FAST: Frequency-Aware Spatio-Textual Indexing for In-Memory Continuous Filter Query Processing

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Abstract—Many applications need to process massive streams of spatio-textual data in real-time against continuous spatio-textual queries. For example, in location-aware ad targeting publish/subscribe systems, it is required to disseminate millions of ads and promotions to millions of users based on the locations and textual profiles of users. In this paper, we study indexing of continuous spatio-textual queries. There exist several related spatio-textual indexes that typically integrate a spatial index with a textual index. However, these indexes usually have a high demand for main-memory and assume that the entire vocabulary of keywords is known in advance. Also, these indexes do not successfully capture the variations in the frequencies of keywords across different spatial regions and treat frequent and infrequent keywords in the same way. Moreover, existing indexes do not adapt to the changes in workload over space and time. For example, some keywords may be trending at certain times in certain locations and this may change as time passes. This affects the indexing and searching performance of existing indexes significantly. In this paper, we introduce FAST, a Frequency-Aware Spatio-Textual index for continuous spatio-textual queries. FAST is a main-memory index that requires up to one third of the memory needed by the state-of-the-art index. FAST does not assume prior knowledge of the entire vocabulary of indexed objects. FAST adaptively accounts for the difference in the frequencies of keywords within their corresponding spatial regions to automatically choose the best indexing approach that optimizes the insertion and search times. Extensive experimental evaluation using real and synthetic datasets demonstrates that FAST is up to 3x faster in search time and 5x faster in insertion time than the state-of-the-art indexes.

I. INTRODUCTION

Nowadays, many applications rely on processing and analyzing spatio-textual data. Example applications include social networks (e.g., Facebook), micro-blogs (e.g., Twitter), web search for local places and events, and location-aware ad targeting. These applications process spatio-textual data at a massive scale and in real-time. For example, 500 million tweets [1][2] and 9 million Foursquare check-ins [3] are being generated and processed daily. These applications require efficient spatio-textual indexing to support this scale of spatio-textual data.

In this paper, we focus on the indexing of continuous spatio-textual filter queries. This type of queries appears in many applications, e.g., location-aware publish/subscribe systems [4], information dissemination [5], and sponsored search [6]. A continuous spatial-keyword filter query consists of a spatial range and an associated set of keywords. For a stream of spatio-textual objects, a continuous spatio-textual filter query identifies the objects that fall inside the spatial range of the query and that contain all the keywords of the query.

Example 1: Figure 1 illustrates a sample location-aware e-coupon application in a location-aware publish/subscribe system. Three users show interest in promotions represented by the three continuous spatio-textual queries $q_1$, $q_2$, and $q_3$. Promotion $o_1$ matches Query $q_1$ because $o_1$ is located inside $q_1$’s spatial range, and contains all the keywords of $q_1$.

Recently, several access-methods have been proposed to handle continuous spatio-textual queries in streaming environments, e.g., [1][7][8]. These access methods integrate a spatial index (e.g., a spatial grid, the R-tree [9], or the quadtree [10]) with a textual index (e.g., the inverted list [11], or the ordered-keyword trie [12]). However, these access-methods do not account for the frequencies and the popularity of some of the keywords within the indexed spatio-textual queries. Consider Figure 2 that illustrates the frequencies of keywords in a set of 50,000 tweets. The frequencies of the keywords follow a Zipfian distribution [13]. This distribution has many infrequent keywords and few frequent keywords. Although the distribution of the frequencies of keywords is Zipfian, the exact ranking and frequencies of keywords may not be known and the frequencies of keywords may change overtime. Also, new keywords get introduced to the vocabulary and it is estimated that 1000 new words are added to the Oxford dictionary every year [14]. Also, some infrequent keywords may become frequent, e.g., Hurricane Irma. Furthermore, the distribution of the frequent keywords is non-uniform across the space as illustrated in Figure 3.

Existing indexes treat queries with frequent keywords in the same way as it treats queries that contain infrequent keywords. For example, when using inverted lists [11], a

1http://blog.oxforddictionaries.com/august-2013-update
query is indexed based on a single keyword. This keyword is usually the least-frequent keyword. Inverted lists are well-suited for queries with infrequent keywords. However, the inverted list structure has the following two limitations: (1) it suffers from poor performance for queries that only have frequent keywords because the inverted lists associated with these frequent keywords can be very large, and (2) it assumes the knowledge of the entire vocabulary of keywords and their frequencies. However, in real scenarios, e.g., when processing tweets, the entire vocabulary and the ranking of the keywords are not known a priori.

Another popular textual index is the ordered-keyword trie \([12]\) that is a variation of the traditional trie structure \([14]\). The ordered-keyword trie indexes keywords instead of characters in the traditional trie structure. The ordered-keyword trie offers better textual filtering for queries with no infrequent keywords. However, the ordered-keyword trie suffers from the following limitations: (1) it has a large memory-footprint, and (2) it does not quickly prune queries with infrequent keywords unless the indexed keywords have a total order based on their frequencies. Having a total order of keywords based on their frequencies requires prior knowledge of the entire vocabulary of keywords and their frequencies, which may not be feasible. It is challenging to support efficient indexing of continuous spatio-textual queries in a streaming environment due to the following reasons:

- The massive scale of the indexed queries as it is typical to deal with millions of rapidly arriving continuous queries.
- Spatio-textual objects are streamed at a high rate, and it is required to process these objects against millions of indexed queries with minimal latency.
- The locations and frequencies of spatio-textual data and queries are not uniformly distributed. Hence, an efficient index needs to account for the varying distributions of spatial and textual aspects of the indexed queries.
- The assumption of knowing the entire vocabulary of keywords in advance is not valid in many situations, e.g., as in processing social media posts.

To address these challenges, we introduce FAST, a Frequency-Aware Spatio-Textual access method for indexing continuous queries in a streaming environment. FAST is designed as a main-memory index to minimize indexing and searching time and to meet the real-time processing requirements of rapidly-arriving spatio-textual data and queries.

FAST treats the frequencies of keywords and their distribution in space as first-class properties of spatio-textual queries. FAST integrates a variant of the incomplete spatial pyramid structure \([15]\) with a new textual index, termed the adaptive keyword index (AKI) to boost the spatial and textual pruning power of FAST. The spatial pyramid is a multi-resolution spatial index that is being adopted in many spatio-textual indexes, e.g., \([16, 17]\). AKI accounts for the frequencies of the keywords, and automatically distinguishes between frequent and infrequent keywords. AKI allows FAST to quickly prune queries that have infrequent keywords. Queries that have no infrequent keywords are indexed in a more selective way in FAST. Moreover, instead of searching for all the keywords at all the levels of the pyramid, FAST adopts frequency-aware spatial indexing, where queries containing infrequent keywords are indexed only at the top level of the spatial pyramid. This reduces the number of keywords being searched while descending the spatial pyramid. Because of this frequency awareness, FAST is 3x faster than the state-of-the-art indexes in terms of search time.

The textual index AKI is designed to reduce the memory footprint of FAST by distinguishing between queries with no infrequent keywords and queries that have some infrequent keywords. FAST requires less memory for queries that have some infrequent keywords by attaching the queries only to the least-frequent keyword and not to all keywords in the query. Also, FAST improves the pruning power for queries with no infrequent keywords by attaching these queries to longer sequences of cascaded keywords that appear in the query. Hence, FAST demands more space only when higher pruning power is needed. When queries span multiple spatial nodes inside FAST’s spatial pyramid, FAST adopts a spatial sharing technique to further reduce its memory footprint. These optimizations results in reducing the memory footprint of FAST by up to one-third of that of the state-of-the-art indexes.

