GraphCPP: A Data-Driven Graph Processing System for Concurrent Point-to-Point Queries

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Abstract—With the widespread adoption of graph processing technology in fields such as map navigation and network analysis, a considerable number of point-to-point query tasks run concurrently on the same underlying graph, imposing a high demand on the throughput of graph query systems. However, existing graph processing systems either focus on optimizing the speed of individual point-to-point queries, neglecting the throughput of concurrent queries, or follow the concurrent execution schema of point-to-all algorithms, overlooking the optimization potential of point-to-point algorithms. Due to redundant data access overhead and computational expenses, existing solutions exhibit poor overall throughput when executing concurrent point-to-point queries.

This paper introduces GraphCPP, the first graph process system designed for concurrent execution of point-to-point query tasks. It enhances the throughput of concurrent query tasks through data access sharing and hot path computation sharing. GraphCPP is novel in two ways. Firstly, based on the observation that traversal paths for different query tasks overlap significantly, GraphCPP proposes a data-driven caching execution mechanism. Through fine-grained graph chunk scheduling, this mechanism enables data sharing among concurrent tasks, thereby enhancing data access efficiency. Secondly, recognizing the frequent computation of the same hot vertices and paths by distinct tasks, GraphCPP proposes a dual-level computation sharing mechanism. This mechanism accelerates the convergence of new queries by sharing computed values of hot vertices and paths. In our evaluation on datasets such as xx, we compare GraphCPP with state-of-the-art point-to-point query systems and concurrent graph processing systems. The results demonstrate that GraphCPP incurs only xx preprocessing overhead and xx storage overhead, achieving a throughput improvement of xx-xx times compared to SGraph, Tripoline, Pnp, and Glign.

Index Terms—graph process, point-to-point queries, concurrent jobs, data access similarity, computational similarity.

I. INTRODUCTION

GENERALLY, large-scale concurrent point-to-point query tasks are executed on the same underlying graph. For instance, in logistics, Google Maps[6] determines the optimal route between two locations; in social network analysis, Facebook[7] recommends potential friends to users by exploring the relationship chain between two users; and in financial risk analysis, Alipay[8] analyzes how risk propagates from one entity to another. These popular applications highlight the demand for executing large-scale concurrent point-to-point

queries on the same underlying graph. Unlike traditional graph query methods, point-to-point queries specifically analyze associated vertices between two specific vertices, without the need to consider complex queries for the entire graph or its large-scale subsets. This targeted query strategy results in significant differences between point-to-point query algorithms and point-to-all query algorithms, offering substantial optimization potential for point-to-point queries. However, current general-purpose concurrent graph computing systems[4] typically employ conventional methods to execute point-to-point queries, overlooking optimizations for their traversal processes. Existing point-to-point query solutions[1][2][3] primarily focus on accelerating the efficiency of individual queries, neglecting optimization for concurrent queries. Overcoming two key challenges is essential to efficiently execute concurrent point-to-point query tasks.

Firstly, when executing concurrent point-to-point query tasks, failure to consider data access similarity results in redundant access to overlapping data. Specifically, different query tasks initiate from distinct starting points and traverse different paths to reach their respective endpoints. Due to the power-law distribution characteristics of graphs, these query paths naturally overlap on some popular routes (as demonstrated in Section x, with an overlap rate of approximately 30%). However, since the overlapping portions of data accessed by different query tasks vary, they traverse along different paths to access overlapping graph data. Consequently, existing query systems adopt a conservative strategy, assigning each task the responsibility of accessing its required data. This implies that data access for each task is entirely independent, even if their traversal paths highly overlap. For example, if the path of one query pair is a subset of the path of another query pair, it still necessitates reloading data from the overlapping portions, preventing the benefits of reusing cached data.

Secondly, in addition to redundant access, different query tasks also need to redundantly compute distance values for popular paths. Similarly, due to the power-law distribution characteristics of graph data, a few popular vertices frequently appear in optimal paths for different queries (as illustrated in Section x, with calculations for highly connected vertices constituting approximately 30%). As different query tasks do not share computations, they redundantly calculate the hot paths connecting popular vertices. Moreover, popular vertices often possess a large number of neighboring vertices, and the repetitive traversal of these vertices leads to an explosive growth in computational expenses. Although some existing systems attempt to implement computation sharing through a global index[2][1], the efficiency and accuracy of computation

sharing are restricted due to the expensive computational, storage, and update costs.

To address the challenges mentioned above, this paper proposes a data-driven concurrent point-to-point query system called GraphCPP. It enhances the throughput of concurrent point-to-point query systems through data sharing and computation sharing mechanisms.

In GraphCPP, we firstly introduce a data-driven caching execution mechanism that transforms the traditional $task \rightarrow data$ scheduling approach into a $data \rightarrow task$ scheduling approach, thereby enabling the sharing of overlapping graph structure data among multiple tasks. Under this execution mechanism, GraphCPP first determines the scheduling order of data: it logically partitions graph structure data into fine-grained chunks at the LLC level. Subsequently, it associates query tasks with the relevant graph chunks based on the graph block where the active vertices of the query tasks reside. The higher the number of associated tasks, the higher the priority for scheduling that chunk. As the set of active vertices changes in each round, and the number of associated tasks for shared chunks needs updating in each round, GraphCPP adopts an associated task-triggering mechanism to achieve $data \rightarrow task$ scheduling. After loading the graph chunks into the LLC in priority order, the system utilizes the associated information obtained in each round to trigger the batch execution of associated tasks for the current chunk, efficiently accessing shared data.

GraphCPP proposes a dual-level computation sharing mechanism that incorporates a global index and a core subgraph index. It identifies vertices in the graph with a significant number of connecting edges as hot vertices and the paths between these hot vertices as hot paths. Despite the limited quantity of hot vertices and hot paths, they frequently appear in the traversal paths of different query tasks. 1) Global Index Mechanism: The global index maintains information about a small number of hot vertices and their connections to other vertices. These hot vertices serve as intermediary nodes for various query paths, providing pruning values for the majority of queries. Through the global index, the first level of computation sharing is achieved. 2) Core Subgraph Mechanism: The core subgraph primarily maintains hot paths connecting hot vertices in the graph. Notably, the number of hot vertices in the core subgraph is an order of magnitude larger than that in the global index, enabling a broader coverage. Specifically, it starts by filtering highly connected hot vertices from the original graph data. Subsequently, it extracts hot paths from the convergence results of each query, storing their values in the core subgraph. During the query process, the core subgraph functions like a highway network, facilitating traversal from one hot vertex to another. This process is akin to entering a highway from a hot vertex and utilizing the fast lanes (hot paths) on the highway network to swiftly reach other high-speed stations (hot vertices). Despite maintaining more hot vertices, the core subgraph's overall scale is significantly smaller than that of the entire graph. Additionally, the values in the core subgraph, representing hot paths between hot vertices, can be obtained without computation, resulting in minimal additional overhead during the query process.

System	Pnp				Tripoline				SGraph				Glign			
Number of concurrent query tasks	1	4	8	16	1	4	8	16	1	4	8	16	1	4	8	16
Instructions ($\times 10^{14}$)	7.28	7.41	7.32	7.4	5.9	5.68	6.1	5.57	3.69	3.54	3.28	3.73	1.55	1.76	1.49	1.61
LLC loads ($\times 10^{12}$)	28.3	27.6	28.5	27.9	15.7	16.2	15.6	15.9	8.2	8.6	8.5	8.4	5.7	5.5	5.8	5.4
LLC miss ratio	45.8%	52.6%	60.3%	70.2%	40.3%	52.4%	64.8%	72.4%	42.5%	57.1%	63.8%	69.5%	32.4%	47.2%	55.4%	67.3%
Runtime (hour)	72.96	30.29	27.65	20.11	53.42	19.76	12.31	8.84	27.24	11.96	7.28	5.36	15.47	6.18	4.32	2.19

TABLE I: Performance comparison of existing systems for processing concurrent point-to-point queries

Lastly, GraphCPP further enhances the performance of concurrent queries by predicting the traversal paths of different query tasks and driving the batch execution of highly overlapping similar query tasks.

