3), (v_6, 4)$	$(v_8, 0), (v_9, 1)$
v_9	$(v_9, 0), (v_6, 3), (v_4, 6), (v_8, 6), (v_1, 8)$	$(v_9, 0)$

Given a road network G, the 2-hop labeling technique assigns each vertex $v \in V$ a label $\mathsf{L}(v)$ containing a set of pairs $(u, \mathsf{dis}(u, v))$, i.e., $\mathsf{L}(v) = \{(u, \mathsf{dis}(u, v)) | u \in V\}$. The 2-hop labels of all vertices have the following property. Given any two vertices v and v' of the road network G, the distance between v and v' is $\mathsf{dis}(v, v') = \min_{u \in \mathsf{L}(v) \cap \mathsf{L}(v')} \mathsf{dis}(v, u) + \mathsf{dis}(v', u)$. In other words, the distance between any two vertices can be computed via an intermediate hop. For example, Table 2 shows the 2-hop labels for all vertices of the road network G in Figure 2. We can observe that $\mathsf{L}(v_2) = \{(v_2, 0), (v_1, 4)\}$ and $\mathsf{L}(v_7) = \{(v_7, 0), (v_4, 1), (v_6, 2), (v_1, 4)\}$. The vertex v_1 is the only common label vertex in $\mathsf{L}(v_2)$ and $\mathsf{L}(v_7)$. Thus, $\mathsf{dis}(v_2, v_7) = \mathsf{dis}(v_2, v_1) + \mathsf{dis}(v_1, v_7) = 4 + 4 = 8$. Based on the 2-hop label, the reverse 2-hop label is defined as follows.

Definition 5.1. **(Reverse 2-hop Label)** *Given a road network G and 2-hop labels of all vertices in G, the reverse 2-hop label of a vertex v, denoted by $\widetilde{\mathsf{L}}(v)$, consists of pairs $(u, \mathsf{dis}(u, v))$ with $(v, \mathsf{dis}(u, v)) \in \mathsf{L}(u)$, i.e., $\widetilde{\mathsf{L}}(v) = \{(u, \mathsf{dis}(u, v)) | \forall u,\ (v, \mathsf{dis}(u, v)) \in \mathsf{L}(u)\}$.*

If a vertex v is included in the 2-hop label of u, the reverse 2-hop label of v contains u. For instance, in Table 2, $(v_1, 4) \in \mathsf{L}(v_2)$ and $(v_2, 4) \in \widetilde{\mathsf{L}}(v_1)$. The reverse 2-hop label is mainly used for the distance computation, which can benefit Problem 1 a lot. The 2-hop label only supports distance computation between two vertices. Given 2-hop labels of a road network, if we want to find the k nearest neighbors of a vertex v, we should compute the common 2-hop label vertices of v and every other vertex, which is time consuming. With the help of reverse 2-hop label, we only need to compute the common 2-hop label vertices of v and v's k nearest neighbors, and thus improving the query efficiency. Note that, we assume that the pairs $(v, \mathsf{dis}(u, v))$ in both 2-hop label and reverse 2-hop label are in *ascending* order w.r.t., $\mathsf{dis}(u, v)$. Besides, when the context is clear, we use the notations $v \in \mathsf{L}(u)$ and $v \in \widetilde{\mathsf{L}}(u)$ to denote $(v, \mathsf{dis}(u, v)) \in \mathsf{L}(u)$ and $(v, \mathsf{dis}(u, v)) \in \widetilde{\mathsf{L}}(u)$ for simplicity.

Next, we introduce another technique used in R2T, i.e., trie. The trie is an ordered tree to represent a set of keywords. Its root node is an empty node. Each non-leaf node is labeled with one character, and each leaf node contains the last character of a keyword. The path from the root node to a leaf/intermediate node represents a keyword/prefix in the trie. As an example, Figure 4 depicts a trie representing the keywords set in Figure 2(b). The nodes n_4 and n_7 denote the prefix "bab" and keyword "baby", respectively.

Based on the reverse 2-hop label and trie, we formally define our proposed index as follows.

Definition 5.2. **(Reverse 2-hop Label Based Trie)** *Given a road network G and a vertex $v \in V$, a reverse 2-hop label based trie of v, denoted by $\mathsf{R2T}(v)$, consists of the reverse 2-hop label of v and the trie of v w.r.t. $\widetilde{\mathsf{L}}(v)$, i.e., $\mathsf{R2T}(v) = (\widetilde{\mathsf{L}}(v), \mathsf{T}(v))$. In particular, $\mathsf{T}(v)$ is a trie of v to represent all the keywords contained in the vertices in $\widetilde{\mathsf{L}}(v)$, i.e., $\forall v' \in \widetilde{\mathsf{L}}(v), \forall kw \in \mathsf{doc}(v')$.*

For example, in Table 2, $\widetilde{\mathsf{L}}(v_6) = \{(v_6, 0), (v_7, 2), (v_9, 3), (v_8, 4)\}$ and the keywords set w.r.t. $\widetilde{\mathsf{L}}(v_6)$ is {"cloud", "school", "bus", "station", "cinema", "baby", "center"}. Correspondingly, Figure 5 depicts $\mathsf{T}(v_6)$.

Combining Figures 4 and 5, we can find that each $\mathsf{T}(v)$ is a part of the complete trie. If we directly keep the entire $\mathsf{T}(v)$ for $\mathsf{R2T}(v)$, it has two drawbacks: (1) redundant storage and (2) repeated trie traversal. To this end, we use a node array to store $\mathsf{T}(v)$. Specifically, the node array consists of a set of $(\mathtt{ID}(n), \mathsf{B}(n))$ for every leaf node n of $\mathsf{T}(v)$, where $\mathtt{ID}(n)$ is the ID of n in the complete trie of the road network and $\mathsf{B}(n)$ consists of bitmaps of trie nodes along the path from root node to n. Note that, the bitmaps of root node, leaf nodes, and the nodes whose bitmaps are the same as leaf nodes are not stored. In $\mathsf{T}(v)$, a node n's bitmap is defined below: (1) Each bitmap has $|\widetilde{\mathsf{L}}(v)|$ bits, and each bit represents a vertex in $\widetilde{\mathsf{L}}(v)$. (2) A bit is "1" if the represented vertex has a keyword containing the prefix denoted by n; otherwise the bit is "0"; and all bits of the root node are "1". We take the node n_2' of $\mathsf{T}(v_6)$ in Figure 5 as an example. Since $|\widetilde{\mathsf{L}}(v_6)| = 4$, each bitmap of $\mathsf{T}(v_6)$'s node has 4 bits, representing v_6, v_7, v_9, and v_8, respectively. n_2' denotes the prefix "b". According to Figure 2(b), "b" $\preceq$ "bus" $\in \mathsf{doc}(v_7)$ and "b" $\preceq$ "baby" $\in \mathsf{doc}(v_9)$. Thus, the bitmap of n_2' is "0110". Figure 5 shows the bitmaps for every node of $\mathsf{T}(v_6)$.

In Figure 5, we can observe that there are a lot of "0" bits in bitmaps, which can be further compressed. Let b_1 and b_2 be the bitmaps of nodes n_1 and n_2, respectively, and n_2 be the child node of n_1. For the same bit of b_1 and b_2, if both bits are "0", we delete the corresponding "0" bit from b_2. Back to Figure 5, the bitmaps of n_2' and n_3' are "0110" and "0010", respectively. Since the first and last bits of n_2' and n_3' are all "0", we can delete the first and last bits of n_3', and the compressed bitmap of n_3' is "01". The compressed bitmap for every node of $\mathsf{T}(v_6)$ is listed below the original bitmap in Figure 5. After getting the compressed bitmaps, we can construct the $\mathsf{B}(n)$ for each leaf node of $\mathsf{T}(v)$. Take the leaf node n_5' of $\mathsf{T}(v_6)$ in Figure 5 as an example. $\mathtt{ID}(n_5') = n_7$, and the $\mathsf{B}(n_5')$ consists of the compressed bitmaps from n_2' to n_3', i.e., $\mathsf{B}(n_5') = \{0110, 01\}$. In the same way, we can construct $(\mathtt{ID}(n), \mathsf{B}(n))$ for every leaf node of $\mathsf{T}(v_6)$. Figure 6 illustrates the $\mathsf{R2T}(v_6)$ for vertex v_6. Next, we analyze the size of $\mathsf{R2T}(v)$.

Theorem 5.1. *The size of $\mathsf{R2T}(v)$ is bounded by $O(\log |V|)$.*

5.2 R2T Construction

Given a road network G, the construction of $\mathsf{R2T}(v)$ for every vertex $v \in V$ includes two parts, i.e., the constructions of $\widetilde{\mathsf{L}}(v)$ and $\mathsf{T}(v)$.

The construction of $\widetilde{\mathsf{L}}(v)$. First, we use existing 2-hop labeling algorithms [24] to compute the 2-hop label for every vertex. Then, we traverse the 2-hop label to get the reverse 2-hop label. Specifically, if $(u, \mathsf{dis}(u, v)) \in \mathsf{L}(v)$, we add the pair $(v, \mathsf{dis}(u, v))$ to $\widetilde{\mathsf{L}}(u)$.

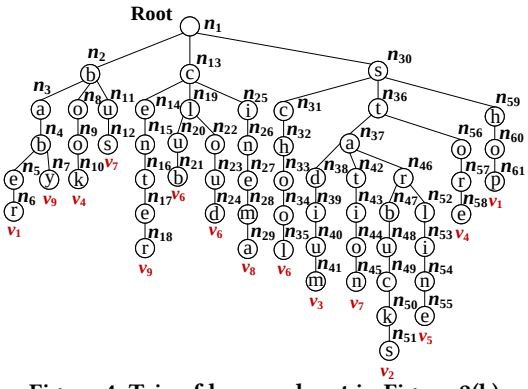


Figure 4: Trie of keywords set in Figure 2(b)

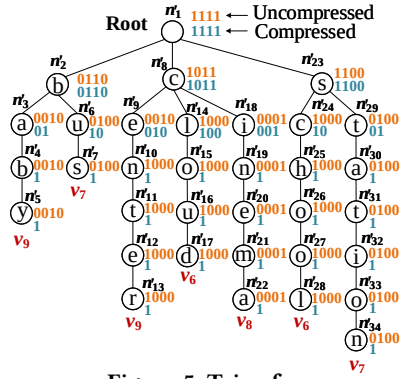


Figure 5: Trie of v_6

R2T(v_6)			
$\widetilde{L}(v_6) = \{(v_6, 0), (v_7, 2), (v_9, 3), (v_8, 4)\}$			
T(v_6)	Leaf Node	ID(n)	B(n)
	n'_5	n_7	{0110, 01}
	n'_7	n_{12}	{0110, 10}
	n'_{13}	n_{18}	{1011, 010}
	n'_{17}	n_{24}	{1011, 100}
	n'_{22}	n_{29}	{1011, 001}
	n'_{28}	n_{35}	{1100, 10}
	n'_{34}	n_{45}	{1100, 01}

Figure 6: R2T(v_6)

Finally, we should sort the pairs $(u, \text{dis}(u, v))$ of both $\mathsf{L}(v)$ and $\widetilde{\mathsf{L}}(u)$ in ascending of $\text{dis}(u, v)$.

The construction of $\mathsf{T}(v)$. $\mathsf{T}(v)$ is stored in the form of node array. Hence, this step mostly focuses on how to construct the node array. First, we construct (1) a complete trie for the specified road network, and (2) a trie for each vertex $v \in V$ according to $\widetilde{\mathsf{L}}(v)$. Then, for each trie of $v \in V$, we compute the bitmap and the compressed bitmap of every node by traversing the trie in a depth-first manner. When visiting a leaf node n, we should (1) add n to the node array; (2) find the $\mathsf{ID}(n)$ in the complete trie; and (3) backtrack to the root node to add the compressed bitmap to $\mathsf{B}(n)$. Take the construction of $\mathsf{R2T}(v_6)$ in Figure 6 as an example. We first traverse the root node n'_1 of trie in Figure 5, and compute n'_1's bitmap and compressed bitmap, which are "1111" and "1111", respectively. In the same manner, we visit the nodes n'_2, n'_3, n'_4, and n'_5, and compute the corresponding bitmaps and compressed bitmaps. Since n'_5 is a leaf node, we backtrack to the root node, and get $\mathsf{B}(n'_5) = \{0110, 01\}$. The bitmap of n'_4 is not added to $\mathsf{B}(n'_5)$ as it is the same as that of n'_5. Then, we add n'_5, $\mathsf{ID}(n'_5) = n_7$, and $\mathsf{B}(n'_5) = \{0110, 01\}$ to the node array. In the same way, we can traverse the whole trie, and get the complete $\mathsf{T}(v_6)$ as depicted in Figure 6.

It is worth noting that, since the constructions of $\widetilde{\mathsf{L}}(v)$ and $\mathsf{T}(v)$ for different vertices are independent of each other. Thus, we can construct R2T of different vertices in parallel. Next, we analyze the time and space complexities of $\mathsf{R2T}(v)$ construction.

Theorem 5.2. *The time and space complexities of* $\mathsf{R2T}(v)$ *construction are* $O(\log^2 |V|)$ *and* $O(\log^2 |V|)$*, respectively.*

5.3 R2T Maintenance

In this section, we present the maintenance of R2T. For the index maintenance, we have to answer two questions: *Q1*: Which part of R2T is influenced under the road network changes? *Q2*: How to maintain the influenced part of R2T? In the following, we detail the index maintenance considering two categories: (1) the keywords update and (2) the road network structure update.