FAST does not require prior knowledge of the entire vocabulary of keywords or their frequencies. FAST captures this information dynamically as queries get inserted or deleted. Also, FAST employs a lazy cleaning mechanism that removes the expired queries and updates the index structure to reflect the current frequencies of the query keywords.

The main contributions of this paper are as follows:

\(^2\)https://www.trendsmap.com
In this section, we introduce the problem definition, and describe the data structures relevant to FAST. Table I summarizes the notations used.

### TABLE I: Notations used throughout the paper.

| Notation  | Description                                                                 |
|-----------|------------------------------------------------------------------------------|
| o         | A spatio-textual data object                                                  |
| O         | A stream of spatio-textual data objects                                       |
| q         | A spatio-textual query                                                       |
| Q         | The set of indexed spatio-textual queries                                     |
| o.loc     | The geo-location of a data object                                             |
| t.exp     | The expiration time of a query                                                |
| q.MBR     | The spatial range of a query                                                  |
| o.text q | The keyword of a data object (query)                                          |
| [text]    | The number of keywords in text                                                |
| θ         | The frequent-keyword threshold                                                |
| Np        | A spatial pyramid node                                                       |
| currenttime | The current wall-clock time                                                   |
| Nl        | A textual node                                                               |
| RIL       | Ranked-keyword inverted list                                                  |
| OKT       | Ordered-keyword trie                                                         |

- We introduce FAST, a frequency-aware spatio-textual index for continuous spatio-textual filter queries in a streaming environment. FAST is equipped with a new adaptive keyword index (AKI) that adaptively accounts for the frequencies of keywords and does not require prior knowledge of the vocabulary of keywords or their frequencies.
- FAST is designed as a light-weight index that uses a frequency-aware spatial pyramid and spatial-sharing of query lists to improve the performance of the search operation with an optimized memory footprint.
- We propose a light-weight cleaning mechanism that lazily removes the expired queries, and dynamically re-adjusts the structure of the index to account for changes in the frequencies of the keywords of the indexed queries.
- We present a mathematical analysis that aids in tuning the parameters of FAST.
- We conduct an extensive performance study of FAST using real and synthetic datasets. When compared to the state-of-the-art indexes, results demonstrate that FAST is 3x faster in search time, 5x faster in insertion time, and requires up to one-third of the memory needed by the state-of-the-art index.

The rest of this paper proceeds as follows: Section II presents notations used throughout the paper and presents the data structures related to FAST. The structure and the main algorithms of FAST are presented in Section III. The performance evaluation of FAST is presented in Section IV. Section V highlights the related work, and Section VI contains concluding remarks.

### II. PRELIMINARIES

In this section, we introduce the problem definition, and describe the data structures relevant to FAST. Table I summarizes the notations used.

- A spatio-textual data object, say $o$, is of the form $o = [oid, loc, text]$, where $oid$ is the identifier of the object, $loc$ is the geo-location of the object, and $text$ is the set of keywords associated with the data object.
- A continuous spatio-textual filter query, say $q$, is of the form $q = [qid, MBR, text, t.exp]$, where $qid$ is the identifier of the query, $MBR$ is the spatial range of the query represented as a minimum bounding rectangle, i.e., $[x_{min}, y_{min}, x_{max}, y_{max}]$, and $text$ is the set of keywords associated with the query. The continuous query $q$ remains registered in the index until Timestamp $t.exp$, where $t.exp$ is the expiration timestamp of the query.
- For a streamed spatio-textual data object, say $o$, the objective is to match $o$ with all the continuous queries that have their spatial and textual criteria satisfied by $o$'s location and textual data. The formal definition of spatio-textual matching is as follows:

**Definition 1: Spatio-Textual Matching.** A spatio-textual data object $o$ matches a continuous spatio-textual query $q$ when the spatial location of the object, i.e., $o.loc$, is located inside the spatial range of the query $q.MBR$, i.e., and when the keywords of the object, i.e., $o.text$, contain all the keywords of the query, i.e., $q.text$.

**Problem Statement.** In this paper, we study the problem of matching an unbounded stream of spatio-textual objects $O$ against a set of continuous spatio-textual queries $Q$.

**Example 2:** We use the example given in Figure 4 throughout the rest of the paper. The figure contains the following nine continuous queries $\{q_1, \cdots, q_9\}$. Spatio-textual Object $o_1$ falls inside the spatial range of Queries $q_1$ and $q_7$. However, $o_1.text$ fully contains the keywords of only $\{q_1\}$. Thus, $q_1$ is reported as the result of matching $o_1$ against indexed queries.

### B. RELATED STRUCTURES

In FAST, we integrate a spatial index with a new textual indexing approach, termed the adaptive keyword index AKI. To motivate the need for AKI, we describe existing textual indexing approaches and discuss their limitations. The two most widely adopted textual indexing approaches are: (1) the ranked-keyword inverted list (RIL) [11], and (2) the ordered-keyword trie (OKT) [12]. In addition to describing related textual indexes, we outline the structure of the AP-tree, the state-of-the-art spatio-textual index [1].
RIL \cite{11} is a data structure for indexing textual items that contain multiple keywords. A spatio-textual filter query, say $q$, can be regarded as a textual item as it contains a set of keywords, i.e., in $q.text$. In RIL, textual items are usually indexed based on their least-frequent keyword. Every keyword has a posting list of textual items attached to this keyword. Figure 5(a) illustrates textual-only indexing of the queries in Example 2 using RIL. The keywords are usually ranked based on prior knowledge of their frequencies. This imposes a limitation on the efficiency of RIL as prior knowledge of the vocabulary of keywords and their frequencies may not be feasible. RIL has low memory requirements and has good search performance for objects indexed on infrequent keywords that have short posting lists, e.g., as in the posting lists attached to keywords $k_6$ and $k_7$. The performance of RIL deteriorates when searching for frequent keywords that have long posting lists, e.g., $k_1$. In Figure 5(a), the posting lists of the dotted keywords are visited when searching for the keywords of $O_1$ in Example 2. Because textual items are indexed on a single keyword, search in RIL requires an additional verification step to remove queries whose keywords are not fully contained in the search keywords, e.g., when searching for queries that match the keywords of $o_1$, $q_6$ is initially retrieved as part of the posting list of $k_1$, $q_6$ is removed as $q_6.text \not\subset o_1.text$.

OKT \cite{12} is a variation of the traditional trie structure \cite{14} for indexing textual items. The main difference between the traditional trie and OKT is that the traditional trie indexes strings using characters while OKT indexes textual objects, e.g., documents, using keywords. Figure 5(b) illustrates textual-only indexing of the queries in Example 2 using OKT. In this figure, keywords are assumed to be ordered lexicographically. OKT offers better textual filtering than RIL for objects with no infrequent keywords. However, OKT has higher memory requirements than RIL and does not provide early pruning for indexed objects that contain infrequent keywords, e.g., $k_6$ and $k_7$. Search in OKT follows the traditional trie search algorithm. For example, in Figure 5(b), the shaded queries attached to dotted keywords are retrieved as the resultset when searching for the keywords of $O_1$ in Example 2. In contrast to RIL, no additional verification is required when searching OKT as indexing in OKT is based on all the keywords of the indexed item.