This paper makes the following contributions:

1) We analyze the performance bottlenecks of existing graph processing systems when handling concurrent point-to-point query tasks and propose leveraging the similarities in data access and computation among concurrent tasks to enhance throughput.
2) We develop GraphCPP, a dynamic data-driven concurrent processing system for point-to-point queries. It achieves data sharing and computation sharing among concurrent tasks and introduces a strategy for batch execution of similar tasks.
3) we compare GraphCPP with state-of-the-art point-to-point query systems and concurrent graph processing systems, using a workload that includes six real-world graphs[14][15][16][17] and six applications[18][21][22][23][24][27]. Our experiments demonstrate that, GraphCPP improves their performance by 1.73 13 times.

II. BACKGROUND AND MOTIVATION

Most existing solutions[3][2][1] are primarily focused on accelerating the speed of individual queries. However, in practical scenarios, there is a significant number of graph query tasks concurrently running on the same underlying graph. For instance, statistics from CAGIS[9] indicate that location service open platforms constructed by companies such as Baidu Maps[10], Amap[11], Tencent Maps[12], and Huawei Maps[13] receive a daily average of up to 160 billion location service requests. The substantial demand for concurrent point-to-point queries poses a high requirement for the throughput of graph traversal systems. However, as illustrated in table 1, we demonstrate that existing systems exhibit low throughput when handling large-scale concurrent queries(Details are given in Section x). The root cause of this undesirable outcome is the significant redundancy in data access and computation among concurrent tasks. To qualitatively analyze the aforementioned issues, we conducted performance evaluations on parallel point-to-point queries using XXXXX (machine configuration), selecting XXXXX (the current best solution) on XXXXX (graph dataset).

A. Preliminaries

Definition 1: $(Graph)$ We use $G = (V, E)$ to denote a directed graph, where V is the set of vertices, and E is the set of directed edges formed by vertices in V (for undirected graphs, edges can be split into two directed edges with different directions). We use $|V|$ and $|E|$ to represent the number of vertices and edges, respectively.

Definition 2: $(Graph\ Partition)$ We use $P_i = (V_{P_i}, E_{P_i})$ to denote the i_{th} graph partition of a directed graph, where V_{P_i} represents the set of vertices in the graph partition, and E_{P_i} is the set of directed edges composed of vertices in V_{P_i}. In a distributed system, different machine-specific graph partitions P_i are distinct. We partition the graph using edge cuts[36][38], where the same vertex may appear on different computing nodes, but there is only one primary vertex, while the others are mirror vertices. This way, the program only needs to deal with the vertices and edges on the local node.

Definition 3: $(Point\text{-}to\text{-}Point\ Query)$ We use $q_i = (s_i, d_i)$ to denote the query corresponding to task i, where s_i and d_i represent the source and destination vertices of q_i, respectively. If the execution of the point-to-point query algorithm on the graph yields a convergent path for q_i, this path is referred to as the optimal path between s_i and d_i.

Definition 4: $(Bounds)$ In mainstream point-to-point query systems, a pruning-based query strategy is widely adopted, where *bounds* provide conservative pruning values. Specifically, *bounds* can be further categorized into *upper bounds* (UB) and *lower bounds* (LB). UB represents the current known optimal path value from the source to the destination vertex, while LB signifies a conservative predicted path value from the current vertex v to the destination vertex, with the predicted LB being less than or equal to the actual optimal path value from vertex v to the destination vertex. Following the triangle inequality on the graph, if the value of a path is greater than UB or exceeds UB when adding the value of LB, the path is definitely worse than existing paths and needs to be pruned. The values of upper and lower *bounds* need indexing to be derived, essentially constituting a form of computation sharing.

Definition 5: $(Core\ Subgraph)$ We use $G_{core} = (V_{hot}, E_{hot}, Index_{hot})$ to represent the *core subgraph*, where V_{hot} is the set of *hot vertices* , E_{hot} abstracts the *hot paths* between vertices in V_{hot} as edges, and $Index_{hot}$ represents the path values corresponding to E_{hot}. A *hot vertex* refers to a vertex in a graph with a significant number of edges. A *hot path* is defined as the optimal path between two *hot vertices*. A *hot index* denotes the path value of a *hot path*.

Definition 6: $(Index)$ The *index* records the optimal query path values between vertex pairs. GraphCPP sorts vertices by degree, selecting $k + m$ vertices with the highest degrees. Note that, values for k and m are generally user-determined, with k usually set to 16, and m typically one order of magnitude larger than k. The first k vertices serve as *global vertices*, while the remaining vertices function as *core subgraph vertices*. The *global index* records optimal query path values to all vertices in the graph. The

(a) Data access similarities between concurrent tasks

(b) The proportion of high-degree vertices in the overlapping data

(c) Storage overhead for global indexes

(d) Computation overhead for global indexes

(e) The impact of graph updates on global indexes

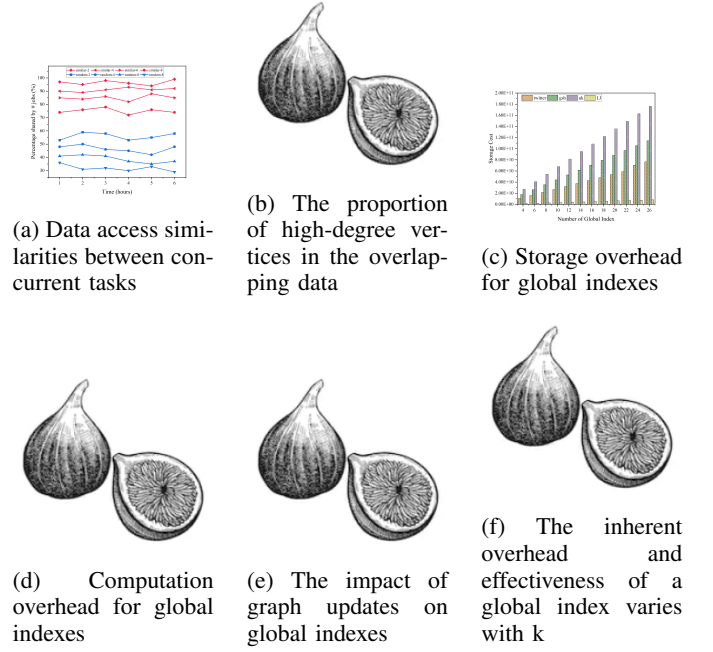(f) The inherent overhead and effectiveness of a global index varies with k

Fig. 1: Redundant data access overhead and computational overhead of concurrent point-to-point query tasks

core subgraph index only records query path values between hot vertices in the subgraph.

B. Performance Bottlenecks in Concurrent Point-to-Point Query Tasks

In this section, we have implemented the concurrent version of the existing linear pairwise query system[3][2][1] and the pairwise version of the existing concurrent graph computing system[4]. Our objective is to quantitatively elucidate the performance bottlenecks of current concurrent pairwise query solutions.