5.3.1 Keywords Update. The first category is the keywords update, including inserting/deleting a keyword into/from $\mathsf{doc}(v)$ of v.

Answering Q1. Recall that $\mathsf{R2T}(v)$ consists of $\widetilde{\mathsf{L}}(v)$ and $\mathsf{T}(v)$, where only $\mathsf{T}(v)$ stores the keywords information. Therefore, the insertion and deletion of keywords only affect $\mathsf{T}(v)$. Specifically, assume that we insert/delete a keyword into/from $\mathsf{doc}(v)$ of vertex v. All $\mathsf{T}(v')$ with $v \in \widetilde{\mathsf{L}}(v')$ need to be updated.

Answering Q2. Assume that $v \in \widetilde{\mathsf{L}}(v')$. We discuss insertion and deletion of keywords separately. (1) Inserting a keyword kw into $\mathsf{doc}(v)$. First, we find the leaf node n representing the keyword kw in the trie of v'. If the trie does not contain such node, we should insert a new leaf node n into the trie to represent kw. Second, we should update the bitmaps of the nodes along the path from n to the root node. Specifically, for the existing nodes that denote the prefix of kw, we should set the bit representing v to "1". For new added nodes, we should create new bitmaps and the corresponding compressed bitmaps. Finally, in $\mathsf{T}(v')$, if the leaf node n is newly added, we should add it to $\mathsf{T}(v')$. Thereafter, we only need to update the $\mathsf{B}(n')$ of leaf nodes n', whose representing keywords have the same prefix as kw, based on the second step. (2) Deleting a keyword kw from $\mathsf{doc}(v)$. First, in the trie of v', for the nodes that denote the prefix of kw, we should set the bit representing v to "0". Next, in $\mathsf{T}(v')$, we delete the leaf node and its $(\mathsf{ID}(n), \mathsf{B}(n))$. Also, for the leaf nodes n' whose representing keywords have the same prefix as kw, we update the $\mathsf{B}(n')$ as the first step.

5.3.2 Road network structure update. Another category of update is the update of road network structure, including the change of edge's weight and inserting/deleting edges/vertices.

Answering Q1. If the road network structure updates, it affects the distance between two vertices, meaning that both 2-hop label and reverse 2-hop label may change. Since the R2T index is constructed based on the reverse 2-hop label, both $\widetilde{\mathsf{L}}(v)$ and $\mathsf{T}(v)$ may be influenced.

Answering Q2. As mentioned above, the road network structure update may influence reverse 2-hop label. Using existing 2-hop label maintenance algorithms [4, 39–41], we can compute the updated 2-hop label and reverse 2-hop label. Based on the updated reverse 2-hop label, we can maintain R2T index. We discuss the maintenance in two cases. (1) A new pair $(u, \text{dis}(u, v))$ is added to $\widetilde{\mathsf{L}}(v)$. For this case, we can utilize the keywords insertion method to update $\mathsf{T}(v)$ by inserting the keywords of u into the trie of v one by one. One difference should be highlighted is that when updating bitmaps, we should insert a bit into bitmaps to represent u. (2) A pair $(u, \text{dis}(u, v))$ is deleted from $\widetilde{\mathsf{L}}(v)$. Similar to the first case, we can use the keywords deletion method to update $\mathsf{T}(v)$ by deleting the keywords of u from the trie of v one by one. Note that, when updating bitmaps, we should delete the bit representing u from bitmaps.

Algorithm 1: Instant Query Algorithm (IQA)

Input: a query $q = (q.loc, q.str)$, parameters k and τ, a trie T of G
Output: a set $\mathcal{R}$ of k geo-textual objects

1 $R \leftarrow \emptyset$; $C \leftarrow \emptyset$;
2 $AN \leftarrow$ find active nodes of T for $q.str$ [13];
3 **if** $AN = \emptyset$ **then**
4 **return** $\mathcal{R}$;
5 **for** $\forall v \in \mathsf{L}(q)$ **do**
6 **if** $\mathsf{T}(v)$ *does not contain the leaf nods of AN* **then**
7 $v' \leftarrow \mathrm{Min}\widetilde{\mathsf{L}}(v)$; // Computing the vertex with the minimal score using Algorithm 2
8 $C \leftarrow C \cup (v', v, \mathsf{score}(q, v'))$;
9 **while** $|\mathcal{R}| < k \wedge C \neq \emptyset$ **do**
10 $(v', v, \mathsf{score}(q, v')) \leftarrow \arg\min_{(v', v, \mathsf{score}(q, v')) \in C} \mathsf{score}(q, v')$;
11 $C \leftarrow C - (v', v, \mathsf{score}(q, v'))$;
12 **if** $v' \notin \mathcal{R}$ **then**
13 $\mathcal{R} \leftarrow \mathcal{R} \cup v'$;
14 $v'' \leftarrow \mathrm{Min}\widetilde{\mathsf{L}}(v)$; // Computing the next vertex with the minimal score using Algorithm 2
15 $C \leftarrow C \cup (v'', v, \mathsf{score}(q, v''))$;
16 **return** $\mathcal{R}$;

6 QUERY PROCESSING ALGORITHMS

Using R2T index, we propose the query processing algorithms.

6.1 Instant Query Algorithm

First, in this section, we present an algorithm, called Instant Query Algorithm (IQA), to handle the first case of Problem 1, i.e., when a user types in a query string for the first time, the query returns the top-k geo-textual objects with the minimal scores. With the help of the R2T index introduced in the previous section, the query can be efficiently handled. First, we propose some lemmas, which establish the solid base to design IQA.

Lemma 6.1. *Given a vertex $v \in G$,*

$$\bigcup_{v' \in \mathsf{L}(v)} \widetilde{\mathsf{L}}(v') = V \tag{2}$$

Lemma 6.1 shows that, for a vertex v, all the reverse 2-hop labels $\widetilde{\mathsf{L}}(v')$ of $v' \in \mathsf{L}(v)$ constitute the vertex set of the road network. For example, in Table 2, $\mathsf{L}(v_2) = \{(v_2, 0), (v_1, 4)\}$ and $\widetilde{\mathsf{L}}(v_2) \cup \widetilde{\mathsf{L}}(v_1) = V$. Based on Lemma 6.1, we can compute the distance from a vertex to all the other vertices by using the reverse 2-hop labels. Moreover, the reverse 2-hop label also enable the computation of the nearest neighbors in a progressive way as shown in the following lemma.

Lemma 6.2. *Given a vertex $v \in G$, for a vertex $v' \in \mathsf{L}(v)$, let $v'' = \arg\min_{v'' \in \widetilde{\mathsf{L}}(v')} \mathrm{dis}(v', v'')$. Note that $v'' \neq v$. Then, the nearest neighbor of v is*

$$v'' = \arg\min_{v'' \in \widetilde{\mathsf{L}}(v'), v' \in \mathsf{L}(v)} \mathrm{dis}(v, v') + \mathrm{dis}(v', v'') \tag{3}$$

According to Lemma 6.2, in each reverse 2-hop label of $v' \in \mathsf{L}(v)$, we can find the nearest neighbor of v'. Then, among all reverse 2-hop labels, the vertex with the minimal distance to v is the nearest neighbor of v. For instance, in Table 2, $\mathsf{L}(v_4) = \{v_4, v_1\}$. In $\widetilde{\mathsf{L}}(v_4)$, the closest vertex to v_4 is v_5 with $\mathrm{dis}(v_4, v_5) = 1$. In $\widetilde{\mathsf{L}}(v_1)$, the nearest vertex to v_1 is v_1 with $\mathrm{dis}(v_1, v_1) = 0$. Since $\mathrm{dis}(v_4, v_5) = 1$ and $\mathrm{dis}(v_4, v_1) = 3$, v_5 is the nearest neighbor of v_4. Lemma 6.2 can also be extended to our problem as follows.

Corollary 6.1. *Given a query $q = (q.loc, q.str)$, for a vertex $v \in \mathsf{L}(q)$, let $v' = \arg\min_{v' \in \widetilde{\mathsf{L}}(v)} \mathsf{score}(q, v')$. Then, the vertex with the minimal score w.r.t. q is*

$$v' = \arg\min_{v' \in \widetilde{\mathsf{L}}(v), v \in \mathsf{L}(q)} \mathsf{score}(q, v') \tag{4}$$

In other words, the minimal score vertex is among the vertices, which have the minimal score in the reverse 2-hop label of $v' \in \mathsf{L}(v)$. Motivated by Corollary 6.1, we develop IQA to find the k vertices with the minimal score. The basic idea of IQA is to progressively return the vertices with the minimal score among all reverse 2-hop labels of $v \in \mathsf{L}(q)$. To this end, we should find the vertex with the minimal score for each reverse 2-hop label of $v \in \mathsf{L}(q)$. Then, in each round, we select the vertex with the minimal score among all reverse 2-hop labels of $v \in \mathsf{L}(q)$, and add it to the results. Assume the vertex with the minimal score is in $\widetilde{\mathsf{L}}(v)$. After this, we should compute the next vertex with the minimal score in $\widetilde{\mathsf{L}}(v)$ for the next round processing. IQA repeats the selection of vertices having the minimal scores until all results are found.

Algorithm 1 shows the pseudo-code of IQA. First, IQA computes the active nodes in the complete trie of the road network (line 2). Here, the active node is the node whose represented string/keyword's edit distance to $q.str$ is not larger than τ. It is worth mentioning that, the active nodes are mainly used to compute the score of the vertex, which will be illustrated later. If there is no such active node, it means that all vertices do not match the $q.str$. IQA returns empty result (lines 3-4). Otherwise, IQA finds the vertex with the minimal score for each reverse 2-hop label of $v \in \mathsf{L}(q)$ (lines 5-8). Then, IQA repeatedly selects the vertex with the minimal score among all reverse 2-hop labels until all results are found (lines 9-15). Finally, IQA returns the top-k geo-textual objects (line 16).

Example 6.1. *We illustrate Algorithm 1 using the road network in Figure 2. Let $q = (v_9, \text{"sto"})$, $k = 3$, $\tau = 1$, and $\alpha = 0.5$. Table 3 shows the details of the query processing. In Table 3, it is worth mentioning that (1) "−" means that the reverse 2-hop label does not have vertices matching "sto"; (2) the number next to vertex indicates the vertex's score; and (3) in each row, we mark the vertex with the minimal score in red color. In the* Initialization *row, we find the vertices with the minimal score for $\widetilde{\mathsf{L}}(v_6)$, $\widetilde{\mathsf{L}}(v_4)$, and $\widetilde{\mathsf{L}}(v_1)$, which are v_7, v_4, and v_1, respectively. In the first round, v_4 of $\widetilde{\mathsf{L}}(v_4)$ has the minimum score among all reverse 2-hop labels, and it is added to the result set. Then, we should find the next vertex having the minimal score in $\widetilde{\mathsf{L}}(v_4)$, which is v_5. In the second round, v_4 of $\widetilde{\mathsf{L}}(v_1)$ has the minimal score. But, v_4 has been in the result set. We only need to find the next vertex with the minimal score in $\widetilde{\mathsf{L}}(v_1)$, which is v_1. In the same way, we find the vertices v_7 and v_5 in the following two rounds. In the end, we get the final result set $\{v_4, v_7, v_5\}$.*

Next, we introduce how to find the vertex with the minimal score in a reverse 2-hop label using R2T index. Note that, we have to keep in mind that the vertex with the minimal score should satisfy the prefix edit distance constraint in Definition 3.2. Recall that, at the

Table 3: Illustration of Algorithm 1

Operation	The vertex with minimum score in $\widetilde{\mathsf{L}}(v)$					Result
	$\widetilde{\mathsf{L}}(v_9)$	$\widetilde{\mathsf{L}}(v_6)$	$\widetilde{\mathsf{L}}(v_4)$	$\widetilde{\mathsf{L}}(v_8)$	$\widetilde{\mathsf{L}}(v_1)$	
Initialization	–	v_7 (0.71)	v_4 (0.25)	–	v_4 (0.46)	$\varnothing$
Select v_4 of $\widetilde{\mathsf{L}}(v_4)$	–	v_7 (0.71)	v_5 (0.79)	–	v_4 (0.46)	$\{v_4\}$
Select v_4 of $\widetilde{\mathsf{L}}(v_1)$	–	v_7 (0.71)	v_5 (0.79)	–	v_1 (0.83)	$\{v_4\}$
Select v_7 of $\widetilde{\mathsf{L}}(v_6)$	–	–	v_5 (0.79)	–	v_1 (0.83)	$\{v_4, v_7\}$
Select v_5 of $\widetilde{\mathsf{L}}(v_4)$	–	–	v_7 (0.79)	–	v_1 (0.83)	$\{v_4, v_7, v_5\}$

Table 4: Illustration of Algorithm 2

Bitmap	$\mathsf{BTag}[v_6][n_{45}]$		
	Initialization	Compute the vertex with the minimum score	Compute the second vertex with the minimum score
1100	$\langle 0, 0\rangle$	$\langle 2, 2\rangle$	$\langle -, -\rangle$
01	$\langle 0, 0\rangle$	$\langle 2, 1\rangle$	$\langle -, 2\rangle$

Algorithm 2: Min$\widetilde{\mathsf{L}}(v)$

Input: a set AN of active nodes, $\mathsf{R2T}(v)$ index of a vertex v
Output: a vertex v' with the minimal score in $\widetilde{\mathsf{L}}(v)$

1 $v' \leftarrow \varnothing$; $MinScore \leftarrow +\infty$;
2 **if** $\mathsf{BTag}[v] = \varnothing$ **then**
3 initialize $\mathsf{BTag}[v]$;
4 **for** *each active node* $an \in AN$ **do**
5 find a leaf node n of an using binary search;
6 **for** $i \leftarrow an.depth$ *to* 1 **do**
7 **if** $i = an.depth$ **then**
8 $\mathsf{BTag}[v][n][i].y = \mathsf{BTag}[v][n][i].y + 1$;
9 **else**
10 $\mathsf{BTag}[v][n][i].y = \mathsf{BTag}[v][n][i+1].x$;
11 $\mathsf{BTag}[v][n][i].x \leftarrow$ the position of $\mathsf{BTag}[v][n][i].y$-th "1" bit in bitmap $\mathsf{B}[v][n][i]$;
12 **if** $\mathsf{BTag}[v][n][i].x = null$ **then**
13 break;
14 $i--$;
15 $v'' \leftarrow (\mathsf{BTag}[v][n][i].x)$-th vertex in $\widetilde{\mathsf{L}}(v)$;
16 **if** $\mathsf{score}(q, v'') < MinScore$ **then**
17 $v' \leftarrow v''$;
18 $MinScore \leftarrow \mathsf{score}(q, v'')$;
19 **return** v';

beginning of Algorithm 1, we have computed the active nodes in the complete trie. The edit distances between the prefixes represented by those active nodes and $q.str$ are no larger than τ. Hence, if a vertex's keyword contains the prefix denoted by an active node, the vertex is a candidate of the minimal score vertex. Thus, a naive method is to compute the score for all candidates in the reverse 2-hop label. However, this naive method is not progressive. In the sequel, we devise a method to progressively return the minimal score vertex in a reverse 2-hop label.