The AP-tree \cite{11} is the current state-of-the-art structure for indexing continuous spatio-textual queries in a streaming environment. When indexing queries, the AP-tree arbitrates between spatial and textual partitioning using an expensive cost function. The AP-tree integrates spatial decomposition using a variation of OKT. The main limitations of the AP-tree are: (1) the AP-tree does not account for the frequencies of keywords to prune queries having infrequent keywords, and (2) the AP-tree is based on the memory intensive OKT, and has a large memory footprint. Figure 5(c) illustrates how the queries in Example 2 are indexed using the AP-tree. Matching in the AP-tree visits all relevant spatial and textual nodes. Figure 5(c) illustrates the spatial and the textual nodes, i.e., the shaded nodes, that are visited when matching $O_1$ in Example 2. The AP-tree requires a verification step to remove non-relevant queries, e.g., $q_6$.

III. FAST INDEX DESIGN AND ALGORITHMS

Given the inherent property that the frequencies of keywords follow a Zipfian distribution, an efficient spatio-textual index needs to account for the frequencies of occurrence of the keywords in real-time and to distinguish between the frequent and infrequent ones.

We equip FAST with a new textual index termed, the adaptive keyword index (AKI). AKI is a text-only index and does not have any spatial discrimination abilities. AKI is integrated with a spatial pyramid to distinguish between queries that are indistinguishable textually. Figure 6(b) illustrates an AKI that textually indexes all queries in Example 2.

AKI is designed as a multi-level hash map of textual nodes with keywords as the key to the hash map (see Figure 6). A textual node, say $N_t$, contains one or both of the following: (1) a list of queries attached to this node, i.e., $N_t, qlist$, and (2) a hash map to children’s textual nodes with keywords as the key of the hash map, i.e., $N_t.children$. Textual nodes are identified using a unique textual-path of keywords, e.g., in Figure 6(b), Query $q_3$ is attached to Textual Node $[k_1,k_3]$, as $q_3$ is stored under the path $k_1,k_3$, where Keywords $k_1$ and $k_3$ are the keywords in $q_3$. 

Fig. 5: Relevant textual indexes and spatio-textual indexes.
Textual nodes in AKI are assigned to levels. A top-level textual node has no parent textual node and is identified using a textual-path with a single keyword, e.g., in Figure 6(b). Textual Nodes \([k_1], [k_2], [k_3], [k_6], [k_7]\) are top-level textual nodes. Leaf textual nodes do not have child nodes, e.g., in Figure 6(b). Textual nodes \([k_7], [k_1]k_3\) are leaf textual nodes. Levels of textual nodes in AKI are incrementally numbered, where the top level is numbered Level 1, as illustrated in Figure 6.

Also, for every keyword, say \(k_i\), the total number of queries having \(k_i\), in the textual content of queries, is stored in a hash table termed the frequencies map. For example, in Figure 6(a), the frequencies map indicates that there are five queries containing Keyword \(k_1\), i.e., \(q_1, q_2, q_3, q_5\) and \(q_6\).

In AKI, queries are first indexed to top-level textual nodes using their least-frequent keyword similar to RIL. The least-frequent keyword is identified using the frequencies map and not using prior ranking of the keywords. A textual node remains infrequent as long as the number of queries that must be attached to this node in the RIL manner, i.e., the queries do not have any other infrequent keywords to be attached to, is less than a specific threshold, termed the frequent-keyword threshold \(\theta\).

**Definition 2: Frequent-keyword threshold \(\theta\).** The frequent-keyword threshold distinguishes between the infrequent and the frequent textual nodes. Initially, all textual nodes are infrequent and queries are indexed in the RIL manner, i.e., using a single keyword. When the number of queries that must be attached to an infrequent textual node, say \(N_i\), in the RIL manner exceeds \(\theta\), \(N_i\) is marked as frequent.

For example, in Figure 6(a), assume that the frequent-keyword threshold is two. Before inserting \(q_9\), the number of queries attached to all textual nodes is \(\leq 2\) and all textual nodes are top-level and are infrequent. \(q_9\) has a single keyword \(q_7\) and the Textual Node \([k_3]\) has two queries attached to it. First, we attempt to transfer some of the queries attached to \([k_3]\) to any other infrequent textual node. However, this is infeasible as \(q_5, q_6\) only contain keywords \(k_1, k_2, k_3\) and Textual Nodes \([k_1], [k_2], \) and \([k_3]\) have \(\theta\) queries attached to them. Hence, Textual Node \([k_3]\) is marked as frequent and all queries attached to \([k_3]\) get inserted to frequent textual nodes using a lexicographic ordering of their keywords. We use the lexicographic ordering of keywords as we assume no prior knowledge of the frequencies of keywords, and we cannot use the frequencies map to provide a total order on the keywords because values in the frequencies map change over time with the insertion and removal of queries.

This requires marking Textual Nodes \(k_1\) and \(k_2\) as frequent as well. In Figure 6(a), queries attached to Textual Nodes \([k_1]\), \([k_2]\), and \([k_3]\) will be re-attached to these textual nodes using the first keyword in their textual content according to a lexicographic ordering of keywords. In Figure 6(b), \(q_9\) is attached to \([k_3]\). Also, \(q_1, q_2, q_3, q_5\), and \(q_6\) should be attached to \([k_1]\). However, the number of queries attached to the frequent Textual Node \([k_1]\) exceeds \(\theta\). The level of \([k_1]\) is 1 and AKI uses more keywords to distinguish queries to be attached to \([k_1]\) as illustrated in Figure 6(b). Textual Nodes \([k_1]k_2\) and \([k_1]k_3\) are created at Level 2, and Textual Node \([k_1]k_2k_3\) is created at Level 3 to distinguish between \(q_1, q_2, q_3, q_5,\) and \(q_6\) textually. \([k_1]k_3\) is marked as infrequent because only \(q_5\) is attached to it. \([k_1]k_2\) is marked as frequent because the textually indistinguishable queries \(q_1, q_2, \) and \(q_3\) are attached to it.

Although the number of queries attached to \([k_1]k_2\) exceeds \(\theta\), these queries are indistinguishable textually and contain exactly the same keywords. Hence, no further discrimination can be performed by the AKI because AKI is a text-only index. AKI lacks any spatial discrimination power, and if we desire to spatially distinguish between queries attached to \([k_1]k_2\), we need to integrate spatial pruning abilities with AKI. FAST integrates AKI with a spatial pyramid to combine spatial and textual pruning abilities.

Figure 6: The adaptive keyword index AKI.

(a) Before inserting \(q_9\) (b) After inserting \(q_9\)

Notice that, in contrast to RIL, AKI attempts to restrict the length of the lists of queries attached to textual nodes to prevent long lists of queries. However, AKI may contain long lists of queries that are textually indistinguishable. It is a desirable property of text indexes to group textually indistinguishable queries. Also, AKI has lower space requirements than that of OKT as AKI requires a lower number of index nodes as illustrated in Figures 5(b) and 6(b).

AKI is adaptive and uses the frequent-keyword threshold to create more textual nodes when a higher level of textual discrimination is required. The frequent-keyword threshold \(\theta\) is very crucial to the performance of FAST. We discuss the experimental tuning of the value of \(\theta\), and compare the performance of AKI against both RIL and OKT in Section IV.

