Chapter 2

Literature Review

Our proposed neighborhood queries are inspired by the usefulness of window functions in relational analytic queries [59]. A window function in SQL specifies a set of partitioning attributes A and an aggregation function f. Its evaluation first partitions the input records based on A to compute f for each partition, and each input record is then associated with the aggregate value corresponding to the partition that contains the record. Several optimization techniques [12, 5] have also been developed to evaluate complex SQL queries involving multiple window functions.

However, the semantic and evaluation of the window function are restricted by the relational model. As been analyzed previously, SQL window functions require tuples to be sorted in order to form individual windows. However such a need is hard to meet in other data domains. Therefore, optimization techniques that are developed for the relational model become inapplicable in other domains. Nevertheless, there are quite a few works that related to the neighborhood queries that we have proposed and we summarize them in this section.

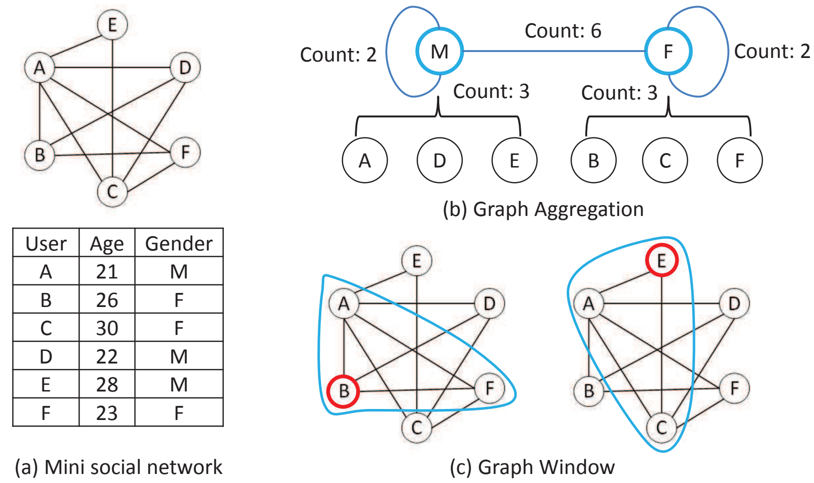
2.1 Graph Window Queries

2.1.1 Graph Aggregation

Previous graph data analytics focus on graph aggregation [61, 52, 13, 48], which are different from Graph Window Queries (GWQ). In a general model, graph aggregation comprises three steps: (1) partition graph based on attributes of vertex (and/or edges), (2) aggregate each partition to form Aggregated Nodes, and (3) link each aggregate node to form one Aggregated Graph. An illustration of the Graph Aggregation is shown in Figure 2.1 (b). In the first step, the input graph is partitioned on the"Gender" attribute of vertexes which results in two partitions. In the second step, two aggregated nodes are formed, i.e., M (stands for Male) containing nodes A, D, E and F (stands for female) containing nodes B, C, F. In the third step, the links between M and F are added, with the "count" attached on each links. Differently, Graph Window Queries perform graph analytics from the vertex-centric perspective. In GWQ, the neighborhood structure of each vertex form overlapping partitions. Then, analytics are computed over each neighborhood structure. In Figure 2.1 (c), the neighborhood structure of B and E are highlighted. Clearly, the GWQ is different from graph aggregation and they could not model each other.

2.1.2 Reachability Queries and Indexes

Classic reachability queries, which answer whether two vertexes are connected, have been studied extensively in literature. To facilitate fast query processing, many indexes are proposed [15, 16, 53, 57]. Although our graph window queries can be built on top of the reachability queries, directly using these techniques is inefficient. For example, the most related reachability query to our k-hop window query is the k-reach query [16] which test if an input pair of vertexes is within a k-hop distance. In order to compute the k-hop window query for n vertexes, there would be $\theta(n^2)$



User	Age	Gender
A	21	M
B	26	F
C	30	F
D	22	M
E	28	M
F	23	F

Figure 2.1: Illustration of Graph Aggregation and Graph Window Queries. (a) is an example social network, (b) is graph aggregation, (c) is the window of vertexes B and E.

reachability tests. This would be inefficient on graphs with over millions of vertexes.

2.1.3 Top-k Neighborhoods

In [55], the authors investigated the problem of finding the vertexes that have top-k highest aggregate values over their h-hop neighbors. This is similar to our k-hop query, while the difference is that they focus on providing pruning techniques to select the k best vertexes and our graph window query aims to compute the analytics for each vertex. Therefore, in our setting, the pruning techniques in [55] does not take effect and would be equivalent to the non-indexed approach as described in Section **??**.