In $\mathsf{T}(v)$ of $\mathsf{R2T}(v)$, we store the bitmap for the nodes of trie. Each bit of the bitmap indicates whether the keyword of corresponding vertex contains the prefix represented by the trie node. (1) For a node of trie, the vertices, whose keyword includes the prefix denoted by the node, have the same textual similarity. (2) In the reverse 2-hop label, the vertices are in ascending order of the distances. Based on the above two facts, for an active node, the vertex with the minimal score is just the vertex represented by the first "1" bit in the corresponding bitmap of the active node. In the same way, the vertex denoted by the second "1" bit in the bitmap of the active node is the second minimal score vertex. Using this property of the active node, for a reverse 2-hop label, we can compute the minimal score vertex for each active node. The vertex having the smallest score among all active nodes is the minimal score vertex in the reverse 2-hop label.

Next, we introduce how to find the minimal score vertex for an active node. Finding the minimal score vertex for an active node is only to find the first "1" bit in the bitmap of the active node. A straightforward way is to convert the compressed bitmap to the full bitmap, and we can quickly find the vertex of the first "1" bit. However, this method is inefficient since it has to convert the compressed bitmaps from the active to the root node. In view of this, we devise a novel method via traversing the compressed bitmaps from the active node to the root node with the help of an auxiliary structure BTag, which is defined as follows.

Definition 6.1. *A* BTag *of a bitmap is a pair of* $\langle x, y\rangle$*, which denotes that the position of* y*-th "1" bit is* x*.*

$\langle x, y\rangle$ of a bitmap means that from the first bit to the x-th bit, there are y "1" bits. For example, let a bitmap be "110011", the BTag $\langle 5, 3\rangle$ indicates that the fifth bit is the 3-th "1" bit in "110011". The BTag has the following property.

Lemma 6.3. *Given two trie nodes* n_1 *and* n_2*, two pairs* $\langle x_1, y_1\rangle$ *and* $\langle x_2, y_2\rangle$*, which are the* BTags *of the bitmaps of* n_1 *and* n_2*, respectively. Assume that* n_1 *is a child node of* n_2*. If* $y_2 = x_1$*, the vertex represented by the* x_1*-th bit in the bitmap of* n_1 *and the vertex denoted by the* x_2*-th bit in the bitmap of* n_2 *are the same.*

For instance, in Figure 5, the compressed bitmaps of n'_2 and n'_6 are "0110" and "10", respectively. Both $\langle 1, 1\rangle$ of "10" and $\langle 2, 1\rangle$ of "0110" represent the second vertex in $\widetilde{\mathsf{L}}(v_6)$, i.e., v_7. Lemma 6.3 not only enables us to traverse the compressed bitmaps in a bottom-up manner to get the minimal score vertex for an active node, but also allows us to get the next minimal score vertex in the same way.

Based on the above discussion, we propose an algorithm to find the vertex with the minimal score in a reverse 2-hop label, whose pseudo-code is depicted in Algorithm 2. Initially, when Algorithm 2 computes the minimal score vertex for the first time, it initializes BTag (lines 2-3), i.e., to set BTag as $\langle 0, 0\rangle$. Then, Algorithm 2 computes the minimal score vertex for each active node (lines 4-18). For each active node, it first gets a leaf node containing the bitmap of the active node using binary search (line 5). Note that, there may be multiple such leaf nodes. We only select any one of them. Next, Algorithm 2 traverses the bitmaps from the active node to the child of the root node for getting the position of the minimal score vertex of the active node (lines 6-14). Finally, the minimal score vertices of all active nodes are found, and the one having the smallest score among all active nodes is returned (lines 15-19).

Example 6.2. *We employ the computation of the vertex with the minimal score in* $\widetilde{\mathsf{L}}(v_6)$ *for the active node* n_{36} *(i.e., the column* $\widetilde{\mathsf{L}}(v_6)$ *in Table 3) to illustrate Algorithm 2. In Table 3, Algorithm 2 finds the vertex with the minimal score twice, i.e., in the rows of* initialization *and* Select v_7 of $\widetilde{\mathsf{L}}(v_6)$*. Table 4 shows the details of* BTag *for the whole processing. For the active node* n_{36}*, we need to traverse two bitmaps,*

i.e., "1100" and "01". At the initialization step, the BTag*s of "1100" and "01" are both* $\langle 0, 0\rangle$*. When finding the first minimal score vertex, the* BTag*s of "1100" and "01" are* $\langle 2, 2\rangle$ *and* $\langle 2, 1\rangle$*, respectively, meaning that the second vertex in* $\widetilde{\mathbb{L}}(v_6)$ *is the result. Thus,* v_7 *is found. When finding the second minimal score vertex, the* BTag*s of "1100" and "01" are* $\langle -, -\rangle$ *and* $\langle -, 2\rangle$*, respectively, indicating that no qualified vertex exists. Therefore, the result is empty.*

Optimizations. We present two optimizations to speed up Algorithms 1 and 2.

Optimizations 1. Algorithm 1 computes the minimal score vertex for each reverse 2-hop label (lines 5-8) for initialization. To improve the efficiency, we can first compute the lower bound of the score for a reverse 2-hop label. If the lower bound is larger than the current minimal score, the reverse 2-hop label definitely does not exist the minimum score vertex among all reverse 2-hop labels. Hence, we can skip the minimal score vertex computation for this reverse 2-hop label. Specifically, we can use Equation 1 to compute the lower bound of the score for the reverse 2-hop label $\widetilde{\mathbb{L}}(v)$. The spatial similarity is the minimal distance between q and the vertex in $\widetilde{\mathbb{L}}(v)$, and the textual similarity is the minimal edit distance between $q.str$ and the strings represented by active nodes.

Optimizations 2. Algorithm 2 needs to compute the minimal score vertex for every active node (lines 4-18). If the number of active nodes is large, it is costly. Actually, many active nodes have a parent-child relationship, and the vertices denoted by the bitmap of a child active node is a subset of that of its father active node. Thus, we need to only compute the minimal score vertex for father active nodes.

The time and space complexities of IQA are analyzed below.

Theorem 6.4. *The time and space complexities of IQA are* $O((k + \log|V|)\cdot|AN|\cdot\sqrt{\log|V|})$ *and* $O(\log|V|\cdot|AN|\cdot|q.str|)$*, respectively.*

6.2 Instant Update Algorithms

In this section, we present how to update the query results when the query string changes. A straightforward method is to query from the scratch. However, this method is not efficient, especially when updates are frequent. To this end, we extend Algorithms 1 and 2 to update the query results. We only need to modify three places in Algorithms 1 and 2. First, at the initialization step, Algorithm 1 should compute the first minimal score vertex for each reverse 2-hop label (lines 5-8). For the update algorithm, we can reuse the minimal score vertex found in the previous query, and the initialization can be omitted. Second, Algorithm 2 computes the minimal score vertex by traversing the bitmaps of active nodes and their ancestor nodes from the first bit, during which BTags are used. For the update algorithm, we can reuse the visited vertices, and traverse the bitmap from the current bit. Third, we have to recompute the score of previous query results based on the new query string to prune the unqualified vertices. Next, we detail the second modification for three cases as follows.

Case I: Inserting character(s) at the end of the query string. If the query string changes, the active nodes change accordingly. Let AN and AN' be the active nodes before and after inserting character(s) at the end of the query string. Then, it satisfies that $\forall an' \in AN'$, we can find an active $an \in AN$ such that $an = an'$ or an' is a descender node of an. If $an = an'$, we can still use the bitmap and corresponding BTag of an for an' to find the minimal score vertex. If an' is a child node of an, we should initialize the BTag of an' through an. Specifically, let $\langle x', y\rangle$ and $\langle x, y\rangle$ be the BTag of an' and an, respectively. Then, x' can be set to y. In the same way, we can iteratively derive the BTag for the bitmap of a descender node.

Case II: Deleting character(s) at the end of the query string. Let AN and AN' be the active nodes before and after deleting character(s) at the end of the query string. AN and AN' have the following relationship. $\forall an' \in AN'$, $\exists an \in AN$ such that $an = an'$ or an' is an ancestor node of an. Since the bitmaps of an's ancestor nodes have been accessed in the previous query, we can directly use existing BTags of an.

Case III: Inserting/deleting character(s) at random position of the query string. Let AN and AN' be the active nodes before and after deleting character(s) at random position of the query string. There are four relationships between AN and AN': $\forall an' \in AN'$, $\exists an \in AN$ such that (1) $an = an'$, or (2) an' is a descender node of an, or (3) an' is an ancestor node of an, or (4) an' has not descender and ancestor relationship with every previous active node in AN. For the first three relationships, we can use the Cases I and II to process the update. For the fourth relationship, it means that the active node is totally new. Thus, we should assign a new BTag for it, and traverse the bitmap of new active node from the first bit.

6.3 Multiple Query Strings

Sections 6.1 and 6.2 mainly aim at a single query string. In this section, we discuss how to handle multiple query strings. After the user types in a query string, if the result does not meet his/her expectation, he/she may proceed to type in more query strings. The methods proposed in Sections 6.1 and 6.2 can also be extended to tackle multiple query strings. In particular, we discuss the extension of Algorithms 1 and 2 for the case of multiple query strings.

When a new query string $q.str'$ is added, Algorithm 1 should find new active nodes for $q.str'$ (line 2). Then, it iteratively computes the vertex with the minimal score to find the top-k results by using Algorithm 2 (lines 5-15), which is the same as the case of a single query string. Specifically, Algorithm 2 computes the vertex with the minimal score for each active node (lines 4-18). For a single query string, the first "1" bit in the bitmap of active node is the minimal score vertex. But, for multiple query strings, we should compute the scores of vertices denoted by "1" bits in the bitmap of active node until the lower bound of vertex's score is larger than the current minimum score. The lower bound of vertex's score can be computed using Equation 1, where the textual similarity is the sum of the minimal prefix edit distance for all query strings. In addition, if a vertex's prefix edit distance w.r.t. previously entered query strings is larger than τ, it cannot become the final result and thus can be skipped the score computation.

7 PERFORMANCE STUDY

In this section, we evaluate the performance of our proposed index and algorithms using real-world road networks. All algorithms were implemented in C++, and compiled by GCC 7.5.0 with -O3 optimization. Our experiments were conducted on a machine running on Ubuntu server 18.04.5 LTS version with two Intel Xeon 2.40GHZ processors and 512G main memory.

Table 5: Statistics of road networks

Dataset	Region	$\|V\|$	$\|E\|$	$\|\mathsf{doc}(V)\|$	$\|W\|$
NY	New York City	264,346	733,846	157,100	6,556
FLA	Florida	1,070,376	2,712,798	343,452	16,656
EU	Eastern USA	3,598,623	8,778,114	780,749	33,522
WU	Western USA	6,262,104	15,248,146	1,580,430	52,316
CTR	Central USA	14,081,816	34,292,496	2,782,249	78,658
USA	Full USA	23,947,347	58,333,344	4,118,452	112,353

Datasets: We employ six publicly available real-world road networks in experiments. The road networks are from DIMACS[1]. The keywords of vertices are obtained from OpenStreeMap (OSM)[2]. For each road network, we get the points of interest (POI) in the corresponding area with a bounding box. The keywords of each POI are mapped to the closest vertex on the road network. Table 5 lists the statistics of road networks, where $|\mathsf{doc}(V)|$ denotes the occurrences of keywords in the road network, i.e., $|\mathsf{doc}(V)| = \sum_{v \in V} |\mathsf{doc}(v)|$, and $|W|$ represents the number of distinct keywords in the road network.