Redundant data access overhead We observe that when concurrent pairwise query tasks execute graph traversal on the same underlying graph, a significant portion of their traversal paths exhibits clear data access similarities. As shown in Figure 3x, our data indicates that there is a substantial overlap in data access among concurrent tasks, with a higher overlap ratio for similar tasks (more details are provided in Section xx). However, in the traditional $task \rightarrow data$ scheduling mode, different tasks independently execute queries, leading to competition for limited cache space to store their respective graph data chunks, even if these data chunks are identical. This results in severe cache thrashing and a reduction in the performance of processing concurrent pairwise queries. Table 1 illustrates that, with an increase in the number of concurrent tasks, the cache miss rate for query tasks sharply rises. Although the overall performance of concurrent execution surpasses linear execution, the average query time per task significantly increases with the growing number of query tasks due to the mentioned redundant data access overhead. It is essential to note that the total execution time in the concurrent mode is the maximum among the execution times of these

tasks, while in the sequential mode, it is the sum of all task execution times.

Redundant Computational Overhead Unlike point-to-all queries[28][43], point-to-point query algorithms[18][22][21] employ a targeted traversal strategy, significantly narrowing down the query scope. This focused exploration is a result of the algorithm's inherent selectivity. Given the power-law distribution characteristics of graph data, a significant portion of traversal paths in point-to-point queries involves hot vertices. While hot vertices make up only a small fraction of the total vertices (XX%), they are prevalent in the traversal paths of many tasks (XX%). Furthermore, the proportion of hot vertices in graph data marked by higher levels of sharing is even more pronounced. This suggests that various query tasks redundantly calculate hot paths between hot vertices, revealing computational similarities among concurrent tasks. Over a graph snapshot period, computational results for identical vertex pairs remain consistent, indicating significant redundancy in computational efforts across concurrent tasks. Additionally, due to the frequent possession of numerous outgoing and incoming edges by hot vertices, the computational overhead they introduce far exceeds that of ordinary vertices.

Some existing solutions utilize a global indexing mechanism[2][1] to achieve computational sharing associated with global vertices. However, the global indexing mechanism has inherent flaws. **Flaw 1**: The global index requires recording path values between hot vertices and regular vertices. In large-scale graphs, the computational and storage costs of establishing the index can be substantial, as depicted in Figures 3 and 4, where the costs increase proportionally with the number of global index vertices. **Flaw 2**: In point-to-point queries on streaming graphs, each round of graph updates introduces new edges and edge deletions. The global index needs to dynamically update the index relationships between high-degree vertices and every vertex based on the latest graph snapshot. This implies that any update to the streaming graph will impact all vertex indices, as illustrated in Figure 5, where a small number of graph updates lead to extensive updates in the global index. **Flaw 3**: Different datasets have different data distribution patterns, making it challenging to choose an appropriate number of index vertices to balance the efficiency of computational sharing and the overhead of the index itself. As shown in Figure 6, selecting the same number of index vertices on different datasets results in significant variations in inherent costs and the effectiveness of computational sharing. In summary, the global indexing mechanism incurs expensive costs, and the fluctuation in required costs for different datasets is considerable. Therefore, existing systems often conservatively choose the number of global indices (e.g., 16 vertices in Tripoline[2] and SGraph[1]) to avoid excessive costs. However, this also limits the coverage range of global indices, preventing efficient computational sharing.

C. Our Motivation

Inspired by the observations mentioned above, we derive the following insights:

data access similarity: A significant portion of traversal paths in different query tasks displays substantial overlap, indicating a similarity in data access patterns(As shown in Figure 1). However, existing solutions fall short in concurrently supporting point-to-point queries and facilitating data sharing among tasks, resulting in redundant data access. This observation motivates the development of an efficient, fine-grained data-sharing mechanism. By allowing various tasks to share access to the same data at different times, this mechanism aims to reduce data access costs and enhance the throughput of concurrent queries.

computational similarity: The core subgraph, consisting of hot vertices and paths in the original graph, is frequently traversed by various tasks, highlighting computational similarity among different query tasks(As shown in Figure 2). Existing graph traversal systems either neglect computational similarity[3] or employ a costly global indexing mechanism [2][**?**], limiting the effectiveness of computational sharing. This observation inspires the creation of a lightweight, dual-layered indexing mechanism to share computational results of overlapping hot paths across different query tasks.

III. Overview Of GraphCPP

A. System Architecture

To enhance the efficiency of concurrent point-to-point queries, we introduce GraphCPP, a meticulously designed, data-driven system tailored for concurrent query tasks. Developed after a thorough examination of the computational intricacies inherent in such queries, GraphCPP aims to achieve data and computation sharing among concurrent point-to-point tasks. As depicted in the figure above, GraphCPP incorporates an efficient data-driven caching execution mechanism, leveraging data similarity among concurrent tasks to facilitate shared access to overlapping data. Additionally, it introduces a dual-level computation sharing mechanism, enabling computations for identical hot vertices and paths to be shared across different query tasks. Furthermore, GraphCPP employs path prediction for various queries, promoting the bulk execution of similar queries with overlapping paths and maximizing the utilization of data similarity.

Data Access Sharing Mechanism. This mechanism aims to achieve precise sharing of graph structure data by leveraging data access similarities among concurrent tasks. The process unfolds as follows: initially, similar to other distributed graph computing systems[42][56], it partitions the original graph data into coarse-grained segments, distributing them for parallel processing across different machines. Subsequently, a fine-grained chunk manager further divides these coarse-grained segments into fine-grained graph chunks. The next step involves establishing connections between query tasks and graph data chunks. Specifically, if a query task q_i has active vertices in a graph chunk b_i, a relationship between q_i and b_i is established. Following this, a graph chunk priority scheduling mechanism prioritizes graph chunks with a higher number of associated tasks for loading into the Last Level Cache (LLC). Consequently, the system filters out all query tasks linked to graph chunks present in the LLC, allowing them to be executed in batches on the shared graph chunks.
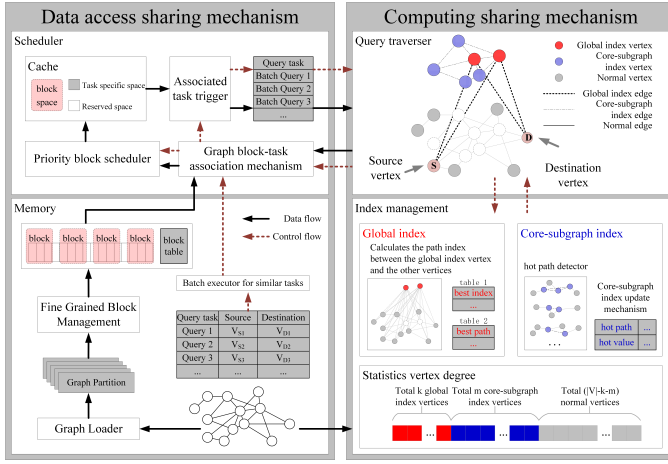
Fig. 2: System architecture diagram

computation Sharing Mechanism. GraphCPP optimizes shared path computation by leveraging dual-level index information (global index and core subgraph index) for concurrent query tasks. The process consists of three phases: 1) Preprocessing Phase: Gather degree information for all vertices in the original graph data. Sort vertices in descending order based on degrees. Select vertices ranked from 1 to k as global vertices and vertices ranked from $k+1$ to $k+m$ as core subgraph vertices. 2) Index Building Phase: Execute a point-to-all query algorithm before queries start. Compute the best path values from global vertices to all vertices in the graph (e.g., SSSP algorithm for PPSP tasks). For directed graphs, calculate outbound and inbound path values for global vertices; for undirected graphs, only one calculation is needed. Dynamically maintain the core subgraph through a runtime method. The core subgraph doesn't need precomputation for hot paths but explores them dynamically after each query, adding them to the core subgraph structure. 3) Computation Sharing Phase: Global vertices, acting as intermediaries for numerous paths, are used at the beginning of a query to compute the path value for a reachable path. This path may not be the best path but serves as a reference for pruning queries; In pruning traversal based on upper and lower bounds, the global index estimates path values for query paths earlier, enabling earlier pruning of unsuitable paths. This constitutes the first level of computation sharing; The core subgraph, maintaining best path values between hot vertices, acts as a highway network between query tasks. When a query task traverses hot vertices in the core subgraph, it connects to the highway, allowing quick traversal from entrance to exit vertices without recalculating path values. This constitutes the second level of computation sharing.