Converting Frequent Textual Nodes to Infrequent Ones. AKI keeps track of the frequencies of the keywords of the indexed queries in the frequencies map. Whenever a query is removed, the frequencies of the keywords of the removed query are updated in the frequencies map. This maintains the dynamic differentiation between frequent and infrequent keywords. Also, updating the frequencies map enables converting frequent textual that are no longer frequent, and marking them as infrequent as explained in Section II-A3.
Frequency-Aware Spatial Indexing

Adaptive textual indexing using AKI is insufficient for indexing spatio-textual queries that share the same set of keywords and have different spatial locations. An efficient spatio-textual index needs to adapt to the spatial and textual selectivities of the indexed queries. In Figure 8(a), Queries $q_1$, $q_2$, and $q_3$ are attached to the textual node $[k_1k_2]$ and cannot be distinguished from each other textually. However, these queries are located at different spatial regions, i.e., can be distinguished from each other spatially. In FAST, we integrate the spatial pyramid with AKI to achieve spatial-textual pruning. The spatial pyramid is a multi-level and a multi-resolution index. Every level in the spatial pyramid contains a spatial grid with a specific granularity. Levels in the spatial pyramid are numbered bottom up and level 0 is the lowest pyramid level.

**Definition 3:** **Granularity** at pyramid level $i$ $\text{gran}(i)$: the number of pyramid nodes per dimension at level $i$. The top level of the pyramid has a single pyramid node covering the entire indexed space and has a granularity of one. The second level from the top in the spatial pyramid has a granularity of two and contains four cells that covers the entire space.

Let $\text{gran}_{\text{max}}$ be the maximum supported granularity in FAST. $\text{gran}_{\text{max}}$ is the pyramid granularity at level 0, i.e., the lowest pyramid level. The top level in the spatial pyramid is numbered $\log_2(\text{gran}_{\text{max}})$, e.g., if $\text{gran}_{\text{max}}$ equals 2, the top level in the spatial pyramid is numbered 1. We discuss the experimental tuning of $\text{gran}_{\text{max}}$ in Section IV.

We calculate the granularity at level $i$ as follows:

$$
\text{gran}(i) = \frac{\text{gran}_{\text{max}}}{2^i}
$$

(1)

**Definition 4:** **SideLen(i)** is the side length of a spatial pyramid node at level $i$.

We define $\text{SideLen}_{\text{min}}$ as the smallest possible side length size in the spatial pyramid. $\text{SideLen}_{\text{min}}$ is the side length of spatial pyramid nodes at level 0, i.e., the lowest spatial pyramid level. We calculate the side length of spatial pyramid nodes at level $i$ as follows:

$$
\text{SideLen}(i) = \text{SideLen}_{\text{min}} \times (2^i)
$$

(2)

Every spatial pyramid node within any level, say $i$, has a specific spatial coordinate. To map a spatial location, say $(x_1, y_1)$ into the spatial coordinate $(x(i), y(i))$ of a pyramid node at level $i$, we use the following equations:

$$
x(i) = \left\lfloor \frac{x_1}{\text{SideLen}(i)} \right\rfloor
$$

$$
y(i) = \left\lfloor \frac{y_1}{\text{SideLen}(i)} \right\rfloor
$$

(3)

To reduce the space required by the spatial pyramid, only spatial pyramid nodes that contain queries are instantiated. Empty spatial pyramid nodes are not instantiated and do not consume any memory, e.g., the shaded spatial pyramid node within Level 0 in Figure 8(b). To support this space optimization, all spatial pyramid nodes are accessed using a hash table. The key to the hash table is the address of the spatial pyramid node. The value is a pointer to the spatial pyramid node. The address of a spatial pyramid node is calculated using a function of the level number $i$ and the grid coordinates $(x_c,y_c)$ of the spatial pyramid node as follows:

$$
\text{address}(i,x_c,y_c) = i \times \text{gran}_{\text{max}}^2 + y_c \times \text{gran}(i) + x_c
$$

(4)

For example, the address of the spatial pyramid node at Level 0 with grid coordinates $(1,0) = 0 \times 2^2 + 0 \times 2 + 0 = 0 = 1$.

**Spatial-Sharing of Query Lists.** Each spatial pyramid node contains an AKI instance. To optimize the space required by FAST, we share lists of queries when a query spans multiple spatial pyramid nodes while being attached to infrequent top-level AKI textual nodes. Figure 8(a) illustrates two spatial pyramid nodes with two separate AKI indexes. Notice that Query $q_7$ spans two spatial nodes. In Figure 8(b), we avoid creating two separate lists of queries to be attached to Keyword $k_1$. We share a single list of queries between two AKI indexes. This reduces the space required for one list of queries. Spatial-sharing of query lists happens at the granularity of keywords. For example, in Figure 8(b), query lists attached to Textual Nodes $[k_5]$ and $[k_7]$ are not shared as these lists do not contain any queries that span more than one spatial pyramid node.

Notice that when a spatial pyramid node, say $N_p'$, employs spatial-sharing of query lists with another spatial pyramid node, say $N_p''$, $N_p'$ may also point to a few extra queries that overlap only with Node $N_p''$. For example, in Figure 8(b), Query $q_1$ is attached to both spatial pyramid nodes. However, $q_1$ spans only the top spatial pyramid node. This is acceptable and does not introduce overhead in the matching processing as the length of the shared lists is restricted to the frequent-keyword threshold $\theta$. Before marking an AKI textual node as frequent, we check if a spatially-shared query list is attached to the AKI textual node. We separate the spatially-shared lists and remove non-spatially overlapping queries to reduce the length of $\text{qlist}$ that is attached to the AKI textual node to prevent unnecessary marking of textual nodes as frequent.

**Frequency-Aware Spatio-textual Indexing.** Initially, all queries are indexed at the top level of the spatial pyramid. When the number of queries attached to a frequent AKI textual node exceeds a specific threshold, e.g., Textual Node $[k_1k_2]$ in Figure 8(b), queries are partitioned to descend to a lower spatial pyramid level, i.e., to a spatial pyramid level with higher resolution. A spatial pyramid node in any spatial pyramid level, say $i$, other than Level 0, potentially covers four children spatial nodes in the spatial pyramid level directly below $i$, i.e., $i - 1$. When the number of queries attached to a frequent textual node exceeds $4\theta$, the queries are sorted based on their ranges. Queries having area less than the median of the sorted query list descend to a lower pyramid level. Queries with smaller ranges are chosen to descend as these queries...
have higher probability of joining different spatial nodes at the lower pyramid level. This adaptively captures the difference in frequencies across different spatial regions.

Figure 8 illustrates the hybrid structure of FAST. In this figure, a two-level spatial pyramid is integrated with AKI. Assume that the frequent-keyword threshold is two. For the sake of illustration, assume that queries descend when the number of queries attached to a frequent textual node exceed \(1 \times \theta \) instead of \(4 \times \theta \). In Figure 8(b), \(q_1\), \(q_2\), and \(q_3\) are all attached to Textual Node \([k_1,k_2]\). This calls for a descent of queries to improve spatial discrimination. \(q_1\), \(q_2\), and \(q_3\) are sorted according to the area of their spatial ranges. \(q_1\) remains in Level 1 of the spatial pyramid while \(q_2\) and \(q_3\) descend to Level 0. Also, Queries \(q_2\) and \(q_3\) are shared between two infrequent AKI textual nodes at Level 0 of the spatial pyramid.

Notice that only queries with no infrequent keywords at level \(i\) descend to level \(i - 1\). For example, \(q_4\) has Keyword \(k_6 \in q_4.text\). No other query contains \(k_6\), and \(k_6\) is an infrequent keyword and the number of queries attached to \(k_6\) is less than \(\theta\). Hence, all queries containing \(k_6\) remain at Level 1, and there is no need to search for \(k_6\) in Level 0. This improves the matching performance by reducing the number of keywords being searched for as the search goes down the spatial pyramid.