Compared Methods: There are three competitors in our experiments, i.e., the naive method, the instant query algorithm (IQA), and the instant update algorithm (IUA). Recall that, the first step of the naive method is to traverse the road network from $q.loc$. We implemented three versions of the naive method by using different techniques to traverse the road network, including **Dijkstra**, **G*-tree**, and **2-hop label**. Note that, for **G*-tree**, we employ the default parameter settings as reported in [25].

Parameter Settings and Metrics: We verify the effect of a set of parameters on algorithms, including the length of query string $|q.str|$, $q.str$'s frequency, the number of $q.str$, $q.str$'s edit distance, α, k, and τ. Table 6 summarizes the values and the default value of all parameters. We report the query time, index construction/update time, and index size in our experiments. For the evaluation of query efficiency, we randomly generate 5000 queries, and finally report the average query time. Note that, we only report empirical results of partial datasets in this paper due to the space limitation and the similar trends in the results of different datasets. Please refer to Appendix for the complete empirical results.

7.1 Evaluation of Instant Query Algorithm

In this section, we study the efficiency of instant query algorithm.

Exp-1: Effect of $|q.str|$. We first verify the effect of the query string length $|q.str|$. We vary $|q.str|$ from 1 to 7, and fix the other parameters to default values. Figure 7(a) shows the experimental results. We can observe that the query time of three baselines increases with the growth of $|q.str|$ while the query time of IQA ascends when $|q.str| \leq 3$. As $|q.str| > 3$, the query time of IQA almost does not change. This is because, for the baselines, the longer $q.str$ is, the less vertices satisfy the textual constraints. Thus, the search spaces of baselines become larger, incurring more query time. For IQA, the number of active nodes increases with the growth of $|q.str|$ when $|q.str| \leq 3$. Since we set the default value of error threshold to 2, the number of active nodes almost keep the same when $|q.str| > 3$. Hence, the running time of IQA almost keep the same as $|q.str| > 3$. Moreover, IQA outperforms each baseline by 1-2 orders of magnitude.

[1]http://www.diag.uniroma1.it// challenge9/download.shtml
[2]https://www.openstreetmap.org/

Table 6: Parameter settings in our experiments

Parameter	Values	Default Value
$\|q.str\|$	1, 2, 3, 4, 5, 6, 7	≤ 10
$q.str$'s frequency	10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}	$\geq 10^{-4}$
# of $q.str$	1, 2, 3, 4, 5	1
$q.str$'s edit distance	0, 1, 2, 3, 4	≤ 2
k	1, 2, 4, 8, 16, 32, 64	32
τ	0, 1, 2, 3, 4	2
α	0, 0.25, 0.5, 0.75, 1	0.5

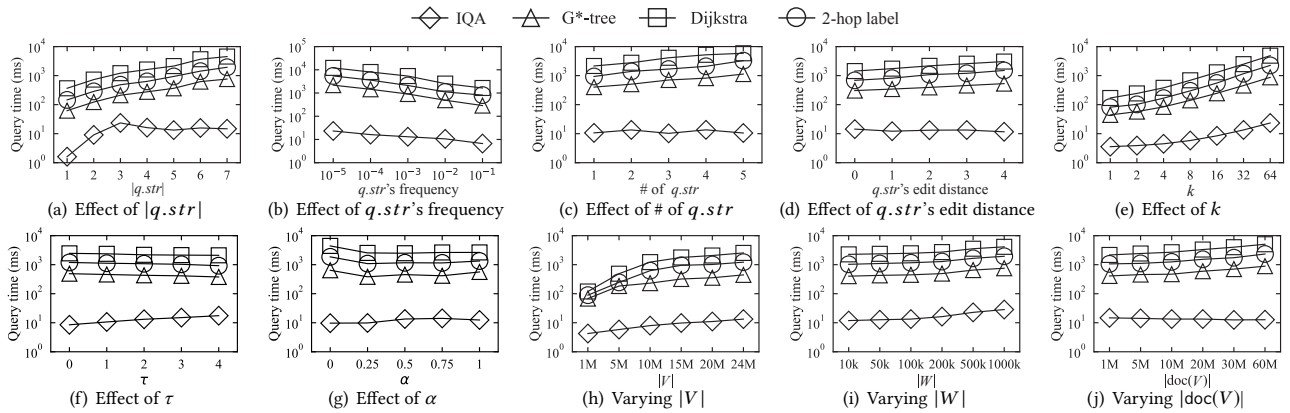
Exp-2: Effect of $q.str$'s frequency. Next, we evaluate the effect of $q.str$'s frequency. Here, the $q.str$'s frequency is $\frac{|V(q.str)|}{|\mathsf{doc}(V)|}$, where $V(q.str) = \{v | \forall v \in V, \exists kw \in \mathsf{doc}(v), q.str \preceq kw\}$. The query time are shown in Figure 7(b). The query time of IQA and three baselines decrease with the increase of $q.str$'s frequency. The reason behind is that if $q.str$ is frequent in the road network, there are more vertices containing $q.str$. Thus, the results are easier to be found, resulting in less query time. Again, IQA is still much faster than the three baselines by more than two orders of magnitude.

Exp-3: Effect of # of $q.str$. In this experiment, we explore the effect of the number of query strings, whose value is varied from 1 to 5. The query time of four algorithms are depicted in Figure 7(c). Specifically, the query time of baselines grow with the increase of the number of query strings while IQA almost keeps the same performance. For the three baselines, if the number of query strings increases, less vertices will satisfy the textual constraint. Hence, the baselines have to traverse more vertices to find the results. IQA finds the minimal score vertices by traversing the bitmaps of active nodes. For multiple query strings, we only need to traverse the bitmaps of active nodes for a single query string. Therefore, the query time of IQA does not change much.

Exp-4: Effect of $q.str$'s edit distance. Recall that our proposed algorithms can tolerate the typos in $q.str$. Thus, we study the effect of $q.str$'s edit distance. To this end, we assume that $q.str$ includes several typos. The $q.str$'s edit distance is the edit distance between $q.str$ and the correct string. Note that, to ensure non-empty query result, we set $\tau = 4$ in this experiment. Figure 7(d) shows the empirical results. We can observe that when the $q.str$'s edit distance increases, the query time of IQA gradually drops while the query time of baselines gradually grows. This is because the larger the $q.str$'s edit distance, the less vertices in the road network satisfy the prefix edit distance constraint, meaning that the baselines need to search more vertices. But, IQA can quickly skip invalid vertices since larger $q.str$'s edit distance leads to less active nodes.

Exp-5: Effect of k. We investigate the effect of k by varying k from 1 to 64. Figure 7(e) plots the query time of four algorithms. As k becomes larger, the query time of four algorithms all increase. The reason behind is that the larger k indicates more results. Hence, all algorithms take more time to query. However, the performance of IQA is still much better than that of baselines.

Exp-6: Effect of τ. Then, we evaluate the effect of error threshold τ on algorithms. The empirical results are reported in Figure 7(f). We can observe that the query time of three baselines decrease



(a) Effect of $|q.str|$ (b) Effect of $q.str$'s frequency (c) Effect of # of $q.str$ (d) Effect of $q.str$'s edit distance (e) Effect of k

(f) Effect of τ (g) Effect of α (h) Varying $|V|$ (i) Varying $|W|$ (j) Varying $|\mathsf{doc}(V)|$

Figure 7: Evaluation of instant query algorithm on USA

while the query time of IQA increases with the growth of τ. If τ becomes larger, (1) more vertices satisfy the textual constraint, and (2) more active nodes will be found. Thus, the baselines spend less time while IQA takes more time. Nonetheless, IQA is still 1-2 orders of magnitude faster than the baselines.

Exp-7: Effect of α. α represents the user preference for score computation in Equation 1. A large α value indicates that users prefer to geo-textual objects with short distances. Otherwise, users prefer to geo-textual objects that match query string better. This set of experiment test the effect of α on algorithms and the results are shown in Figure 7(g). We can observe that when $\alpha = 0$, the baselines take more time. This is because the text pruning abilities of baselines are weak. For other values of α, the performance of all algorithms are stable, meaning that α has little effect on algorithms.

Exp-8: Scalability. In this set of experiments, we verify the scalability of the algorithms. In view of this, we vary the vertex cardinality $|V|$, the number of distinct keywords $|W|$, and the occurrences of keywords $|\mathsf{doc}(V)|$. Figures 7(h), 7(i), and 7(j) plot the query time by changing $|V|$, $|W|$, and $|\mathsf{doc}(V)|$, respectively. In Figure 7(h), with the growth of vertex cardinality, the performance of all algorithms degrade since the larger road network needs more time to find the results. In Figure 7(i), as the number of distinct keywords increases, the performance of four algorithms degrade as well. This is because when the number of distinct keywords grows, the keywords will become less frequent. Hence, all algorithms take more time with the growth of $|W|$, which is consistent with the empirical results of $q.str$'s frequency depicted in Figure 7(b). In Figure 7(j), as the occurrences of keywords increase, the performance of three baselines degrade while that of IQA keeps stable. If the occurrences of keywords grow, the vertices contain more keywords. Thus, the search spaces of three baselines become larger, incurring more query time. On the other hand, the growth of the occurrences of keywords does not affect the complete trie of the road netwrok. Hence, the active nodes found by IQA do not change as well. Therefore, the query time of IQA keeps stable.

7.2 Evaluation of Instant Update Algorithm

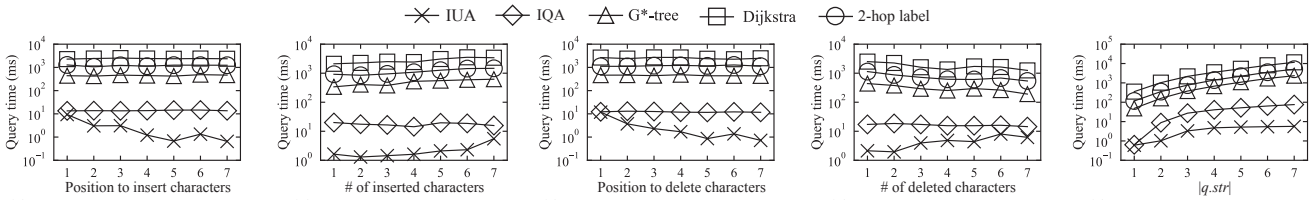
In this section, we evaluate the performance of instant update algorithm. IQA, G*-tree, Dijkstra, and 2-hop label are instant query algorithms used for results update, i.e., to query from the scratch. IUA is the instant update algorithm presented in Section 6.2.

Exp-9: Effect of the position to insert characters. First, we explore the effect of inserting characters into different positions of $q.str$. Here, if we insert the characters into the position i of $q.str$, it means that we insert the characters after the i-th character of $q.str$. Note that, the $|q.str| \geq 7$, and we vary the position from 1 to 7. We insert one character in this experiment. Figure 8(a) depicts the empirical results. Specifically, the query time of all algorithms almost remain the same, except for IUA. Moreover, we can observe that if the insertion position is closer to the end of $q.str$, IUA has better performance. This is because the closer to the end of the query string, the less BTags will be updated. Thus, IUA needs less time to update. In addition, IUA has better performance compared with other algorithms. Specifically, IUA returns results in an average time of 2.1ms while IQA takes 10ms.

Exp-10: Effect of # of inserted characters. Next, we investigate the effect of inserting different number of characters into $q.str$. To this end, we extract characters from a complete keyword, and take the remaining string as $q.str$. Then, in experiments, we insert the extracted characters into $q.str$. In this way, we ensure the query result is non-empty. The query time of all algorithms are shown in Figure 8(b). When the number of inserted characters increases, all algorithms take more query time. This is because when we insert more characters, $q.str$ becomes more accurate. The baselines should traverse more vertices to find the results, and thus need more time to query. For IUA, if we insert more characters, the difference between the original query string and new query string is greater. Hence, IUA has to need more time to update BTags. Although IUA becomes less efficient when more characters are inserted, it is still better than IQA, and is 2 orders of magnitude faster than the baselines.

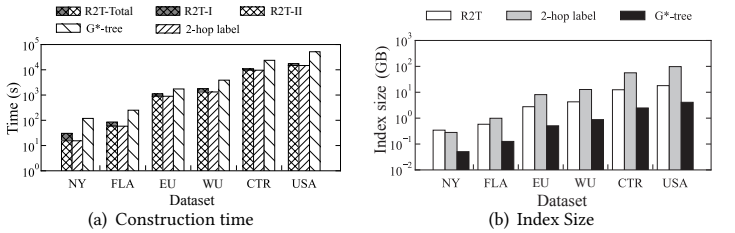
Exp-11: Effect of the position to delete characters. In this experiment, we study the instant update algorithm by deleting characters from different positions of the query string. We vary the deletion position from 1 to 7. Here, the deletion position i means that the i-th character of $q.str$ is deleted. Figure 8(c) depicts the empirical results. As observed, the closer the deletion position is to the end of $q.str$, the better performance of IUA. The reason behind is similar with that of Exp-9, i.e., when deleting characters near the end of $q.str$, less BTags need to be updated.