B. Overall Execution Workflow

Algorithm 1 outlines the comprehensive execution process of GraphCPP in handling concurrent query tasks. Assuming partitioning is completed(line 2), we acquire the set $block_{table}$, which includes all graph blocks on the current computing node, and the set Q, which includes all query tasks on the current computing node. Each of them is allocated a segment

of memory. In the third line, we enter a loop processing phase, and queries iterate until convergence is achieved. GraphCPP invokes `ChooseNextSharingBlock` to update the association between query tasks and graph blocks and selects the graph block b_i with the highest priority (line 4). By tallying the associated blocks for each task (i.e., tasks with active vertices in the current block), we can determine all query tasks related to the current graph block b_i (line 5). Next, we load b_i into the cache and parallelly process all associated query operations q_i (line 6). This step embodies the idea of data sharing, i.e., multiple query tasks sharing the result of a single data access. Subsequently, we invoke `GraphCPPCompute` to perform point-to-point query operations q_i on the current block (details are provided in Section (section:xx) . Iterative query task execution follows the Bulk Synchronous Parallel (BSP) model, where each iteration generates a new set of active vertices and updates to form a new query task (line 7). If the new query remains associated with the current graph block b_i, we add q_i to Q_{b_i} and return to the sixth line to continue querying on the graph block b_i(line 9). Otherwise, it signifies that the new task is not associated with the current graph block, and it needs to be saved in the query task set(line 11), at this point, the task is suspended.

Algorithm 1 Concurrent Point-to-Point Queries

1: **function** OVERALLWORKFLOW
2:     MALLOCBUFFERS($block_{table}, Q$)
3:     **while** HAS_ACTIVE($block_{table}$) **do**
4:         $b_i \leftarrow$ CHOOSENEXTSHARINGBLOCK
5:         $Q_{b_i} \leftarrow$ CHOOSEASSOCIATEDQUERIES(b_i)
6:         **for each** $q_i \in Q_{b_i}$ **do**
7:             $new\_query \leftarrow$ GRAPHCPPCOMPUTE(q_i, b_i)
8:             **if** HAS_ASSOCIATED((b_i, new_query)) **then**
9:                 Q_{b_i}.Push(new_query)
10:            **else**
11:                 Q.Push(new_query)
12:            **end if**
13:         **end for**
14:     **end while**
15: **end function**

The presented algorithm illustrates the overall workflow of GraphCPP. In the subsequent sections, we will delve into the detailed explanations of two optimization mechanisms: data access sharing and compute sharing.

C. Data Access Sharing Mechanism

In Section 2.2, we observed a significant overlap in graph structure data access among concurrent tasks. Under the existing processing mechanism, this overlapping data cannot be shared and utilized. However, for point-to-point query tasks on the graph, the order of data access does not affect the correctness of the results. The core idea of our data sharing mechanism is to transform the original $task \rightarrow data$ linear task scheduling order into a $data \rightarrow task$ fine-grained concurrent task scheduling order. This allows us to leverage data similarity among concurrent query tasks, amortize data

access overhead, enhance cache utilization efficiency, and consequently, improve system throughput. We will address two key challenges in the following sections: 1) How to determine the shared data segments? 2) How to implement data sharing among multiple tasks? Finally, we will describe additional measures to further exploit data access similarity.

a) Determine Shared Data Segments

Determine the granularity of shared graph partitions. Distributed memory graph computing systems need to load data into the cache to improve data access efficiency. Ideally, the data of shared graph partitions should fully fit into the Last-Level Cache (LLC) to avoid frequent eviction and reloading of different parts of partitions. However, the granularity of graph partitions should not be too small, as it would increase synchronization overhead in task processing. We use the formula x to determine an appropriate size for shared graph partitions. Here, B_S represents the size of the graph structure data for the shared partition, G_S represents the size of the graph structure data for the partition it belongs to, $|V|$ is the total number of vertices on the partitioned graph, V_S represents the average space required to store state information for a vertex, N is the number of concurrent query tasks, LLC_S is the size of the LLC cache, and R_S is the size of reserved redundant space, which can be used to store data such as indexes. The two terms on the right side of the formula represent graph structure data and task-specific data, respectively (their sizes are proportional to the scale of the graph partition and the number of concurrent query tasks). The right side of the formula represents the size of the available space per task after deducting the reserved cache space. Using this formula, we determine the maximum granularity for each shared graph partition under the premise of adapting to LLC capacity.

$$B_S + \frac{B_S}{G_S} \cdot |V| \cdot V_S \cdot N \leq LLC_S - R_S \qquad (1)$$

Logical Partitioning. Once the granularity of shared graph blocks is established, GraphCPP can proceed with the logical partitioning during the graph preprocessing phase. This process involves subdividing coarse-grained graph partitions on the distributed system into finer-grained shared graph blocks. Pseudocode for partitioning graph blocks in GraphCPP is presented in algorithm 2:

The logical partition function takes two parameters: one is the graph partition structure data P_i recorded in edge table format, and the other is the set of graph blocks $block_{table}$ owned by the partition (Line 1). In Line 2, we utilize a dictionary structure called $block_{map}$ to collect information about graph blocks. Its key records the source vertex ID of an edge, and its value records the number of outgoing edges corresponding to that vertex. In Line 4, GraphCPP iterates through each edge in the partition. If the edge has already been loaded into the current partition, the count of outgoing edges for that partition is incremented (Line 6). If the vertex is added to the dictionary for the first time, the count of outgoing edges for the partition is set to 1 (Line 8). After processing each edge, there is a check to determine if the current block is full (Line 11). If the block is full, the current block is added to the $block_{set}$ (Line 12), and the recorded block information is

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Algorithm 2 Logical Partition Algorithm

1: **function** PARTITION($P_i, block_{table}$)
2:     $block\_map \leftarrow$ null
3:     **for** each $e \in P_i$ **do**
4:         **if** $e.src$ in $block\_map$ **then**
5:             $block\_map[e.src]$ ++
6:         **else**
7:             $block\_map[e.src] \leftarrow 1$
8:         **end if**
9:         **if** block_map.size() $\geq B_S$ **then**
10:             $block_table$.push($block\_map$)
11:             $block\_map$.clear()
12:         **end if**
13:     **end for**
14: **end function**

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cleared (Line 13). This way, when all the data in the partition has been traversed, and each edge in the partition is assigned to a specific graph block, we obtain the collection of logically partitioned graph blocks.

b) Share Similar Data Among Multiple Tasks

Establishing the Association between Shared Blocks and Query Tasks. Through the previous steps, we have achieved fine-grained graph partitioning in a logical manner. Since this partitioning is only logical, the data remains contiguous on the physical storage medium. Therefore, it is easy to determine the partition in which a vertex is located based on its ID. During query execution, each task q_i maintains an active vertex set $Set_{act,i}$ throughout the iterative computation process. It follows the updating strategy: 1) Initially, $Set_{act,i}$ only contains the source vertex Si of the query. 2) Process the active vertices in $Set_{act,i}$ according to the flow of the point-to-point query algorithm, removing the processed vertices from the active set. 3) If a vertex's state changes in this round and it is not pruned, add the vertex to $Set_{act,i}$ for processing in the next round. We first deduce the graph block to which a vertex belongs by reverse inference of its ID and then utilize a specially designed array to store the traversed partitions for each task. Since point-to-point queries adopt a pruning-based traversal strategy, the number of active vertices in each execution round is not high. Therefore, establishing the association between query tasks and their respective blocks can be done with relatively low overhead.