Notice that when queries descend the spatial pyramid, they may be replicated to more than one pyramid node with increased memory overhead. The replication overhead becomes more significant when queries with large spatial ranges descend to lower pyramid-levels with higher resolution because these queries will span multiple pyramid nodes. As a heuristic, to reduce the number of queries with large spatial ranges that descend to lower pyramid levels with higher resolution, we set the lowest spatial pyramid level a query can descend into to be the level having a slide length that is strictly greater than the side length of the query. We refer to the side length of Query \(q\) by \(q.r\), where \(q.r\) is calculated as follows:

\[
q.r = \max((q.x_{\text{max}} - q.x_{\text{min}}), (q.y_{\text{max}} - q.y_{\text{min}})) \tag{5}
\]

The lowest level \(L_{\text{min}}\) of Query \(q\) is calculated as follows:

\[
L_{\text{min}}(q) = \lceil \log_2(\frac{q.r}{\text{SideLen}_{\text{min}}}) \rceil \tag{6}
\]

We analyze the replication of queries in Appendix A.

### A. Algorithms

In this section, we present the indexing, searching, and cleaning algorithms of FAST.

#### Algorithm 1: Insert( \(q\), level)

1. update frequenciesMap for \(q.text\)
2. \(key_{\text{minfreq}} \leftarrow \text{getLeastFrequentKeyword}(q.text)\)
3. \(PN_{\text{list}} \leftarrow \text{getRelevantPyramidNodes}\)
4. sharedList \(\leftarrow \text{null}\)
5. foreach Pyramid Node \(N_P\) in \(PN_{\text{list}}\) do
   6. \(\text{queue} \leftarrow \{\}\)
   7. \(N_t \leftarrow N_P.get(key_{\text{minfreq}})\)
   8. if sharedList is not null and \(|N_t.qlist| < \theta\) then
      9. \(N_t.qlist \leftarrow \text{sharedList} \leftarrow \text{Merge}(N_t.qlist, \text{sharedList})\)
   else if \(N_t\) is infrequent then
      10. \(N_t.qlist.add(q)\)
      11. if \(|N_t.qlist| < \theta\) then
          12. \(\text{sharedList} \leftarrow N_t.qlist\)
      else
          13. \(\text{queue}.addAll(N_t.qlist)\)
          14. \(\text{mark } N_t \text{ as frequent}\)
      for all Query \(q_e\) in queue do
      15. if \(q_e\) can be inserted to another infrequent textual node then
          16. insert \(q_e\) into the other textual node
      else // insert \(q_e\) to the appropriate frequent textual node based on lexicographic order of the keywords in \(q_e.text\)
          17. \(i = 1\)
          18. \(N_t \leftarrow N_P.get(q_e.text[i])\)
          19. while \(iN_t\) is frequent and \(i \leq |q_e.text|\) do
              20. \(i \leftarrow i + 1\)
              21. \(N_t \leftarrow N_t.children.get(q_e.text[i])\)
              22. \(N_t.qlist.add(q_e)\)
          23. if \(|N_t.qlist| < \theta\) and \(N_t\) is frequent then
              24. \(\text{Mark } N_t \text{ as frequent}\)
              25. \(\text{Split } N_t.qlist\) into the subsequent textual level using one more keyword
          else if \(|N_t.qlist| > \theta\) and \(N_t\) is frequent then
              26. \(\text{dist.add}(\text{queries to descend in } N_t.qlist)\)
      forall Query \(q_d\) in dist do
          27. Insert(\(q_d\), level-1)

1) Insertion Algorithm: First, we update the frequencies of keywords in the frequencies map according to the query being inserted. Then, at the top level of the spatial pyramid, we attempt to attach the incoming query to an infrequent AKI textual node using the least-frequent keyword of the query, i.e., \(key_{\text{minfreq}}\). If the query has more than one infrequent keyword, \(key_{\text{minfreq}}\) is chosen arbitrarily from the set of keywords with the minimum frequency. If the incoming query cannot be attached to any infrequent AKI textual node, we...
Algorithm 2: Match(Data Object o)

1. keywords ← o.text
2. for level = level_max; level >= level_min; level = −− do
3. nextLevelKeywords ← {}
4. N_p ← getSpatialPyramidNode(level, o.loc)
5. if N_p is not Null then
6.     for i = 1; i <= |keywords|; i + + do
7.         N_t ← N_p.get(keywords[i])
8.         if N_t is infrequent then
9.             foreach Query q in N_t.qList do
10.                if q not expired and o.loc inside q.MBR and keywords contains q.text then
11.                    add q to result
12.            else
13.                nextLevelKeywords.add(keywords[i])
14.                SearchFrequent(N_t, i, o, keywords)
15.        keywords ← nextLevelKeywords

Algorithm 3: SearchFrequent(N_t, i, o, keywords)

1. if N_t is infrequent then
2.     foreach Query q in N_t.qList do
3.         if q not expired and o.loc inside q.MBR and keywords contains q.text then
4.             add q to result
5.     else
6.         foreach Query q in N_t.qList do
7.             if q not expired and o.loc inside q.MBR then
8.                 add q to result
9.         for j = (i + 1); j <= |keywords|; j + + do
10.            SearchFrequent(kIndex.children.get(keywords[j]), j, keywords)

Algorithm 4: Clean

1. N_p ← cleaningQueue.dequeue()
2. foreach Textual Node N_i in N_p do
3.     foreach Query q in N_i.qList do
4.         if q.exp < currentDate() and q not marked as deleted then
5.             N_i.qList.remove(q)
6.         else
7.             frequenciesMap(k) ← frequenciesMap(k) − 1
8.             if frequenciesMap(k) == 0 then
9.                 N_p.remove(k)
10.            if N_p has no textual nodes then
11.                FAST.remove(N_p)
12.            else
13.                cleaningQueue.enqueue(N_p)

to remove the expired queries. Algorithm describes the matching algorithm adopted in FAST. The matching process starts from the highest pyramid-level. For a data object, say O, with point spatial location O.loc, at most one pyramid node per level is relevant for matching. The data object that has a point location cannot overlap more than one spatial pyramid node per level because there is no overlap in spatial ranges of pyramid nodes in the same level. We calculate the index of every relevant pyramid node using Equations to . We assume that keywords of the data objects are sorted lexicographically. We retrieve textual nodes for every keyword in O.text, where O.text is the set of keywords of Data Object O that is being matched against FAST. If the top-level textual node, say N_t, is infrequent, we verify the spatial and textual criteria of all queries in N_t.qList. If Node N_t is frequent, children of this node are recursively searched as outlined in Algorithm . In the matching process, spatial validation of queries verifies that the data object is located inside the spatial range of the query. Textual validation verifies that this data object contains all the keywords of the query.

Notice that queries directly attached to frequent textual nodes do not require textual validation as these queries only contain the keywords that constitute the path of the frequent textual node. For example, in Figure consider Query q_1 that is attached to the frequent textual node [k_1 k_2] in Pyramid Level 1. This query has only two keywords k_1 and k_2. More keywords are to exist in q_1, q_1 would have been attached to a child node of [k_1 k_2]. However, queries attached to infrequent textual nodes require textual validation as these queries may contain more keywords than the path of the textual node. For example, in Figure Query q_4 has more keywords, i.e., k_3, than the path of the infrequent textual node [k_k] in Level 1, and hence requires additional textual validation at matching time.