Exp-12: Effect of # of deleted characters. Then, we verify the effect of deleting different number of characters from $q.str$. In view of this, we randomly choose a deletion position in $q.str$, and delete



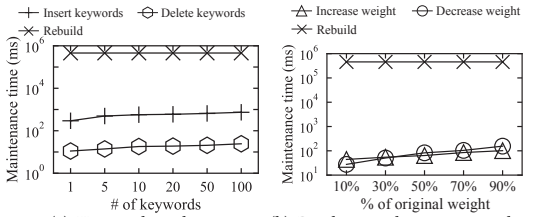
(a) Position to insert characters (b) # of inserted characters (c) Position to delete characters (d) # of deleted characters (e) Instant query simulation

Figure 8: Evaluation of instant update algorithm on USA



(a) Construction time (b) Index Size

Figure 9: Index construction



(a) Keywords update (b) Road network structure update

Figure 10: Index maintenance (WU)

a certain number of characters, which varies from 1 to 7. Empirical results are plotted in Figure 8(d). We have the following observations. With the growth of the number of deleted characters, (1) the query time of baselines drops, (2) the query time of IQA remains unchanged, and (3) the query time of IUA increases slowly. However, IUA is still able to handle the deletion of characters efficiently, and outperforms the baselines by 1-2 orders of magnitude.

Exp-13: Instant query simulation. This experiment simulates the users' instant queries, i.e., to simulate users type in the query string character-by-character. As soon as a character is typed in, we perform the query/update algorithms for the new query string, and return the results. Finally, after the users type in the complete query string, we report the total query/update time, as depicted in Figure 8(e). Note that, the length of query string for this experiment changes from 1 to 7. As expected, the total query time of all algorithms increase if the length of query string becomes larger. Nevertheless, the total query time of three baslines ascends much faster than that of both IUA and IQA. This is because the query information inheritance mechanism of IUA makes it be able to perform update incrementally. In addition, the performance of IUA is much better than other algorithms. For example, as $|q.str| = 7$, IUA can finish the query within 7ms while the fastest baseline (i.e., the G*-tree) takes 2500ms, confirming the superiority of IUA.

7.3 Index Evaluation

In this section, we evaluate the performance of R2T index, including the index construction and maintenance.

Exp-14: Index Construction. First, we investigate the performance of index construction. In this experiment, we take G*-tree and 2-hop label, which are the indexes of baselines, as competitors. Figures 9(a) and 9(b) show the index construction time and index size, respectively. Note that, in Figure 9(a), we split the construction time of R2T into two parts, i.e., R2T-I and R2T-II. Specifically, R2T-I represents the time of computing 2-hop label for every vertex, and R2T-II denotes the time of constructing $\widetilde{\mathsf{L}}(v)$ and $\mathsf{T}(v)$ for every vertex after getting 2-hop labels. In Figure 9(a), we can observe that G*-tree needs the longest time to construct. For R2T, R2T-I takes up most of the construction time. For example, on the road network CT, the time of R2T-I and R2T-II are 1289s and 9626.5s , respectively. R2T-I is 11.8% of the total construction time. In Figure 9(b), G*-tree has the smallest size and 2-hop label has the largest size. The size of R2T is smaller than that of 2-hop label. This is because we remove some vertices without keywords from the reverse 2-hop label, and the bitmap compression strategy is effective.

Exp-15: Index maintenance. Next, we explore the performance of index maintenance. We mainly consider two categories of the road network update, including keywords update and road network structure update. The keywords update is to insert/delete a certain number of keywords into/from $\mathtt{doc}(v)$ of a vertex v. Figure 10(a) plots the index maintenance time for the keywords update. The road network structure update contains the update of edges' weight and the insertion/deletion of edges/vertices. Since the insertion/deletion of edges/vertices can be reduced to the update of edges' weight [41], we mainly consider the update of edges' weight in this experiment. In particular, the update of edges' weight include the cases of increasing and decreasing the weight of an edge. For each road network, we select 1000 edges at random and change their weights. The maintenance time of road network structure update is shown in Figure 10(b). Overall, in both Figures 10(a) and 10(b), the maintenance time is much smaller than the time of rebuilding the index, demonstrating the efficiency of our proposed algorithms.

8 CONCLUSIONS

In this paper, we study the problem of instant error-tolerant spatial keyword queries on road networks. To efficiently answer the queries, we propose a new index called R2T. R2T employs reverse 2-hop label and trie to seamlessly integrate the spatial and textual information for each vertex of the road network. Based on R2T, we present a suite of algorithms to answer the queries. Moreover, we discuss how to construct and maintain R2T. Both theoretical analysis and empirical evaluation demonstrate the efficiency of our proposed index and algorithms. This work is our first step towards the studied problem. In the future, we would like to investigate the instant error-tolerant spatial keyword queries for moving query object or in the distributed environment.

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APPENDIX

A THE PROOF OF THEOREM 5.1

Theorem 5.1. The size of R2T(v) is bounded by $O(\log |V|)$.

Proof. A R2T consists of two parts, reverse 2-hop label and node array. First, the space complexity of 2-hop label is $O(\log |V|)$. Thus, it also requires $O(\log(|V|))$ space to store the reverse 2-hop label. Let y be the average word length, the total number of nodes in the trie corresponding to R2T is $O(y \cdot \frac{|\text{doc}(V)|}{|V|} \cdot \log |V|)$. Each node has a bitmap. The number of bits in the bitmap is equal to the number of labels in the reverse 2-hop label. Before compressing bitmaps, it takes $O(y \cdot \frac{|\text{doc}(V)|}{|V|} \cdot \log |V| + y \cdot \frac{|\text{doc}(V)|}{|V|} \cdot \log |V| \cdot \log |V|) = O(\log^2 |V|)$ space to store the trie and all bitmaps. Let x be the average number of child of a node in the trie. Assumed that the words of vertexes are evenly distributed on the prefix tree. The bitmap of node in level i has $O(\frac{\log |V|}{x^{i-1}})$ bits, and there are x^i nodes in the i-th layer. After compressing the bitmaps, the space cost is $O(1 \cdot \log |V| + \sum_{i=1}^{n-1} x^i \cdot \frac{\log |V|}{x^{i-1}}) = O(\log |V|)$. □

B THE PROOF OF THEOREM 5.2

Theorem 5.2. The time and space complexities of R2T(v) construction are $O(\log^2 |V|)$ and $O(\log^2 |V|)$, respectively.

Proof. R2T(v) construction has two stages, calculating bitmaps and compressing bitmaps. When calculating a bitmap, we should set a certain bit of the bitmap to "1", which takes $O(1)$ time. In the proof of Theorem 5.1, we have showed that there are $O(y \cdot \frac{|\text{doc}(V)|}{|V|} \cdot \log |V|)$ bitmaps. Hence, it needs $O(y \cdot \frac{|\text{doc}(V)|}{|V|} \cdot \log |V|) = O(\log |V|)$ time to calculate all bitmaps. When compressing a bitmap, we should check each bit and the bitmap of its father node. Since the number of bits is equal to the number of labels in reverse 2-hop label, it needs $O(\log |V|) \cdot O(y \cdot \frac{|\text{doc}(V)|}{|V|} \cdot \log |V|) = O(\log^2 |V|)$ time to compress all bitmaps. Therefore, the total time complexity of R2T(v) construction is $O(\log |V| + \log^2 |V|) = O(\log^2 |V|)$.

The space overhead of R2T(v) construction is the storage of uncompressed bitmaps. Thus, the space cost is $O(y \cdot \frac{|\text{doc}(V)|}{|V|} \cdot \log |V| \cdot \log |V| = O(\log^2 |V|)$. □

C THE PROOF OF LEMMA 6.1

Lemma 6.1. Given a vertex $v \in G$,

$$\bigcup_{v' \in \mathsf{L}(v)} \widetilde{\mathsf{L}}(v') = V \tag{2}$$

Proof. We prove it by contradiction. Given a vertex $v \in G$. Assume that $\bigcup_{v' \in \mathsf{L}(v)} \widetilde{\mathsf{L}}(v') \neq V$. Then, there exists a vertex $u \in V$ and $u \notin \bigcup_{v' \in \mathsf{L}(v)} \widetilde{\mathsf{L}}(v')$. According to the definition of reverse 2-hop label, for any vertex $p \in \mathsf{L}(u)$, $u \in \widetilde{\mathsf{L}}(p)$. Since $u \notin \bigcup_{v' \in \mathsf{L}(v)} \widetilde{\mathsf{L}}(v')$, $p \notin \mathsf{L}(v)$, i.e. $\mathsf{L}(v) \cap \mathsf{L}(u) = \varnothing$. This contradicts the property of 2-hop label and the assumption does not hold. The proof is completed. □

D THE PROOF OF LEMMA 6.2

Lemma 6.2. Given a vertex $v \in G$, for a vertex $v' \in \mathsf{L}(v)$, let $v'' = \arg\min_{v'' \in \widetilde{\mathsf{L}}(v')} dis(v', v'')$. Note that $v'' \neq v$. Then, the nearest neighbor of v is

$$v'' = \arg\min_{v'' \in \widetilde{\mathsf{L}}(v'), v' \in \mathsf{L}(v)} dis(v, v') + dis(v', v'') \tag{3}$$

Proof. Let v'' be the nearest neighbor of v and $u \in G$. According to Lemma 6.1 and the definition of 2-hop label, $\text{dis}(v, u) = \min_{u \in \widetilde{\mathsf{L}}(p), p \in \mathsf{L}(v)} dis(v, p) + dis(p, u)$. Since v'' is the nearest neighbor of v, $v'' = \arg\min_{v'' \in \widetilde{\mathsf{L}}(v'), v' \in \mathsf{L}(v)} dis(v, v') + dis(v', v'')$.

Next, we prove $v'' = \arg\min_{v'' \in \widetilde{\mathsf{L}}(v')} dis(v', v'')$ by contradiction. Assume that $v'' \neq \arg\min_{v'' \in \widetilde{\mathsf{L}}(v')} dis(v', v'')$, meaning that there exists a vertex u such that $\text{dis}(v', u) < \text{dis}(v', v'')$. We have $\text{dis}(v, v') + \text{dis}(v', u) < \text{dis}(v, v') + \text{dis}(v', v'') = dis(v, v'')$. It contradicts the fact that v'' is the nearest neighbor of v. Hence, the assumption does not hold. The proof is completed. □

E THE PROOF OF COROLLARY 6.1

Corollary 6.1. Given a query $q = (q.loc, q.str)$, for a vertex $v \in \mathsf{L}(q)$, let $v' = \arg\min_{v' \in \widetilde{\mathsf{L}}(v)} \texttt{score}(q, v')$. Then, the vertex with the minimal score w.r.t. q is

$$v' = \arg\min_{v' \in \widetilde{\mathsf{L}}(v), v \in \mathsf{L}(q)} \texttt{score}(q, v') \tag{4}$$

Proof. Let $q \in G$ and v' be the vertex with the minimal score w.r.t q. For any $u \in G$ and $p \in \mathsf{L}(q)$, accoring to Lemma 6.2 and Equation(1), $\texttt{score}(q, u) = \min_{u \in \widetilde{\mathsf{L}}(p), p \in \mathsf{L}(v)} \texttt{score}(q, u)$. Since v' has the smallest score, $v' = \arg\min_{v' \in \widetilde{\mathsf{L}}(v), v \in \mathsf{L}(q)} \texttt{score}(q, v')$. We prove $v' = \arg\min_{v' \in \widetilde{\mathsf{L}}(v)} \texttt{score}(q, v')$ by contradiction. Assume that $v' \neq \arg\min_{v' \in \widetilde{\mathsf{L}}(v)} \texttt{score}(q, v')$. There exists a vertex that has smaller score than v'. It contradicts the fact that v' is the vertex with the minimal score w.r.t q. Therefore, the assumption does not hold. The proof is completed. □

F THE PROOF OF LEMMA 6.3

Lemma 6.3. Given two trie nodes n_1 and n_2, two pairs $\langle x_1, y_1 \rangle$ and $\langle x_2, y_2 \rangle$, which are the BTags of the bitmaps of n_1 and n_2, respectively. Assume that n_1 is the child node of n_2. If $y_2 = x_1$, the vertex represented by the x_1-th bit in the bitmap of n_1 and the vertex represented by the x_2-th bit in the bitmap of n_2 are the same.

Proof. Let B_1 be the bitmap of n_1 and B_2 be the bitmap of n_2. According to the rule of compression, the number of bits in B_1 is equal to the number of "1" bits in B_2, i.e. the number of vertices represented by B_2 are the same as that of the vertices denoted by all "1" bits in B_1. Thus, the x_1-th bit in B_1 is the x_1-th "1" bit in B_2. As the x_2-th bit in B_2 is the y_2-th "1" bit in $B2$ and $y_2 = x_1$, the x_1-th bit in B_1 and x_2-th bit in B_2 represent the same vertex. □

G THE PROOF OF THEOREM 6.4

Theorem 6.4. The time and space complexities of Algorithm 1 are $O((k + \log |V|) \cdot |AN| \cdot \sqrt{\log |V|})$ and $O(\log |V| \cdot |AN| \cdot |q.str|)$, respectively.