Determining the Priority of Partition Scheduling. After establishing the association between query tasks and their corresponding blocks, we can tally the number of tasks associated with each block. The higher the task count, the more tasks share the block, indicating greater benefits from processing this block. Consequently, blocks with a higher task count are prioritized for placement into the Last-Level Cache (LLC).

Triggering Concurrent Execution of Associated Tasks. Having obtained the shared graph data blocks, based on the association between shared blocks and query tasks, we can infer the active query tasks. These tasks share the graph structure data in the LLC, and we execute these query tasks using a batch computing approach. As shown in Algorithm X, active tasks generate new active vertices after one round of

execution. If these new active vertices remain associated with the current shared block, the query tasks continue execution. Shared blocks always remain in the LLC until all query tasks associated with them are processed, at which point they are evicted.

c) Batch Execute Similar Tasks

At any given moment, a diverse set of random query tasks exists in the task pool, each with distinct query paths. Tasks with high path overlap demonstrate efficient data sharing, while low overlap hinders this efficiency. Notably, we observe that higher task similarity correlates with increased path overlap, resulting in enhanced data access efficiency and reduced redundant synchronous iterations. Task similarity is quantified by calculating distance values between different task starting points (destination vertices). In GrapCPP, we propose a batch execution strategy that is aware of similar tasks, selecting batches of similar tasks from the task pool for execution. This approach further leverages data and computation similarity. Specifically, GraphCPP randomly selects a query task from the task pool, retrieves the starting and destination vertices of the task, and performs BFS algorithm to obtain the neighbor vertex sets Set_S for the starting vertex and Set_D for the destination vertex. Note that, considering that some central nodes may have a large number of neighbor nodes, we set an upper limit of 500 for neighbor nodes. Subsequently, it traverses the task pool, filtering out all queries with starting points in Set_S and destination points in Set_D, treating them as similar tasks to be processed concurrently. It's important to note that if the starting or destination vertex of a query belongs to a high-degree vertex, indexing can be directly used to accelerate the query process without employing regular query steps. Excluding high-degree vertices, the overhead of the k-hop SSSP itself is minimal, and the execution process can be concurrent with regular queries, making the execution cost negligible.

D. Computation Sharing Mechanism

GraphCPP achieves computation sharing through two mechanisms: the global index and the core subgraph index. The inherent overhead of the global index is substantial and directly proportional to the number of global indices. In practice, the number of global vertices is typically kept low (e.g., 16) due to this overhead. However, because of the power-law distribution, these few hot vertices act as hub nodes for various queries. As a result, for most point-to-point queries q_i, a path can be traced from the source vertex s_i through at least one global vertex to the destination vertex d_i While this path may not always be the optimal route for q_i, it serves as a valuable pruning boundary. GraphCPP utilizes the global index to rapidly identify these intermediary paths, constituting the first level of computation sharing. Additionally, the core subgraph mechanism, without preprocessing, reveals optimal paths based on existing query results, facilitating computation sharing for distinct yet overlapping hot paths. Compared to the global index, the core subgraph is lighter, allowing for a broader coverage range by increasing the number of hot vertices. Consequently, more precise pruning bounds are provided, accelerating the convergence speed of pruning queries. Algorithm 3 outlines the pseudocode for the computation sharing mechanism.

Algorithm 3 Shared Computation Algorithm

1: **function** INDEXPREPROCESS(V, k, m)
2:     $Set_{\text{global}}, Set_{\text{core\_subgraph}} \leftarrow$ SortByDegree(V, k, m)
3:     $Set_{\text{global\_index}} \leftarrow$ BuildGlobalIndex(k)
4:     InitCoreSubgraph($m, Set_{\text{core\_subgraph\_index}}$)
5: **end function**
6: **function** SHAREDCOMPUTATION
7:     $bound \leftarrow$ FirstLevelSharing($Set_{\text{global\_index}}, Set_{\text{query}}$)
8:     **while** activeVerticesCount $\neq 0$ **do**
9:         $activeVertex \leftarrow$ GetNextActiveVertex()
10:         **if** $activeVertex \in$ coreSubgraph **then**
11:             UpdateBounds($bound$,
12: SecondLevelSharing($Set_{\text{core\_subgraph\_index}}, Set_{\text{query}}$))
13:         **end if**
14:         **for** each $neighbor$ of $activeVertex$ **do**
15:             UpdateBoundsByNeighbors($neighbor$)
16:         **end for**
17:         activeVerticesCount $\leftarrow$ UpdateActiveVertices()
18:     **end while**
19: **end function**
20: **function** MAINTAINCORESUBGRAPH($Set_{\text{query\_path}}$)
21:     $Set_{\text{hot\_path}} \leftarrow$ ExtractHotPath($Set_{\text{query\_path}}$)
22:     AddToCoreSubgraph($Set_{\text{hot\_path}}$)
23: **end function**

The steps for implementing computation sharing are as follows: 1) Index Preprocessing (Lines 2): After sorting the degrees of vertices, the system selects the top $k + m$ hot vertices with the highest degrees. The first k vertices serve as *global vertices* (where k is user-defined), and the remaining vertices become *core subgraph vertices*. The computation of the global index is completed during preprocessing phrase. GraphCPP executes the SSSP algorithm to calculate the optimal paths (including index values and parent nodes) for k high-degree vertices to all vertices in the graph. The results are stored in an array indexed by the high-degree vertices' IDs. The core subgraph omits the precomputation process, directly reusing the computation results of each query, requiring only initialization during preprocessing. 2) Computation Sharing (Lines 6-19): *Global vertices* act as pivotal nodes for query paths. Most queries have at least one path passing through global index vertices. Although this path may not be the optimal path, it provides a reliable reference for query pruning. Therefore, before executing point-to-point queries, an approximate boundary is determined using the *global index*, representing the first level of computation sharing. Subsequently, an iterative query algorithm is executed, continuously processing new active vertices until all vertices converge. For each active vertex, it is determined whether it belongs to the core subgraph. Initially, the core subgraph is empty and does not participate in sharing. As query tasks execute, the core subgraph gradually accumulates more hot paths. When an active vertex belongs to the core subgraph, the hot path value for the corresponding starting vertex can be directly obtained through the core subgraph, avoiding redundant computation.

Additionally, the core subgraph allows the query boundary to jump directly from one hot vertex to another through the hot path, accelerating the speed of point-to-point queries. 3) Maintain the Core Subgraph (Lines 20-23): To ensure the lightweight nature of the core subgraph, hot paths are not precomputed. Instead, a subset of hot paths is explored from existing optimal paths, reusing previous computation results. Clearly, any path between any two vertices on an optimal path is also an optimal path. Therefore, with minimal overhead, identifying hot vertices from existing results and calculating results between hot vertices using a prefix sum method is sufficient. To achieve this, traversal paths and path values from the source vertex to each intermediate point need to be retained during the query process. Since point-to-point queries inherently require calculating this information, the extra overhead is minimal. Through these steps, we achieve efficient data sharing using a lightweight *core subgraph index*.