Notice that in FAST, Keywords being searched in Pyramid Level l−1 are a subset of keywords being searched in Level l ⊆ o.text, where o is the spatio-textual object being matched.
Recall that matching in FAST is top-down and the lowest pyramid level in FAST is Level 0. All queries attached to an infrequent top-level textual node in Level \(i\) can never descend to be indexed at Level \(i - 1\) for the same spatial range. All infrequent top-level textual nodes at a pyramid node, say \(N_p\), within Level \(i\), correspond to a set of keywords, say \(SU_i\). \(SU_i\) can never exist at a pyramid node, say \(N'_p\), at Level \(i - 1\) that shares the same spatial range with \(N_p\). Hence, at matching time, the Set \(SU_i\) is not considered for matching at Level \(i - 1\).

The final step in the matching process is to remove the expired queries from the resultset and to verify the spatial overlap between the incoming data object and the matched queries.

3) Index Maintenance: Over time, some indexed queries expire, and some new queries get inserted. FAST employs a lazy vacuum-cleaning mechanism that maintains the structure of FAST and updates the frequencies of the keywords of the indexed queries. The vacuum cleaner has the following functionalities: (1) Detect and remove the expired continuous queries, and (2) Reflect the current frequencies of keywords according to the expired and removed queries. Algorithm 4 describes the cleaning procedure used in FAST.

The vacuum cleaner maintains a queue of the pyramid nodes. In every cleaning interval \(I\), the vacuum cleaner visits a pyramid node to be cleaned, say \(N_p\), from the top of the cleaning queue. Then, the cleaner iterates over all textual nodes within \(N_p\) and scans all the queries attached to the textual nodes within \(N_p\) to check for the expired queries, i.e., \(q.texp < current\text{time}\). The vacuum cleaner updates the frequencies of keywords of a removed query. The vacuum cleaner needs to account for the expired queries that span multiple pyramid nodes to avoid updating the frequencies multiple times. When an expired query is first removed, the vacuum cleaner updates the keyword statistics and marks the expired query to prevent updating the statistics more than once.

When the frequency of a keyword in the frequencies map reaches zero, the textual nodes associated with this keyword are removed. When an entire pyramid node becomes empty, the entire node is removed from FAST. Notice that in the lazy cleaning approach, expired continuous queries are not removed instantaneously. Instead, they may remain indexed until the vacuum cleaner touches them. However, this does not affect the correctness of matching in FAST because the matching algorithm in FAST has a refinement step that removes expired queries from the matching result.

Indexing Queries with General Boolean Expressions. FAST supports matching data objects against queries whose keywords are fully contained in the keywords of the incoming data object. Also, FAST is able to support queries with general boolean expressions on their keywords. For example, the textual condition of a query, say \(q\), is to be matched against all data objects that either contains \((k_1 \text{ and } k_2)\) or \((k_3 \text{ and } k_4)\). This textual condition is a boolean expression in the disjunctive normal form (DNF). We address boolean expressions in DNF because boolean expressions represented in the conjunctive normal form (CNF) can be converted to DNF \([18]\). To support queries in DNF, we instantiate a sub-query per conjunction. For example, \(q\) is split into two sub-queries \(q_1\) and \(q_2\), where \(q_1.text = \{k_1, k_2\}\) and \(q_2.text = \{k_3, k_4\}\). Sub-queries \(q_1\) and \(q_2\) have pointers to \(q\). Then, \(q_1\) and \(q_2\) are indexed using the insertion algorithm of FAST.

If a sub-query, e.g., \(q_1\), appears in the matching resultset, the original query, i.e., \(q\), is reported in the final resultset. To avoid duplicate results when more than one sub-query qualifies in the matching process, a flag is added to the original query when it is first added to the matching resultset. This flag is cleared at the end of the matching process.

Matching Objects with Rectangular Spatial Ranges. FAST supports matching data objects with point location. Also, FAST is able to support the matching of data objects with rectangular spatial locations. Matching of rectangle data objects starts from the top level of the spatial pyramid. When the matching algorithm descends the spatial pyramid, the matching algorithm visits all the nodes of the spatial pyramid that overlap the rectangular range of the incoming data object. When a query, say \(q\), spans multiple spatial nodes that overlap the rectangular spatial location of an object being matched, \(q\) may appear multiple times in the matching resultset. The matching algorithm prevents duplicate results by adding a flag to mark queries added to the matching resultset. This flag is cleared at the end of the matching process.

B. Analysis

In this section, we analyze the matching time for FAST. AKI within FAST is proposed to address the limitations of existing textual indexes, i.e., the deterioration in the matching performance in RIL, and the large memory requirements of OKT. RIL’s matching performance deteriorates due to the existence of long posting lists of indexed objects that have no infrequent keywords. OKT has an advantage over RIL in the matching performance as OKT uses multi-level indexing that uses all the keywords of an indexed object. However, this increases the memory footprint of OKT. AKI uses the frequent-keyword threshold \(\theta\) to restrict the number of queries attached to textual nodes. This creates balance between the memory requirements and the matching performance in AKI. We measure the matching performance of an index by the number of index nodes visited during matching.

To analyze the matching performance of AKI, we first study the matching performance (\(MP\), for short) of RIL for a set of keywords \(S\). The total number of textual items visited when matching \(S\) against the indexed objects is

\[
MP_{RIL}(S) = \sum_{j=1}^{[S]} |RIL[s_j]|
\]

(7)

where \([S]\) is the number of keywords being searched in \(S\), and \(|RIL[s_j]|\) is the number of indexed textual items attached to the Keyword \(s_j\).

OKT is a multi-level keyword index that is illustrated in Figure 5(b). The matching process of the keyword Set \(S\) at level \(i\) in OKT iterates over the keywords in \(S\) to find a
subset of matching keywords to proceed to level \( i + 1 \) in OKT (Notice that, in OKT, level numbers increase as we descend the index). OKT assumes a total order of the indexed keywords. For a matched keyword, say \( s_j \), at level \( i \) of OKT, the search proceeds to level \( i + 1 \) with the keyword set \( \{ s_1, s_2, \ldots, s_j \} \). Hence, at level \( i \), the matching time for OKT can be expressed recursively as follows \[12\]:

\[
MP_{OKT}(i, S) = |S| + \sum_{j=1}^{[S]} \alpha_{ij} \times MP_{OKT}(i + 1, S - \{s_1, \ldots, s_j\})
\]  

(8)

where \( \alpha_{ij} \) is the probability of having Keyword \( S_j \) indexed at level \( i \). \( \alpha_{ij} \) depends on the frequencies of the indexed keywords and their probabilities of co-occurrence. The recursion in Equation 8 terminates at the deepest level of OKT, i.e., the largest \(|q.text|\) for any indexed query \( q \). Notice that Equation 8 is a recurrence relation and is not in closed form. However, for datasets with known probabilities of keyword co-occurrence and a bounded \(|q.text|\) for any indexed query \( q \), a closed formula can be devised. For textual items with infrequent keywords, AKI has a similar behavior to that of RIL, yet with a restricted length of posting lists, i.e., \( \theta \). For textual items with no infrequent keywords, AKI has a similar behavior to that of OKT. From Equations 7 and 8 we estimate the matching performance of AKI as follows:

\[
MP_{AKI}(i, S) = \begin{cases} 
|S| \times \theta, \text{infrequent} \\
|S| + \sum_{j=1}^{[S]} \alpha_{ij} MP_{AKI}(i + 1, S - \{s_1, \ldots, s_j\}), \text{frequent} 
\end{cases}
\]

(9)

Similar to Equation 8 the recursion in Equation 9 terminates at the deepest level of AKI.