Proof. Algorithm 1 first finds the active nodes in the trie of the road network, whose time complexity is $O(|AN|)$. Then, Algorithm 1 finds the minimal score vertices for each reverse 2-hop label. Next, Algorithm 1 iteratively selects the minimal score vertices until all results are found. In each round, after Algorithm 1 selects a minimal score vertex, which is in $\widetilde{\mathsf{L}}(v)$, Algorithm 1 should find the next minimal score vertex for $\widetilde{\mathsf{L}}(v)$. Totally, Algorithm 1

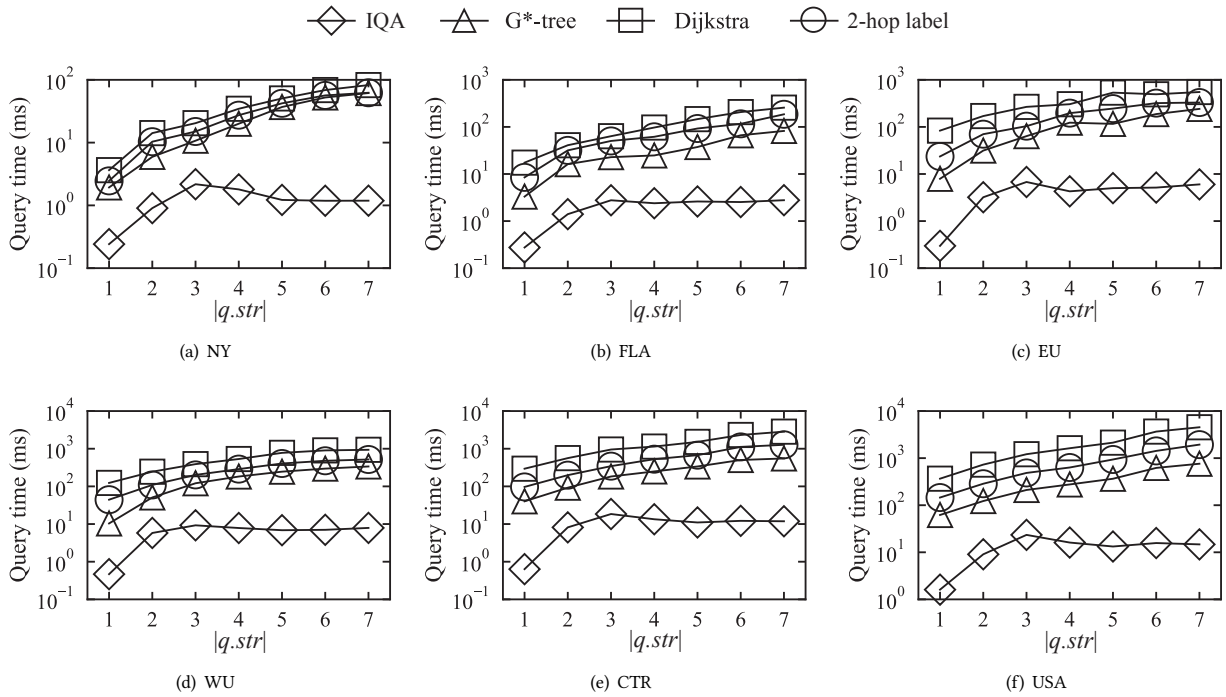

Figure 11: Effect of $|q.str|$

has to find the minimal score vertex $k + |\mathtt{L}(q)|$ times. The average length of $\mathtt{L}(q)$ is $O(\log |V|)$. Thus, $O(k + \log |V|)$ vertices with the minimal score should be found. Algorithm 1 employs Algorithm 2 to find the minimal score vertex. Specifically, Algorithm 2 first computes the minimal score vertex for each active node. The vertex with the smallest score among all active nodes is the minimal score vertex of the reverse 2-hop label. For each active node, Algorithm 2 traverses the bitmaps of the active node to find the minimal score vertex, which takes $O(\sqrt{\log |V|})$ time. For all active nodes, Algorithm 2 takes $O(|AN| \cdot \sqrt{\log |V|})$ time. Therefore, the time complexity of Algorithm 1 is $O(|AN| + (k + \log |V|) \cdot |AN| \cdot \sqrt{\log |V|}) = O((k + \log |V|) \cdot |AN| \cdot \sqrt{\log |V|})$.

The space complexity of Algorithm 1 is bounded by the bitmaps and BTag, which is $O(\log |V| \cdot |AN| \cdot |q.str|)$.

□

H EMPIRICAL RESULTS

This section shows the full version of the empirical results. Figure 11 depicts the results of the effect of query string length $|q.str|$ (i.e., **Exp-1**). Figure 12 plots the results of the effect of $q.str$'s frequency (i.e., **Exp-2**). Figure 13 shows the results of the effect of the number of query strings (i.e., **Exp-3**). Figure 14 illustrates the results of the effect of query string's edit distance (i.e., **Exp-4**). Figure 15 depicts the results of the effect of k (i.e., **Exp-5**). Figure 16 shows the results of the effect of error threshold τ (i.e., **Exp-6**). Figure 17 plots the results of the effect of α (i.e., **Exp-7**). Figure 18 shows the scalability of the algorithms (i.e., **Exp-8**). Figure 19 depicts the results of the effect of inserting characters into different positions (i.e., **Exp-9**). Figure 20 shows the results of the effect of inserting different number of characters into the query string (i.e., **Exp-10**). Figure 21 illustrates the results of the effect of deleting characters from different positions (i.e., **Exp-11**). Figure 22 shows the results of the effect of deleting different number of characters from the query string (i.e., **Exp-12**). Figure 23 depicts the results of simulating user's instant query (i.e., **Exp-13**). Figures 24 to 27 show the results of index construction (i.e., **Exp-14**). In particular, Figure 25 plots the index size of R2T before and after compressing bitmaps, and Figure 27 depicts the index building time of R2T using different numbers of threads. Figure 28 and Figure 29 show the results of index maintenance (i.e., **Exp-15**), including keywords update and road network structure update.