E. Update Mechanism

In practical applications, the underlying graph traversed by query tasks often undergoes dynamic changes, involving edge additions (e_{add}) and edge deletions (e_{delete}). Changes in the graph structure data can lead to errors in index values. Therefore, when dynamic updates occur in the dynamic graph, we not only need to update the graph structure information but also dynamically update the indexes. **Graph structure information update**: GraphCPP stores the out-neighbor of each vertex using an adjacency list. Therefore, we only need to modify the adjacency list of the corresponding out-neighbors based on the source vertex information when an edge is added (or deleted). **Index update**: We adopt an incremental updating approach, sequentially updating the global index and core subgraph index, minimizing redundant computation costs during index updates.

The number of global index vertices is relatively small (k global index vertices), but it records a substantial number of index values ($k \times |V|$ global index values). Storing these index values in a dedicated array might result in excessive bulkiness, but dispersing the index information across individual vertices is a more suitable approach. Each vertex maintains two tables: $table1$ records the parent nodes on the optimal paths to k global vertices, and $table2$ records the index values of the optimal paths from this vertex to k global vertices. Incremental updates are performed on these two tables based on the type of edge update. Specifically, when an edge addition update (e_{add}) occurs, we first obtain the source vertex src, destination vertex dst, and the weight between the two points. We then sequentially check each global index vertex. If $Index_{\text{src}} + weight > Index_{\text{dst}}$, we update $parent_{\text{dst}}$ in $table1$ to src and $Index_{\text{dst}}$ in $table2$ to $Index_{\text{src}} + weight$. Otherwise, there is no need to update the index for that global vertex. In the case of an edge deletion update, we check each global index vertex and determine if $parent_{\text{dst}}$ equals src. If true, it indicates that we have deleted the original optimal path to dst, and we need to recalculate $Index_{\text{dst}}$. Similar to other incremental computation methods[29][30] updates to dst will gradually propagate outward, requiring updates for all

downstream vertices on the optimal paths that pass through dst. If $parent_{\text{dst}}$ is not equal to src, there is no need to update that global index vertex.

The core subgraph index records indexes between a small number of high-degree vertices, requiring the maintenance of at most $m \times m$ index values (where m is orders of magnitude smaller than the graph's data scale). To store this information, we use an independent two-dimensional array for the core subgraph. Specifically, edge additions can introduce new shortcuts, leading to the degradation of original optimal paths into non-optimal ones. In the context of our pruning queries, although non-optimal path indexes can cause early overestimation of boundary values, the iterative process ensures that point-to-point queries still converge towards more optimal paths, ultimately reaching the correct optimal paths. Extracting the latest hot path values from these converged paths completes the update to hot paths. For edge deletion updates, GraphCPP checks if both vertices of the deleted edge appear on some hot path. If yes, the original hot paths are interrupted, rendering all affected hot paths invalid. If only one vertex or no vertices appear on some hot path, the deleted edge does not affect hot paths, and there is no need for an update. Since the core subgraph index reuses the optimal path results from each query, no separate calculation is needed, resulting in overall low overhead.

The above mechanism implements incremental maintenance of graph structure data, global indexes, and core subgraph indexes. Considering that subtle graph updates do not significantly impact the overall computation results, we temporarily store subtle graph updates ΔG until its size exceeds a preset threshold or a certain time interval is reached. Only then do we execute batch graph update operations, further reducing update costs.

IV. EXPERIMENTAL EVALUATION

A. Experimental Setup

Hardware Configuration: The experiments are conducted on an 8-node cluster, each machine equipped with 2 32-core lntel Xeon platinum 8358 CPUs (each CPU has 48MB L3 cache) and 1GB memory. All nodes are interconnected through an lnfiniband network with a bandwidth of 300Gbps. The programs are compiled using gcc version 9.4.0, openMPl version 4.0.3, and withopenMP enabled.

Graph Algorithms: To align with prior work[3][2][1][4], we've selected six benchmark algorithms widely applied in graph clustering, classification, and prediction. These algorithms fall into two categories: graph and undirected graph algorithms. 1) Weighted graph algorithms: Point-to-point shortest path (PPSP)[18][19][20], point-to-point widest path (PPWP)[21], and point-to-point narrowest path (PPNP)[22] are utilized to identify the shortest, widest, or narrowest paths between two vertices. They find extensive applications in social/financial networks, traffic planning, monitoring money laundering activities, and network quality analysis. 2) Unweighted graph algorithms: Breadth-first search (BFS)[23], connectivity[24][25][26], and reachability[27] are the three most common pairwise queries on unweighted graphs. They

are employed to determine the shortest path between two vertices, whether two vertices are connected in an undirected graph, and whether two vertices are connected in a directed graph. These algorithms find widespread use in biconnectivity, higher-order connectivity, and advanced algorithms for graph clustering.

Graph Datasets: The graph datasets used for the aforementioned algorithms are presented in Table x. LiveJournal and Twitter-2010 belong to social network graphs, while UK-2007-05 and Gsh-2015-host represent web-crawl graphs. These datasets exhibit power-law graphs with small diameters and skewed distributions, capturing real-world graph distribution scenarios. Our experiments are based on dynamic graphs, utilizing a snapshot mechanism where graph updates are performed on an unclosed snapshot, and graph queries are executed on a closed snapshot. Unclosed snapshots are periodically transformed into closed snapshots, replacing the original snapshot.

Datasets	Vertices	Edges	Data sizes
LiveJournal[1]	4.8M	69M	526MB
Twitter-2010[2]	41.7M	1.5B	10.9GB
Gsh-2015-host[3]	68.7M	1.8B	13.4GB
UK-2007-05[4]	106M	3.74B	27.9GB

TABLE II: Dataset Information

System Comparison: We conducted a comparative analysis between GraphCPP and existing point-to-point query solutions, including PnP[3], Tripoline[2], and SGraph[1]. In Section x, as SGraph represents the state-of-the-art in point-to-point query systems, the performance of PnP-S, PnP-C, Tripoline-S, and Tripoline-C consistently falls behind SGraph. Therefore, in the subsequent comparative analysis, we did not present the performance results of PnP and Tripoline. Since these systems are not open source, we re-implemented their mechanisms based on the Gemini distributed graph processing framework. Given that PnP, Tripoline, and SGraph do not directly support concurrent operations, we made modifications to enable them to handle multiple jobs simultaneously. Systems with the "-S" suffix execute tasks sequentially, while those with the "-C" suffix handle queries concurrently, managed by the operating system.