2.1.4 Egocentric Networks

Egocentric networks [40, 43] have been playing an important role in network study. The egocentric networks refer to the neighborhood structure of each vertex in a graph. Although there are many works have studied on egocentric networks in structural analysis, they do not consider efficient processing of data analytics (e.g., aggregation) within each egocentric networks. Recently, Jayanta et.al. [44] proposed an EAGR system to summarize attribute information among each vertex's neighborhoods. Their technique is to build an overlay graph to leverage the shared components among vertexes' neighborhoods structures to boost query processing. Technically, EAGR runs in iterations and starts with the vertex-neighborhood mapping as the initial overlay graph. During each iteration, it sorts vertexes in an overlay graph according to their neighborhood information. Then an FP-Tree [26] is built to mining the largest shared components based on the sorted vertexes. As the algorithm iterates, the overlay graph evolves to be sparser.

The main drawback of EAGR is its high demands of resources on the overlay construction. In terms of memory cost, EAGR assume the initial vertex-neighbor mapping can be stored in memory. However, the assumption does not scale well for computing higher hop windows (such as k $\geq$ 2). For instance, a LiveJournal social network graph [1] (4.8M nodes, 69M edges) generates over 100GB mapping information for k=2 in adjacency list representation. If the neighborhood information is resided in disk, the performance of EAGR will largely reduced. In terms of computational cost, EAGR requires to sort all vertexes in a graph and build an FP-Tree in each iteration. When the graph has millions of vertexes, the indexing is largely slow down.

We tackle these drawbacks by adopting a hashing based approach that clusters each vertex according to its neighborhood similarity. During the hashing, a vertex's neighborhood information is computed on-the-fly. As compared to the sorting based approach, we do not require vertex's neighborhood to be resided in memory. In order to reduce the repetitive computation, we adopt a Dense Block heuristic to leverage the shared components among vertexes' neighborhoods. We then propose an estimation scheme that further reduces the number of neighborhood accesses. Experiments show that our schemes outperform EARG in both query processing and memory usage. Our methods are able to perform well even when EAGR algorithm

[1]Available at http://snap.stanford.edu/data/index.html, which is used [44]

fails when neighborhood information overwhelms system's memory, and our methods takes much shorter indexing time.

2.2 k-Sketch Query

Our proposed k-Sketch query is closely related to three areas: automatic news detection, frequent episode mining and top-k diversity query.

2.2.1 Automatic News Detection

An prominent usage of our k-Sketch query is to detect news themes to support *Computational Journalism*. Prior to our work, pioneer works [46, 54, 60] have studied various patterns in sequenced events to discover phenomenal news themes. Example of these news themes are presented in Table 2.1.

Sultana et al. [46] proposed the *Situational Fact* pattern. It aims to find the constraint-measure pair ($\langle C, M \rangle$) where a given event t is a skyline in dimension M among all events matching constraints C. For example, given an event in the following form: [name:Paul George, score:21, rebound:11, assist:5, block:2, steal:3, team:Pacers, opteam:Bulls, date:20130205, result:win], the constrain dimensions are (name, team, opteam, date, result) and the measure dimensions are (score, rebound, assist, block, steal). As shown in Table 2.1, the corresponding *situational fact* selects C = {team, date} and M = {score, assist, rebound} for this event as under such constraint-measure this event is a skyline. *Situational fact* is different from the *rank-aware streak* because it does not consider the consecutive event for a subject.

We etl al. [54] proposed the *One-of-the-Few* pattern to detect news themes with some rarities. *One-of-the-few* aims to select a set of measure dimensions m such that a given event is in not dominated by more than k events in M. For example, given an event in the following form: [name:Oscar Robertson, score:26710, rebound:7804, assist:9887, steal:77, block:4], the *one-of-the-few* selects the measure dimensions $M =$ {score, rebound, assist} as under these dimension, this event is not dominated by other events. Clearly the *one-of-the-few* pattern is different from k-Sketch.

Method	**Example news theme**
Situational facts [46]	Paul George had 21 points, 11 rebounds and 5 assists to become the first Pacers player with a 20/10/5 (points/rebounds/assists) game against the Bulls since Detlef Schrempf in December 1992.
One-of-the-few facts [54]	There is no player in NBA history with more points, more rebounds, and more assists than Oscar Robertson in one's career
Prominent streak [60]	Kobe scored 40+ in 9 straight games!
Rank-aware streak	Kobe scored 40+ in 9 straight games ranked 4th in NBA history!