**Estimation of The Frequent-Keyword Threshold.** We use Equation 9 to estimate an upper bound on \( \theta \). The matching performance of infrequent AKI nodes should not exceed the matching performance of frequent AKI nodes. In the worst case, frequent AKI nodes resemble an OKT index.

\[
\theta \leq \frac{MP_{OKT}}{|S|}
\]

(10)

From Equation 9 the worst-case matching in FAST requires AKI matching at every level of the spatial pyramid. The matching performance in FAST can be estimated as follows:

\[
MP_{FAST}(S) = log(\text{gran}_{\text{max}}) \times MP_{AKI}(0, S)
\]

(11)

where \( log(\text{gran}_{\text{max}}) \) represents the height of the spatial pyramid.

IV. EXPERIMENTAL EVALUATION

In this section, we compare the performance of FAST against the performance of the state-of-the-art index, the AP-tree \[11\].

**Datasets.** Two real datasets, namely, Tweets and Places, and three synthetic datasets, namely, SpatialUni, SpatialSkew, and TextUni, are used in the experimental evaluation. The Tweets dataset consists of 30 million geo-tagged tweets located inside the United States. These tweets are collected over the period from January 2014 to March 2015. The Places \[19\] dataset contains 12.9 million public places inside the United States. Each entry in the Places dataset includes the geo-location and the set of keywords describing a specific place represented by the entry. Frequencies of keywords in both datasets follow a Zipfian distribution, as illustrated in Figure 2. Table III summarizes the details of the real datasets used in the experiments.

The SpatialUni and the SpatialSkew synthetic datasets change the spatial location of entries in the Tweets dataset to follow a uniform and a skewed Gaussian distribution, respectively. The TextUni dataset uses the spatial locations of entries in the Tweets dataset. However, keywords in the TextUni dataset are chosen uniformly from the vocabulary of the Tweets dataset, i.e., the frequencies of keywords follow a uniform distribution. We use the TextUni dataset to study the performance of FAST under a textual distribution that is not Zipfian to demonstrate that FAST is able to maintain its performance under various textual distributions.

**Query Workload.** Entries in datasets are used to construct spatial-keyword filter queries. The geo-location of a dataset entry is used as the center of the spatial range of a query. The default spatial range is a random value between 0% and 1% of the entire spatial range. The default number of query keywords is 3. Table III summarizes the query workload used in the experimental evaluation.

**Object Workload.** The AP-tree requires a training phase. We use 100K random dataset entries as historical training data. To measure the average matching time, we stream 100k data objects generated from the dataset entries against the indexed spatial-keyword queries. In the SpatialSkew dataset, we generate two synthetic object workloads, namely, SpatialSkewL and SpatialSkewO, where the spatial locations of objects in SpatialSkewL follow the same Gaussian distribution as the one for the indexed queries. The spatial locations of objects in SpatialSkewO are skewed away from the spatial locations of the indexed queries.

All implementations are in Java 8. All experiments are conducted on a 64-bit virtual machine running Ubuntu Linux 16.04. This virtual machine is allocated 16 cores each clocked at 2.6MHz. The total memory of the virtual machine is 49GB.

**TABLE II: The datasets used in the experiments.**

| Dataset      | Tweets | Synthetic | Places |
|--------------|--------|-----------|--------|
| Number of entries | 30M    | 50M       | 12.9M  |
| Vocabulary size  | 804K   | 804K      | 854k   |
| Avg num of keywords/Entry | 4      | 4         | 9      |

**TABLE III: The values of the parameters used in the experimental evaluation.**

| Parameter | Value |
|-----------|-------|
| Number of queries (million) | 1.2, 5, 7.5, 10, 20 |
| Number of query keywords | 1, 2, 3, 5, 7 |
| Spatial side-length of a query | .01%, .05%, .1%, .5%, 1%, 5%, 10% |
the object matching time, the query insertion time into the index, and the main-memory footprint of both FAST and the AP-tree.

B. Index Tuning

In this section, we describe how to set the parameters of FAST. The main parameter in FAST is the frequent-keyword threshold θ. In this experiment, we study the performance of AKI and FAST under various frequent-keyword thresholds.

**Performance of Textual Indexes.** In Figure 9 we study the effect of varying the frequent-keyword threshold θ on the performance of AKI. We compare both the matching time and the memory footprint of AKI against both RIL and OKT. In Figure 9(a), notice that AKI achieves keyword matching time that is comparable to that of OKT when θ ≤ 10 while having a memory footprint that is up to one third of that required by OKT. Notice that the performance of OKT and RIL is not affected by varying θ as both RIL and OKT do not have the frequent-keyword threshold parameter. Increasing θ increases the matching time and reduces the memory footprint of AKI. The reason is that as θ increases, the number of textual items attached to infrequent textual nodes increases. Matching textual items attached to infrequent textual nodes requires further validation. This validation increases the overall matching time.

**Performance of FAST.** In Figure 9(c), observe that as we increase the frequent-keyword threshold θ, the matching time of FAST deteriorates. The reason is that the higher the frequent-keyword threshold the longer the list of queries attached to the infrequent textual nodes, as in Figure 9(a). This increases the textual validation time needed to verify the containment of query keywords within the keywords of the streamed data objects. Figure 9(d) demonstrates that the smaller the frequent-keyword threshold the higher the memory requirements of FAST.

The reason is that having a small frequent-keyword threshold results in marking more textual nodes as frequent, and demanding more memory for the splitting of their attached lists of queries. Figure 9 illustrates that using a frequent-keyword threshold between 5 and 10 results in good matching time with moderate memory requirements in FAST. We set the frequent-keyword threshold to 5 throughout the rest of the experiments. The formula of Equation 10 estimates that the worst case value of θ is 13.6 that conforms with the simulation results in

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**The Effect of Varying the Pyramid Granularity.** Figure 10 illustrates the matching time of FAST while varying the finest granularity of the spatial pyramid. From the figure, increasing the granularity of the pyramid within FAST improves the matching time initially. Then, increasing the granularity further does not offer further improvement. Because of this observation, we set the granularity of FAST to 512 as increasing the finest granularity beyond 512 does not improve the matching performance.

**The Cleaning Overhead.** In order to remove the expired queries in FAST, cells of FAST are visited periodically to be cleaned, i.e., every I time units a cell is visited to be cleaned, as described in Section III-A3. Figure 11 illustrates the effect of varying the cleaning interval I on the memory footprint of FAST and the average cleaning overhead, i.e., the average time spent in cleaning. Figure 11(a) illustrates that the cleaning overhead decreases as the cleaning interval increases. Having a very small cleaning interval results in redundant visits to cells that have been recently cleaned. Figure 11(b) illustrates that the memory footprint of FAST increases as the cleaning interval I increases. In our experiments, we set the cleaning interval to 1000 time units as it achieves balance between the cleaning overhead and the memory footprint of FAST.

C. Performance Evaluation

In this section, we study the performance of FAST under various query workloads.

**Performance using the Various Datasets.** We compare the performance of FAST against that of the AP-tree using both the real and the synthetic datasets. Figure 12(a) illustrates that FAST is up to 3x faster than the AP-tree in terms of object matching time. The reason is that FAST accounts for spatial
and textual selectivities at the keyword level, as described in Section III. Figure 12(b) illustrates that FAST is up to 5x faster than the AP-tree in terms of query indexing time. The reason is that FAST benefits from the frequent-keyword threshold to account for the spatial and textual selectivities of data. However, the AP-tree uses an expensive cost formula to arbitrate between the spatial and textual indexing. In terms of the memory footprint, Figure 12(c) illustrates that FAST requires up to 3x less memory than that of the AP-tree. The reason is that FAST integrates AKI with spatial-cell sharing to reduce the size of the textual indexes, and to limit the replication of queries. However, the AP-tree is based on the memory intensive OKT and does not impose any restrictions on the replication of the indexed queries among the index cells. Notice that FAST maintains its performance advantages over the AP-tree under different synthetic distributions of the spatial and textual aspects of the data objects and queries.