Additionally, for a more scientifically rigorous experimental comparison, we benchmarked against the state-of-the-art general concurrent graph computing solution, Glign. When evaluating the overall performance of concurrent queries, we employed a mixed submission approach, generating an equal number of queries for algorithms such as PPsP, PPWP, PPNP, BFS, Connectivity, and Reachability. It is noteworthy that a global indexing mechanism needs to maintain a set of indices for different graph algorithms. To ensure fairness, we calculated the average global indexing cost for the six algorithms. Furthermore, random parameters were set for each query task, maintaining consistency with the baseline: the number of global indices (k) was set to 16, and the core subgraph vertices in GraphCPP were set to 128. All benchmarks were executed 10 times, and the reported experimental results represent the average values.
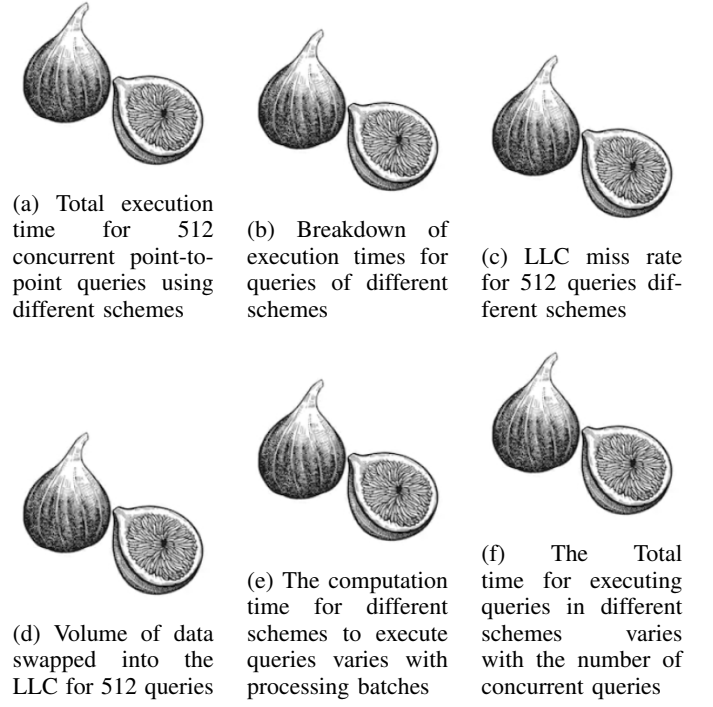

(a) Total execution time for 512 concurrent point-to-point queries using different schemes

(b) Breakdown of execution times for queries of different schemes

(c) LLC miss rate for 512 queries different schemes

(d) Volume of data swapped into the LLC for 512 queries

(e) The computation time for different schemes to execute queries varies with processing batches

(f) The Total time for executing queries in different schemes varies with the number of concurrent queries

Fig. 3: Overall caption for the figure

B. Overall Performance Comparison

Figure 9 depicts the total execution time of xx concurrent jobs using different schemes. For conciseness, only the optimal results are displayed, and due to significant variations in the execution times of different test cases, we normalize the execution time relative to PnP's performance. It is evident that, for all graphs, GraphCPP achieves shorter execution times (and higher throughput) compared to the other schemes. In comparison to SGraph-S, SGraph-C, PnP-S, PnP-C, Tripoline-S, and Tripoline-C, GraphCPP demonstrates an average throughput improvement of approximately xx, xx, xx, xx, xx, and xx times, respectively. This enhancement in throughput is accomplished by reducing data access costs and efficiently pruning the core subgraph in GraphCPP.

To provide a more in-depth analysis of performance, we further divide the total time into data access time and graph processing time. As shown in Figure 10, GraphCPP requires less time for graph data access compared to other systems, and this proportion decreases further as the graph size increases. For example, in the case of Gsh-2015-host, GraphCPP's data access time is reduced by xx times to xx times compared to other systems. Two key factors contribute to GraphCPP's efficiency: 1) identical portions of graph data required by different concurrent jobs only need to load and maintain a single copy in memory, reducing memory consumption; 2) graph data blocks are prioritized and periodically loaded into the LLC based on the number of associated tasks, promoting job reuse and effectively lowering LLC miss rates, minimizing unnecessary memory data transfers. Additionally, thanks to the two-level computing sharing mechanism, GraphCPP's computation time is also lower than that of other systems.

C. Efficiency of Data Access Sharing Mechanism

GraphCPP employs a data sharing mechanism to reduce redundant data access. To qualitatively illustrate the efficiency of this mechanism, we evaluate the LLC utilization of different systems, and the results are presented in Figure 11. Notably, GraphCPP demonstrates lower LLC miss rates compared to the other six systems. In the case of UK-2007-05, GraphCPP's LLC miss rate is only xx, while SGraph-S, SGraph-C, PnP-S, PnP-C, Tripoline-S, and Tripoline-C exhibit LLC miss rates of xx, xx, xx, xx, xx, and xx, respectively. This is primarily attributed to GraphCPP allowing multiple jobs to share a single graph data copy in the LLC, enabling more efficient utilization of the LLC and enhancing data locality for jobs.

Additionally, we track the total amount of data swapped into the LLC by these 16 jobs. Generally, the concurrent execution mode (-C) tends to swap more data into the LLC compared to the sequential execution mode (-S). This is because concurrent jobs lack data sharing, leading to frequent swapping of graph data in and out of the LLC and resulting in more redundant memory data transfers. As illustrated in Figure 12, GraphCPP swaps significantly less data compared to SGraph-S, PnP-S, and Tripoline-S (xx, xx, and xx, respectively, in UK-2007-05). This reduction is attributed to GraphCPP maximizing the similarity in data access among concurrent tasks.

D. Efficiency of the Computation Sharing Mechanism

Figure x evaluates the relationship between the processing time of each system graph and its variation over time. Due to significant differences in the graph processing time of each system, we represent the normalized time as the PnP[3] graph processing time. PnP relies purely on pruning without utilizing an index, reducing preprocessing time but resulting in the longest query computation time. Tripoline[2], leveraging upper-bound pruning and a global index, reduces graph processing time. SGraph[1], employing upper-bound and lower-bound pruning strategies, achieves better pruning effects, requiring fewer vertices to be computed and resulting in shorter graph processing times. While the graph processing time of these three systems may fluctuate slightly based on different query characteristics, overall, the graph processing time remains stable. In contrast, GraphCPP's graph processing time initially aligns with SGraph, as it adopts a global index mechanism similar to SGraph. However, due to the continuous improvement of GraphCPP's core subgraph index mechanism during queries, it can leverage optimizations at the second level to continuously accelerate graph processing time, resulting in a reduction over time; GraphCPP shortens its processing time.

Global Index Overhead: As the number of global indices increases, the time required for maintaining the indices also grows. In our experiments, PnP did not incur maintenance overhead for global indices as it did not utilize them. However, Tripoline[2], SGraph[1], and GraphCPP employed similar global index mechanisms. As shown in Figure x, GraphCPP's index construction overhead is comparable to other systems due to the adoption of the same number of global indices. Nevertheless, GraphCPP achieves higher throughput, allowing it to handle more queries in the same time frame, thereby distributing the global index overhead.

Core Subgraph Index Overhead: We evaluated the impact of the core subgraph index on GraphCPP's performance. With the global index set to 16, GraphCPP-128, GraphCPP-256, and GraphCPP-without represent versions with core subgraph indices of 128, 256 vertices, and without using core subgraph indices, respectively. Table x illustrates the memory space occupied by these three versions of core subgraphs. It is noticeable that GraphCPP-128 and GraphCPP-256 incur only a minimal increase in memory usage compared to GraphCPP-without, all maintaining 16 global indices. This minimal increase is attributed to the fact that core subgraph vertices only store path values to other core subgraph vertices, requiring very little additional space compared to global indices storing path values to all vertices.

TABLE III: Table Title

	Core subgraph scale	Total execution time
GraphCPP-without	1	1
GraphCPP-128	1	1
GraphCPP-256	1	1

Moreover, Table x displays the total execution time of GraphCPP-128, GraphCPP-256, and GraphCPP-without across 16 jobs. Consistently, GraphCPP-256 and GraphCPP-128 outperform GraphCPP-without, with GraphCPP-256 being faster than GraphCPP-128. On Friendster, the processing times of GraphCPP-256 and GraphCPP-128 are only xx and xx times that of GraphCPP-without, respectively. This improvement is attributed to the additional core subgraph vertices enhancing pruning effectiveness and constraining upper and lower bounds.