Table 2.1: Examples of different news themes

Zhang et al.[60] proposed using prominent streak to generate interesting news themes. In [60], a *Prominent Streak* is characterized by two dimensions which are the window length and the minimum value of all events in the window. The objective is to discover the skyline (i.e., non-dominated) streaks where the dominance relationship is defined among streaks of the same subject. Our model differs from [60] in two aspects. First, we look at the global prominence (quantified by the rank) among all subjects rather than local prominence (quantified by the dominance) within one subject. Second, our model provides the best k-sketch for each subject whereas [60] returns a dominating set which could be potentially large.

2.2.2 Frequent Episode Mining

In time sequenced data mining, an episode [42, 65, 47, 35] is defined as a collection of time sequenced events which occur together within a time window. The uniqueness of an episode is determined by the contained events. The objective is to discover episodes whose occurrences exceeding a support threshold. Our sketch discovery differs from the episode mining in three major aspects. First, an episode is associated with a categorical value while our sketch is defined on numerical values. Second, the episodes are selected based on the occurrence, while in sketch, news themes are generated in a rank-aware manner. Finally, episode mining does not restrict its output size, while sketch only outputs the best k news themes. As such, episode mining techniques cannot be straightforwardly applied to sketch discovery.

2.2.3 Top-k Diversity Query

Top-k diversity queries [1, 7, 22, 14] aim to find a subset of objects to maximize a scoring function. The scoring function normally penalizes a subset if it contains similar elements. Our sketch discovery problem has two important distinctions against the top-k diversity queries. First, the inputs of the scoring function are known in advance in top-k diversity queries; whereas in our problem, the ranks of event windows are unknown. Since their calculations are expensive, we need to devise efficient methods to compute the ranks. Second, existing methods for online diversity queries [7, 22, 14] only study the update on a single result set when a new event arrives. However our online sketch maintenance incurs the problem of multiple sketch updates for each new event. Such a complex update pattern has not been studied yet and hence there is a need to develop efficient update scheme.

2.3 Movement Pattern Discovery Query

Previous works related to our trajectory pattern mining query can be grouped into three categories: *co-movement patterns*, *dynamic moving patterns* and *trajectory mining frameworks.*

2.3.1 Flock and Convoy

The difference between *flock* and *convoy* lies in the object clustering methods. In *flock*, objects are clustered based on their distances. Specifically, the objects in the same cluster need to have a pair-wised distance less than *min_dist*. This essentially requires the objects to be within a disk-region of delimiter less than *min_dist*. In contrast, *convoy* clusters objects using density-based spatial clustering [24]. Technically, *flock* utilizes a m^{th}-order Voronoi diagram [34] to detect whether a subset of object with size greater than m stays in a disk-region. *Convoy* employs a trajectory simplification [21] technique to boost pairwise distance computations in the density-based clustering. After clustering, both *flock* and *convoy* use a sequential scanning method to examine each snapshots. During the scan, object groups that appear in consecutive timestamps are detected. Meanwhile, the object groups that do not match the consecutive constraint are pruned. However, such a method faces high complexity when supporting other patterns. For instance, in *swarm*, the candidate set during the sequential scanning grows exponentially, and many candidates can only be pruned after the entire snapshots are scanned.

2.3.2 Group, Swarm and Platoon

Different from *flock* and *convoy*, all the *group*,*swarm* and *platoon* patterns have more relaxed constraints on the pattern duration. Therefore, their techniques of mining are of the same skeleton. The main idea of mining is to grow object set from an empty set in a depth-first manner. During the growth, various pruning techniques are provided to prune unnecessary branches. *Group* pattern uses a VG-graph to guide the pruning of false candidates [51]. *Swarm* designs two more pruning rules called backward pruning and forward pruning [39]. *Platoon* further leverages a prefix table structure to steer the depth-first search. As shown by Li et.al. [38], *platoon* outperforms other two methods in efficiency. However, the three patterns are not able to directly discover GCMPs. Furthermore, their pruning rules heavily rely on the depth-first search nature, which lose their efficiencies in the parallel scenario.

2.3.3 Other Related Trajectory Patterns

A closely related literature to co-movement patterns is the *dynamic moving* patterns. Instead of requiring the same set of object traveling together, *dynamic moving* patterns allow objects to temporally join or leave a group. Typical works include *moving clusters* [31], *evolving convoy* [2], *gathering* [62] etc. These works cannot model our GCMP since they enforce the global consecutiveness on the timestamps of a pattern.

2.3.4 Trajectory Mining Frameworks

Jinno et al. in [30] designed a MapReduce based algorithm to efficiently support T-pattern discovery, where a T-pattern is a set of objects visiting the same place at simliar time. Li et al. proposed a framework of processing online *evolving group* pattern [36], which focuses on supporting efficient updates of arriving objects. As these works essentially differ from co-movement pattern, their techniques cannot be directly applied to discover GCMPs.

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