**The Effect of Varying the Spatial Range.** In this experiment, we vary the spatial ranges of the queries from .01% to 10% of the entire spatial range. Figure 13 illustrates the object matching time and the query indexing time for both the AP-tree and FAST. From the figure, observe that FAST maintains its performance advantage against the AP-tree for both the object matching and the query indexing (insertion) times.

**The Effect of Varying the Number of Keywords.** In this experiment, we measure the object matching time and the query indexing time when changing the number of keywords in the indexed queries from 1 to 7. Figure 14 illustrates that FAST remains up to 3x faster than the AP-tree in terms of the object matching time and up to 5x faster in terms of the query indexing time.

**The Scalability of FAST.** In this experiment, we demonstrate the scalability of FAST against that of the AP-tree when increasing the number of indexed queries from 1 million to 20 million. Figure 15 illustrates that FAST maintains its performance advantage against the AP-tree. When increasing the number of indexed queries, FAST remains 3x faster than the AP-tree in object matching time, 5x faster than the AP-tree in the query indexing time, and requires one third of the main-memory required by the AP-tree.

**V. RELATED WORK**

We classify the related work into the following categories: (1) spatio-textual indexing, (2) publish/subscribe systems, and (3) superset containment search.

**Spatio-Textual Indexing.** Recently, several spatio-textual indexes have been proposed to answer snap-shot queries over spatio-textual data. Examples of these queries include the filter, top-k, and collective group queries. Chen et al. [20] surveys spatio-textual indexes and benchmarks their performance under various spatio-textual queries. The most relevant indexes are the IQ-tree [21] and the R*-tree [8]. These indexes are mainly disk-based and have been outperformed by the AP-tree [1].

**Publish/Subscribe Systems.** One main use case of FAST is in location-aware publish/subscribe systems. Publish/subscribe systems maintain subscriptions for long durations and match incoming messages against stored subscriptions. Publish/subscribe systems can be categorized according to their matching approach into the following categories: (1) content-based [22], (2) TopK-similarity-based [23], and (3) location-aware [24]. These publish/subscribe systems do not simultaneously account for the spatial and textual properties of subscriptions and messages. Recently, several spatio-textual publish/subscribe systems [11, 25] have been proposed. To
the best of our knowledge, the AP-tree [1] is the most relevant work for indexing continuous spatio-textual queries in a streaming environment.

Superset Containment Search. AKI addresses the problem of superset containment search, where it is required to retrieve indexed items with keywords that are fully contained in the search keywords. Several indexes have been proposed to address the superset containment problem, e.g., [5][11][26][27]. OKT [5] and RIL [11] are the most adopted structures for superset containment search. Terrovitis et al. [26, 27] present two structures for superset containment search. However, these structures are mainly disk-based and require knowing the frequencies of the entire vocabulary. AKI is a main-memory index and does not assume prior knowledge of the frequencies of keywords.

VI. CONCLUSION

In this paper, we introduce FAST: a Frequency-Aware Spatio-Textual access method for indexing continuous spatio-textual filter queries in a streaming environment. FAST automatically accounts for both the spatial and textual selectivities of indexed queries to improve the indexing and searching performance. FAST integrates the spatial pyramid with a new textual index and supports a cell-sharing mechanism that reduces the memory required by the index. FAST uses a lightweight lazy-cleaning mechanism to remove the expired queries and to reflect changes in the frequencies of the keywords of the indexed queries. Extensive experimental evaluation using real and synthetic datasets demonstrates that FAST is up to 3x faster in search time and 5x faster in indexing time than the state-of-the-art index. Also, FAST requires up to 3x less memory than the state-of-the-art index.

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APPENDIX

In this section, we estimate the expected replication of queries when indexed at their lowest allowed pyramid levels, i.e., \( E_{rep}(L_{min}(q)) \). As described in Section III, a query can descend down to Level \( L_{min}(q) \), where \( SideLen(L_{min}(q)) \) is strictly greater than the side length of Query \( q \), i.e., \( q.r \). The side length of a query is calculated using Equation 5 and the side length of pyramid nodes at any given level is calculated using Equation 2.

To simplify the analysis, we assume that a pyramid node has a unit side length, i.e., \( SideLen(L_{min}(q)) = 1 \). Notice that \( SideLen(L_{min}(q)) \geq q.r \) \# SideLen(L_{min}(q))/2, i.e., \( 1 \geq q.r > .5 \) for cells with unit side length. To find the expected replication, we assume that the side range \( q.r \) is a random value in the range \([.5, 1]\). Figure 16 gives the
number of replications of Query $q$ in pyramid nodes at level $L_{\min}(q)$. For Pyramid $P$, the replication of Query $q$ can be determined by the placement of the top-left corner of $q$ in Cell $P[L_{\min}(q)][i][j]$, where $i$, $j$ are the coordinates of the point $(q.x_{\min}, q.y_{\max})$. The spatial range of Cell $P[L_{\min}(q)][i][j]$ can be divided into the regions: $A$, $B$, $C$, and $D$. The replication of $q$ in regions $A$, $B$, $C$, and $D$ depends on the placement of $(q.x_{\min}, q.y_{\max})$ across the regions of Cell $P[L_{\min}(q)][i][j]$ is listed in Table IV.

To calculate the expected replication, we integrate the expected replication of the queries across the regions $A$, $B$, $C$, and $D$ as follows:

$$E_{\text{rep}}(L_{\min}(q) + i) = \frac{1}{2} \int_{1.5}^{2} \sum_n \int_{0}^{1} \text{replication} \times \text{Pr(region)}$$

$$= \frac{1}{2} \int_{1.5}^{2} 4 \times r^2 + 2 \times 2 \times r \times (1 - r) + 3 \times 0 + 1 \times (1 - r)^2 \, dr$$

$$= 2 \int_{1.5}^{2} (1 + r)^2 \, dr = 3.08$$

That is less than the worst case replication of 4.

This analysis can be extended to queries indexed at a higher pyramid level ($L_{\min}(q) + i$) as follows:

$$E_{\text{rep}}(L_{\min}(q) + i) = \frac{2}{92} \int_{1.5}^{2} (2^i + r)^2 \, dr$$

Notice that the query replication at levels higher than $L_{\min}(q)$ is less than 3.08. For example, the query replication at pyramid level $L_{\min}(q) + 2$ is equal to 1.4 and at the top pyramid level is equal to 1. Furthermore, if indexed queries have side lengths that follow a uniform distribution, where all possible query replications are equally likely to occur in a spatial pyramid with $n$ levels, the overall expected replication can estimated to be:

$$E_{\text{rep}} = \frac{1}{n} \sum_{i=0}^{n-1} 2 \int_{1.5}^{2} (2^i + r)^2 \, dr$$

That is equal to 1.27 when the number of levels $n$ is 9. The average query replication measured experimentally in FAST is 1.08, that is very close to the estimated query replication.

From this equation, $E_{\text{rep}}$ is equal to 1.27 when the number of levels $n$ is 9. The average query replication measured experimentally is 1.08 that is very close to the estimated query replication.