Update Maintenance Overhead: Tripoline[2], SGraph[1], and GraphCPP share a common global index mechanism, with an equal global index number set to 16. GraphCPP, additionally implementing a second level of sharing through the core subgraph mechanism, incurs additional maintenance overhead. As described in Section xxx, during edge addition updates, there is no need to specifically update the corresponding core subgraph hot paths. In the case of edge deletion updates, only the affected hot paths need to be deleted. Since we do not perform a dedicated computation for the core subgraph but rather extract hot paths from existing results, graph updates only affect the accuracy of the core subgraph mechanism without incurring expensive update maintenance overhead. Furthermore, to minimize update overhead, GraphCPP conducts frequent maintenance only during the initial phase. Maintenance frequency decreases once the establishment of the subgraph reaches 80%. In the absence of graph mutations, previously recorded hot path values remain unchanged, eliminating redundant updates to the core subgraph.

E. Scalability of GraphCPP

Figure 16 illustrates the performance comparison between GraphCPP and six other systems under varying numbers of concurrent PPsP jobs. GraphCPP exhibits superior performance improvement as the number of concurrent jobs

increases. For 2, 4, 8, and 16 concurrent jobs, GraphCPP achieves acceleration ratios of xx, xx, xx, and xx, respectively, in comparison to SGraph-S. This improvement stems from GraphCPP's amortization, which saves more data access and storage costs with an increasing number of jobs. It's important to note that with only one concurrent job, GraphCPP's fine-grained scheduling operations do not occur, resulting in minimal differences in execution time compared to other schemes. According to our tests, the block scheduling cost of GraphCPP constitutes only xx-xx% of the total execution time. Furthermore, due to resource contention, the performance of the concurrent version (-C) is considerably worse than both GraphCPP and the sequential version (-S). Therefore, a simple modification of existing graph processing systems to support concurrent tasks might not be an optimal choice.

Next, we assess the horizontal scalability of GraphCPP. To achieve this goal, we evaluate the performance of different schemes on 1, 2, 4, and 8 nodes. As shown in Figure 18, GraphCPP's performance on 8 nodes is xx-xx times that of a single machine, indicating robust scalability. Moreover, GraphCPP's scalability surpasses that of SGraph[1], PnP[3], and Tripoline[2] due to lower communication costs facilitated by data sharing and core subgraph indexing. Consequently, we believe that GraphCPP can efficiently support practical point-to-point query applications.

V. RELATED WORK

Graph Processing Systems. With the increasing prominence of graph computing as a research focus, an increasing number of diverse types of graph computing systems are being proposed. 1) Single-node in-memory graph computing systems: Ligra[28] accelerates graph computation, especially graph traversal algorithms, by switching between push and pull computation modes. KickStarter[29] and GraphBolt[30] implement incremental processing for streaming graphs. DiGraph [x] efficiently facilitates iterative directed graph processing on the GPU. LCCG[32], DepGraph[33], and TDGraph[34] utilize topology-aware execution methods, reducing redundant computation and data access costs; 2) Single-node out-of-core graph computing systems: GraphChi[35] and X-Stream[36] achieve efficient out-of-core graph processing through sequential storage access. FlashGraph[37] employs a semi-external memory graph engine, achieving high IOPS and parallelism. GridGraph[38] adopts the Streaming-Apply approach to enhance locality and reduce I/O operations. DGraph[39] accelerates graph processing through faster state propagation. GraphM[40] adopts a data-sharing approach, optimizing throughput for concurrent systems; 3) Distributed graph computing systems: Pregel[41] introduces the Bulk Synchronous Parallel (BSP) computation model, addressing the processing needs of graphs with billions of edges in terms of performance, scalability, and fault tolerance. PowerGraph[46] proposes a vertex-cut graph partitioning approach, effectively reducing communication volume and addressing load imbalance caused by high-degree vertices. PowerLyra[49] employs a hybrid computing model, using different computation strategies for high-degree and low-degree vertices. Gemini[43] introduces

a dual-mode computation engine, ensuring scalability while maintaining performance. CGraph[42] uses a data-centric Load-Trigger-Pushing (LTP) model, leveraging temporal and spatial similarities between concurrent tasks to reduce distributed system overhead; The mentioned works are intended for general graph algorithms. However, point-to-point query algorithms, which concentrate on the specific relationships between vertex pairs in a graph, show notable distinctions. These query algorithms can significantly improve execution efficiency through pruning strategies. Nevertheless, general graph computing systems do not inherently accommodate such algorithms.

Point-to-Point Queries. Numerous studies have been conducted on point-to-point queries. On the hardware front, hub^2[50] proposed a dedicated accelerator with a hub-centric approach, accelerating the PPSP process by constraining the search scope of high-degree vertices and pruning the search process. On the software side, Quegel[51] pursued an indexing approach, enhancing query response speed by constructing a distributed static index of the graph during loading. PnP[3] took a pruning route, reducing redundant accesses and computations in point-to-point queries through a universal pruning strategy. Tripoline[2] combined both indexing and pruning, achieving incremental evaluation of queries without prior knowledge by leveraging the triangle inequality principle. SGraph[1] further optimized pruning strategies, employing upper and lower bounds to achieve sub-second latency queries on large graphs with dynamically changing data. The aforementioned efforts focus on optimizing the speed of individual point-to-point queries through mechanisms such as pruning and indexing, overlooking the substantial load posed by large-scale concurrent queries.

Concurrent Graph Computing. Numerous graph computing systems have explored concurrent graph computation, especially in the realm of single-machine memory graph processing systems. For instance, Congra[52] dynamically schedules tasks based on an offline analysis of query tasks' memory bandwidth consumption and atomic operation characteristics. This dynamic scheduling aims to enhance system throughput and resource efficiency without blocking queries due to resource contention. Krill[53] introduces an SAP model that decouples graph structure, algorithms, and attributes. It simplifies attribute data management using attribute buffers and employs graph kernel fusion to reduce memory access by treating all tasks as a cohesive unit. ForkGraph[54] proposes an efficient buffer execution model for concurrent tasks, facilitating data sharing and accelerating overall execution speed through a yield-based scheduling strategy. In the context of single-machine out-of-core graph computing systems, GraphM[40] leverages the temporal and spatial locality of concurrent tasks for data sharing in concurrent graph computation. For distributed graph computing systems, Seraph[55] suggests decoupling graph structure data from task-specific data to enable concurrent tasks to share common graph structure data. MultiLyra[56] and BEAD[57] distribute communication costs among cluster computing nodes through graph and boundary sharing, supporting efficient batch query evaluations. CGraph[42] serves as the distributed version of GraphM[40].

These approaches primarily focus on optimizing data access sharing for concurrent tasks, yet they overlook computation optimization between concurrent tasks and lack specialized optimization for point-to-point queries.

VI. CONCLUSION

Current point-to-point query systems predominantly concentrate on optimizing the speed of individual queries, overlooking the potential for throughput optimization in concurrent scenarios. This paper identifies significant data access and computation similarities among concurrent point-to-point query tasks. Introducing GraphCPP, a data-driven concurrent point-to-point query system, the paper utilizes a data-driven caching execution mechanism to achieve overlapping data access sharing among concurrent queries. Simultaneously, through a two-level computation sharing mechanism, it effectively realizes computation sharing among multiple tasks. Experimental results demonstrate that GraphCPP outperforms state-of-the-art graph query systems, such as SGraph[1], Tripoline[2], and Pnp[3], by a factor of XXX.

VII. ACKNOWLEDGMENTS

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