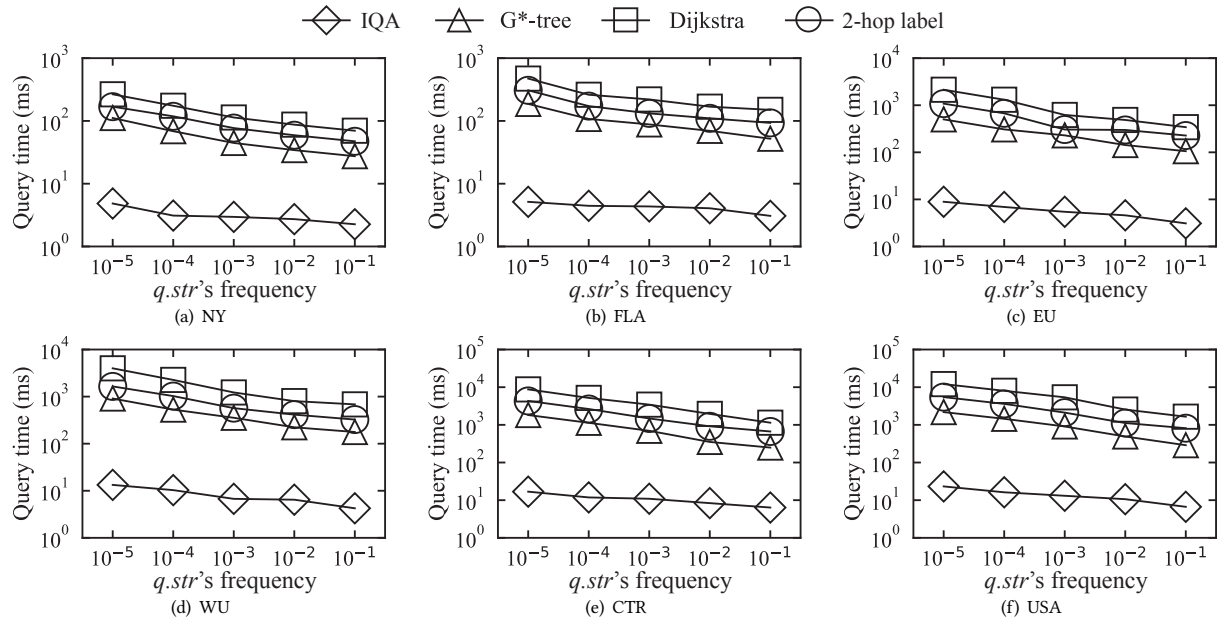

Figure 12: Effect of $q.str$'s frequency

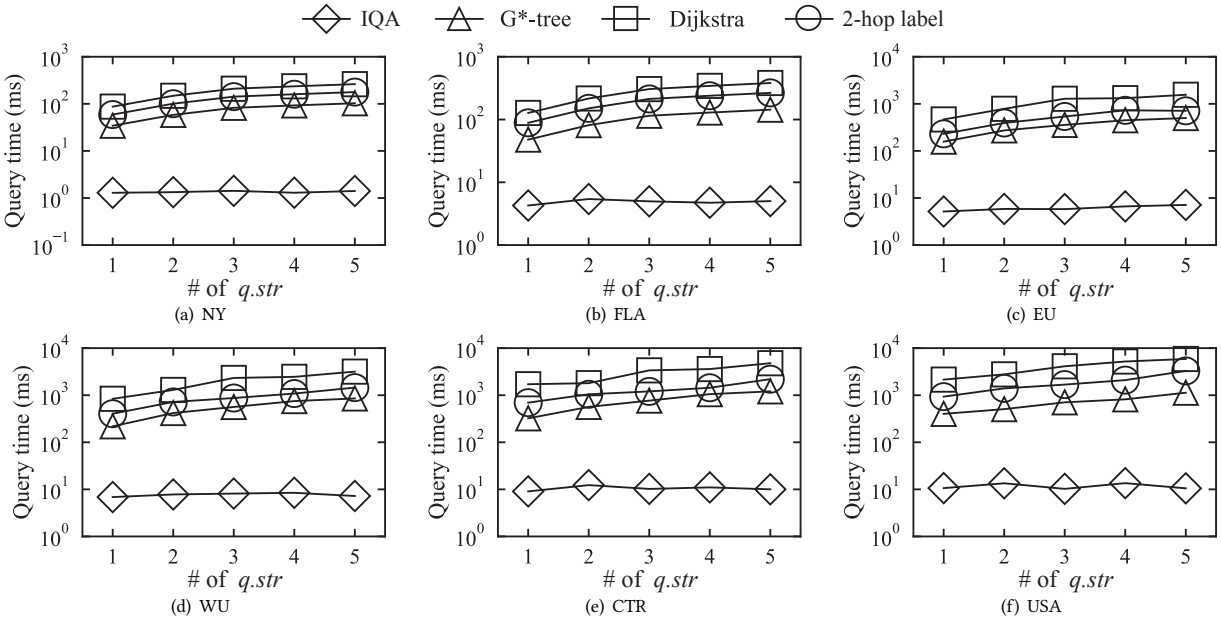

Figure 13: Effect of # of $q.str$

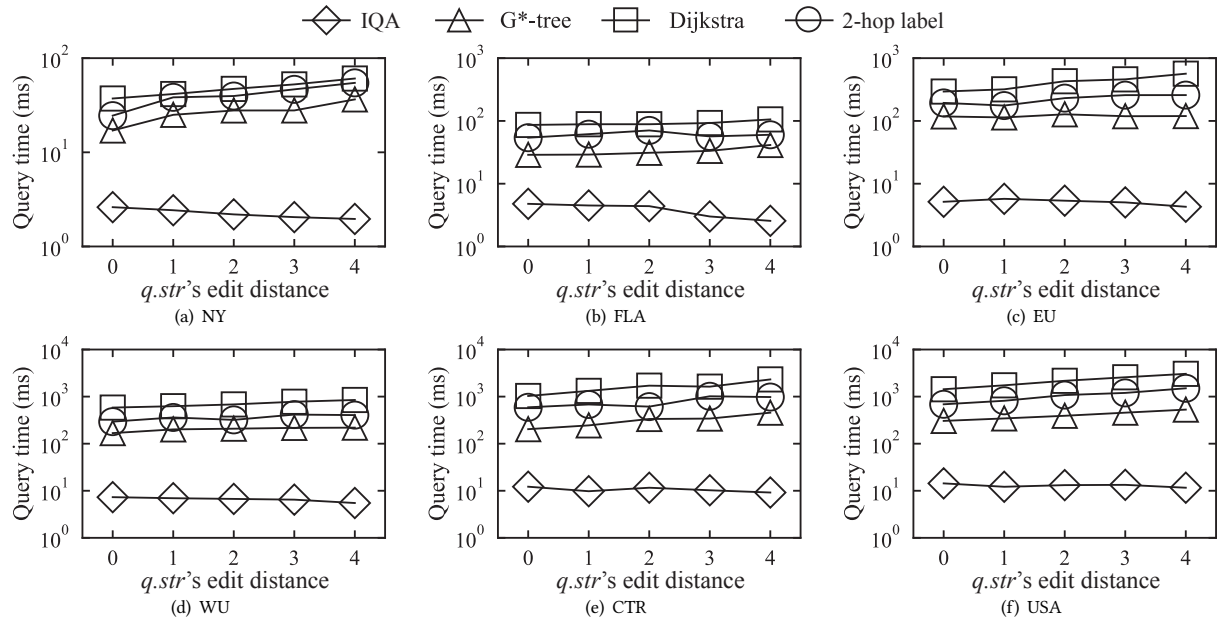

Figure 14: Effect of $q.str$'s edit distance

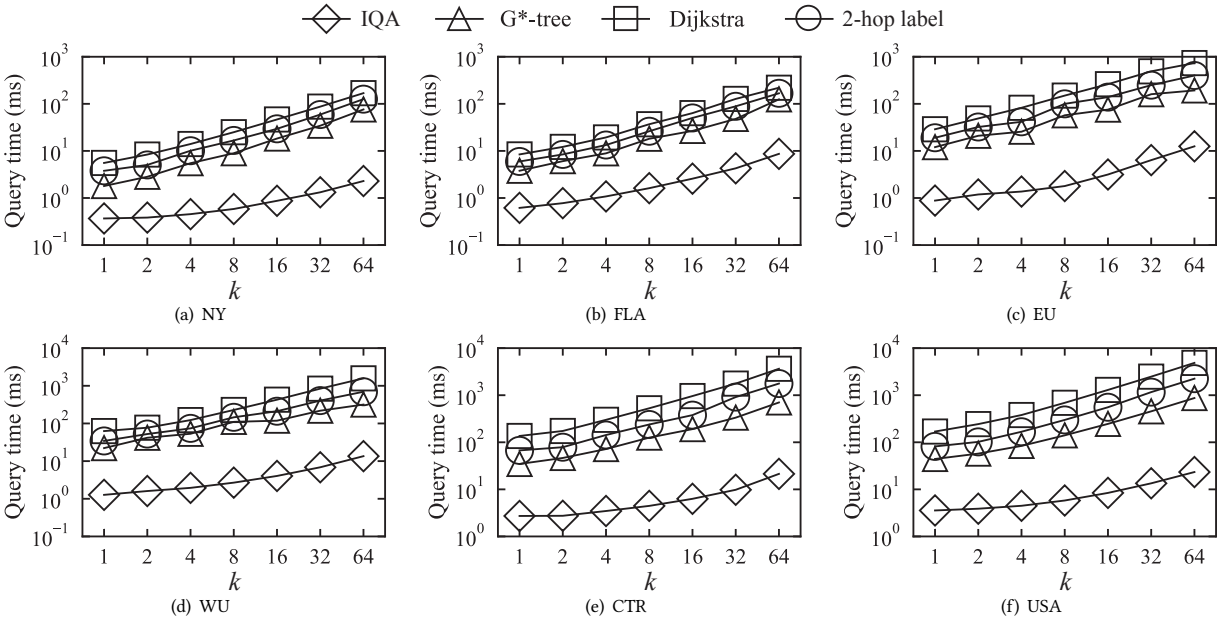

Figure 15: Effect of k

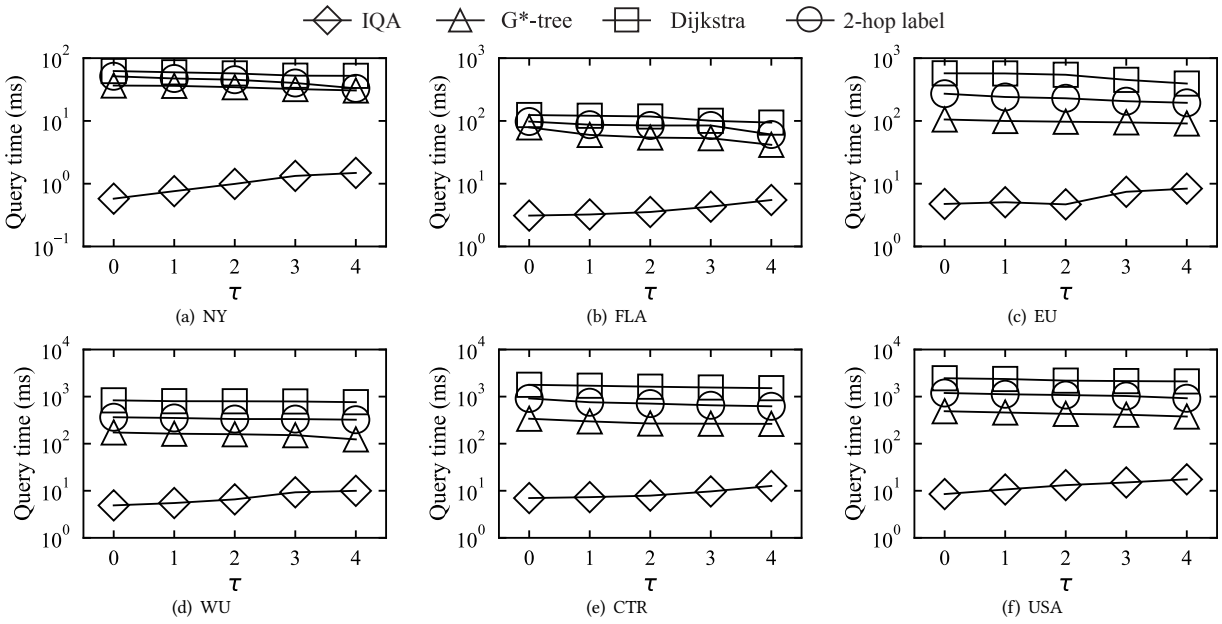

Figure 16: Effect of τ

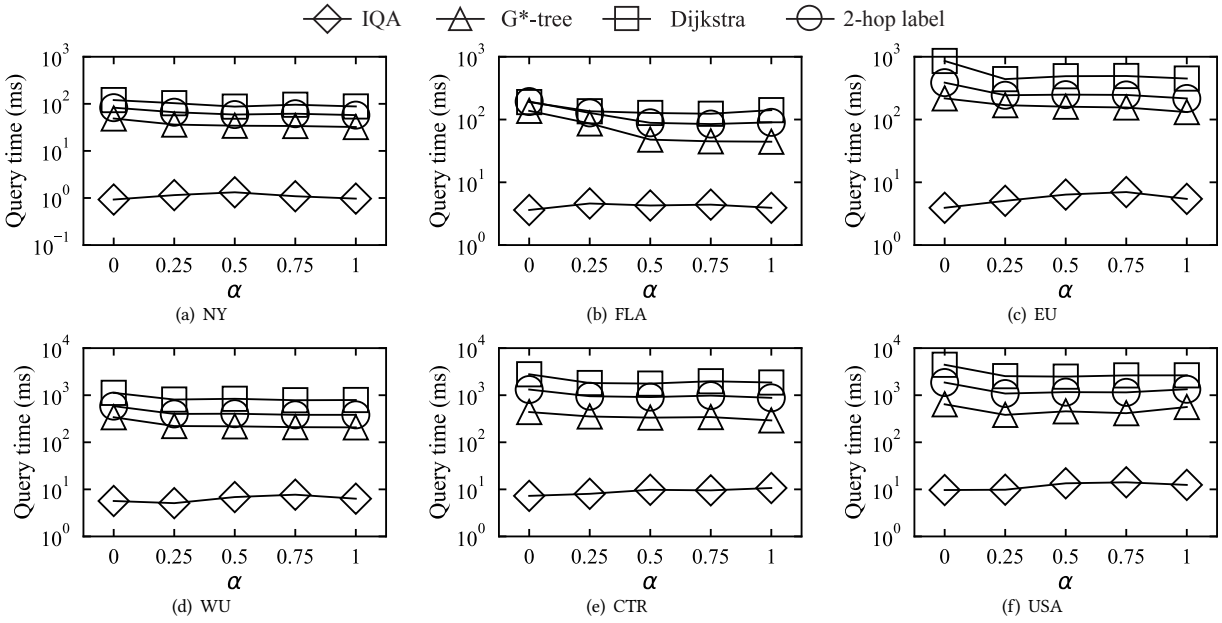

Figure 17: Effect of α

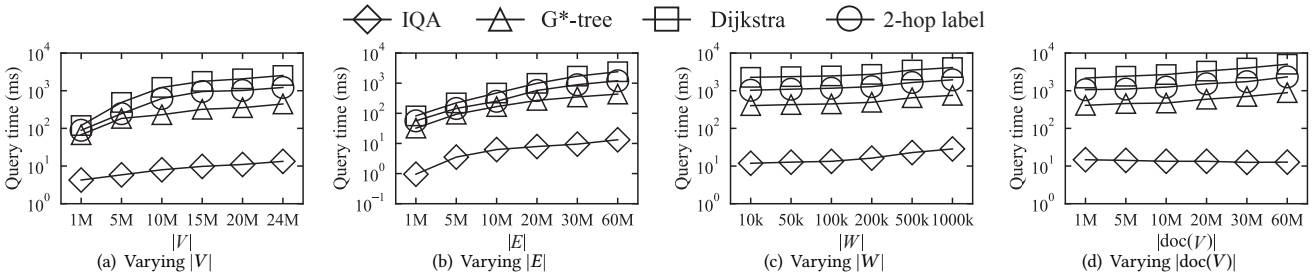

Figure 18: Effect of scalability

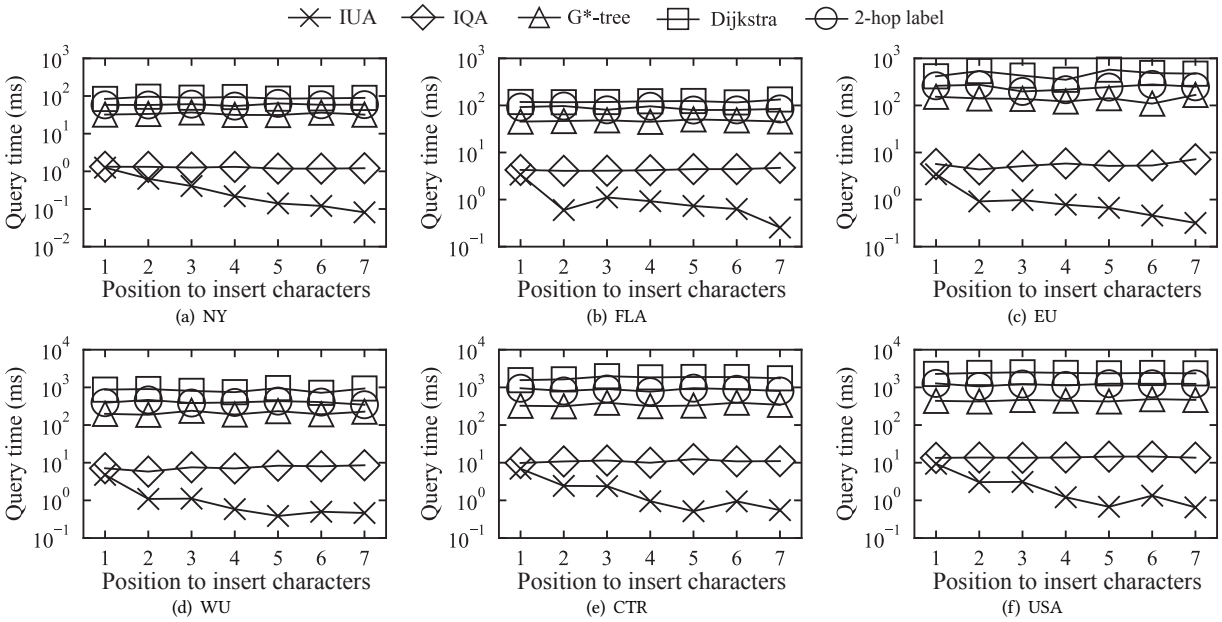

Figure 19: Position to insert characters

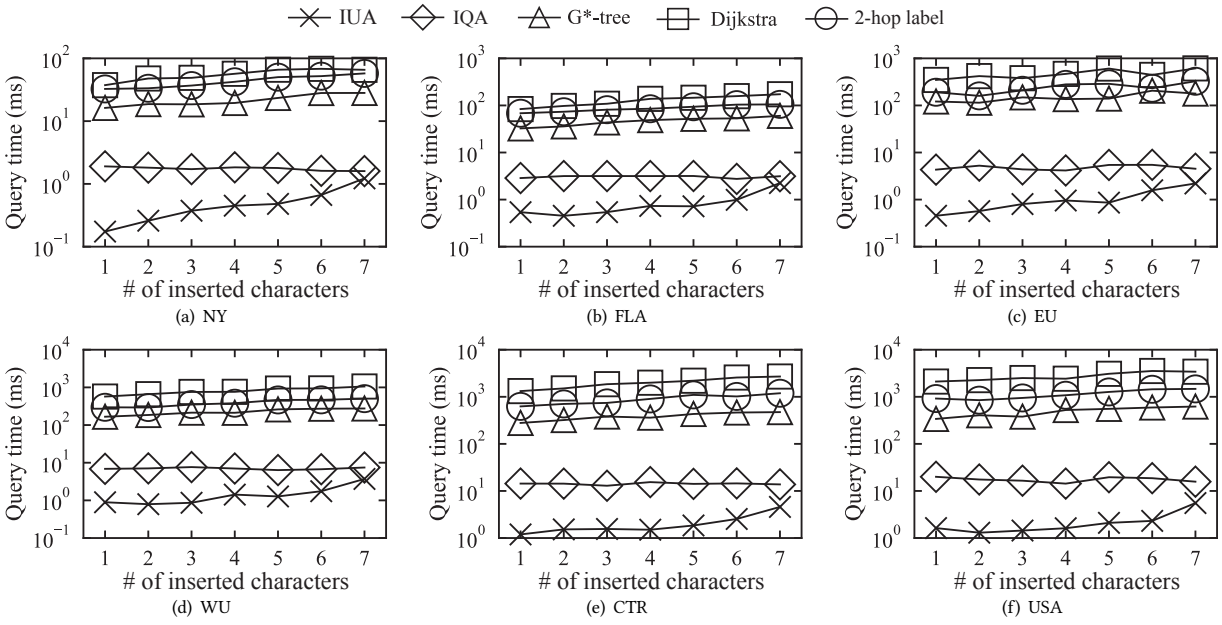

Figure 20: # of inserted characters

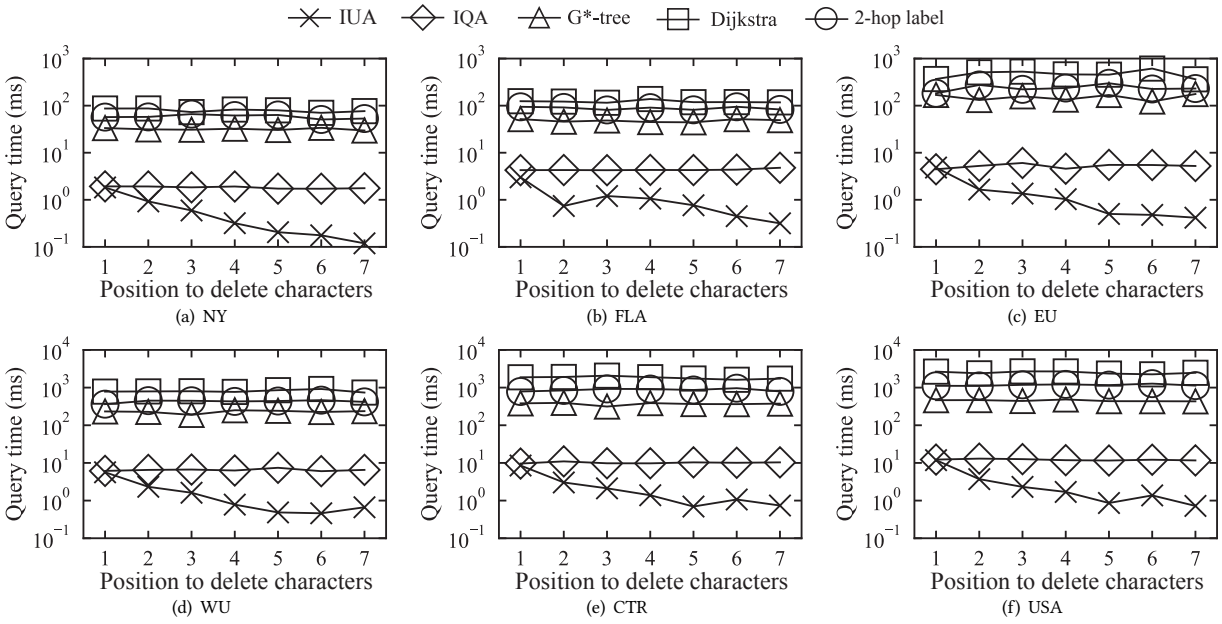

Figure 21: Position to delete characters

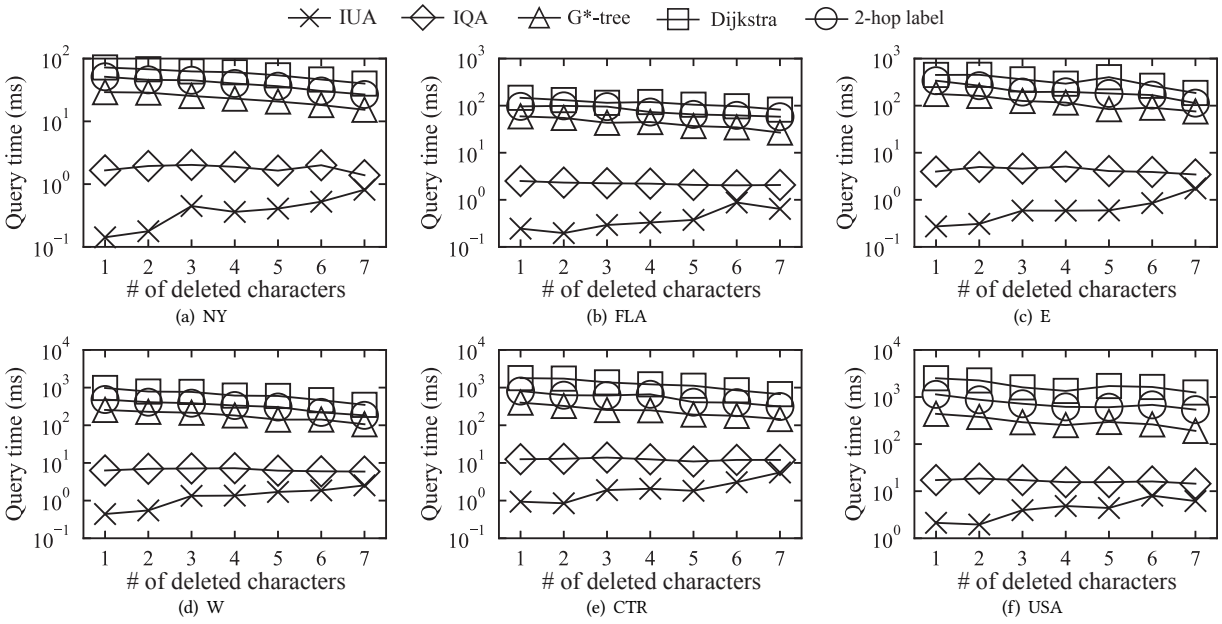

Figure 22: # of deleted characters

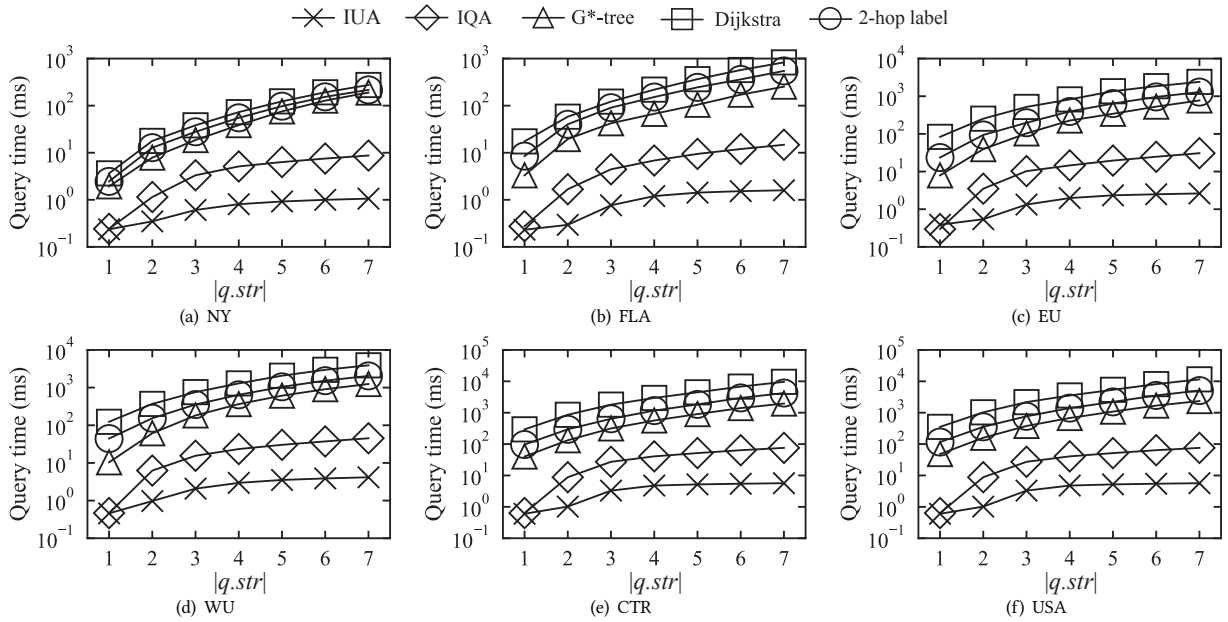

Figure 23: Intant query simulation

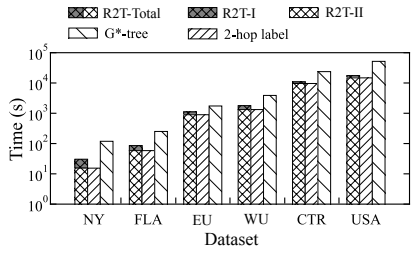

Figure 24: Construction time

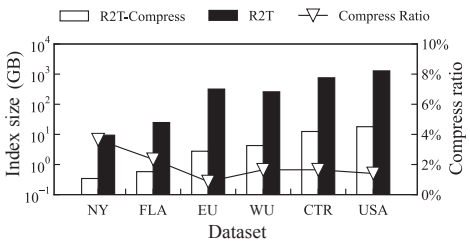

Figure 25: Index size of compression

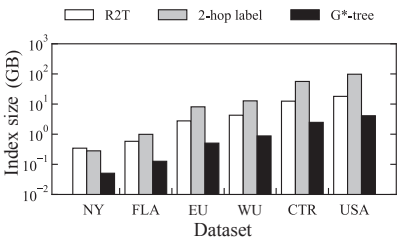

Figure 26: Index size

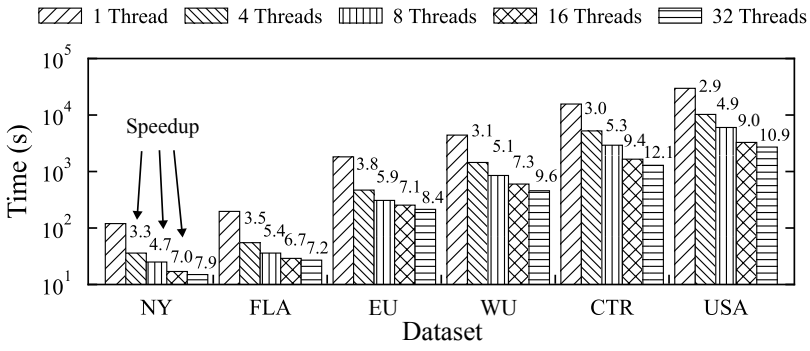

Figure 27: Construction time of multi-threads

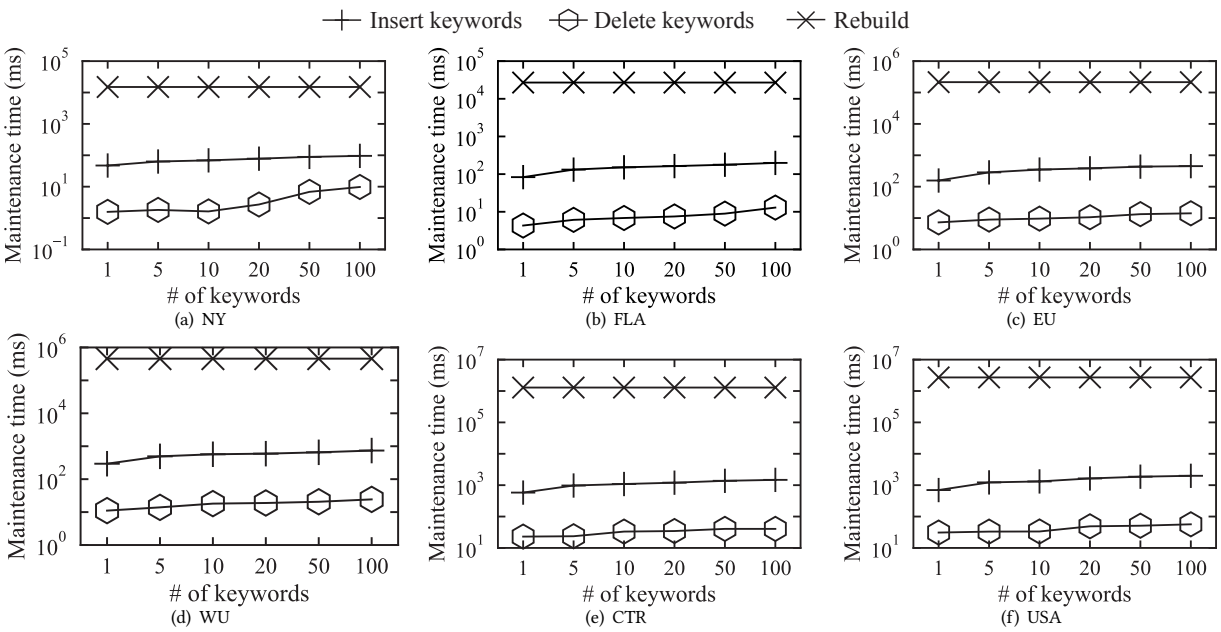

Figure 28: Keywords update

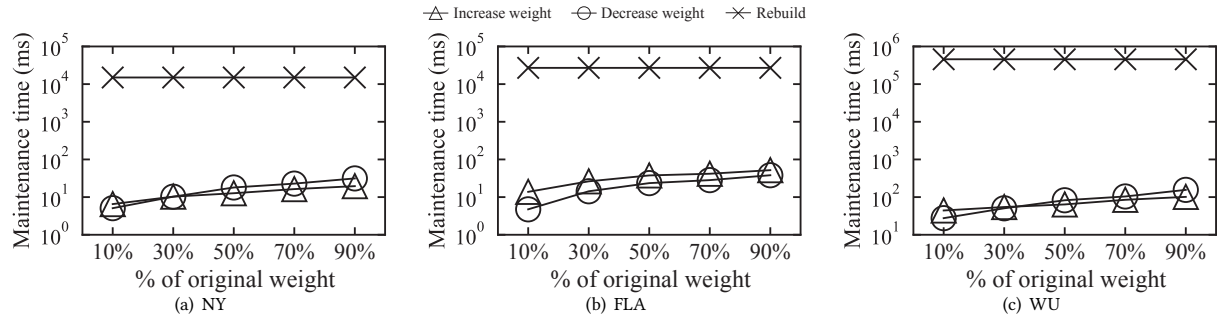

Figure 29: Road network structure update