PARQ: A MEMORY-EFFICIENT APPROACH FOR QUERY-LEVEL PARALLELISM

A Thesis Presented

by

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ABSTRACT

PARQ: A MEMORY-EFFICIENT APPROACH FOR QUERY-LEVEL PARALLELISM

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In the era of big data, people not only enjoy what massive information brings, but also experience the problem of information overload. As the volume of both data and users increasing sharply, more and more studies focus on how to answer a query for interesting information from massive data. However, most memory-based query systems are designed and implemented to optimize the performance in processing a single query and do not support in-memory data sharing among query processing jobs. When they are extended to process multiple concurrent queries, they will suffer the problems of the inefficient use of memory and waste of time.

This thesis aims to design and implement a memory-efficient system, ParQ, which can be adopted by memory-based query systems to realize query-level parallelism. The main idea includes constructing a common memory block for maintaining sharable data. By sharing data, ParQ is able to process multiple queries concurrently while reducing memory usage and running time. We apply ParQ to several existing query systems. The experiment results show that ParQ improves the performance in both job completion time and memory usage when executing multiple concurrent query jobs.

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CHAPTER 1

INTRODUCTION

1.1 Trends and challenges

The future of big data is promising. Data has become a class of asset. In the areas of Internet, telecommunications, finance, and etc., many companies have achieved commercial success by using big data.

On the other hand, the development of big data also faces many challenges, such as, how to reduce data fragment. Nowadays, data is organized into different databases that may belong to different organizations. Even in the same company, data may be maintained by different departments. It is necessary to integrate all the data to better exploit the potential of information.

How to perform data preprocessing is also a big challenge. At the step of data preprocessing, data is cleaned, denoised, and transformed into an easy-to-use structure. Nonstandard preprocessing often leads to inaccuracy, poor quality, and low availability. In big data area, not only data collecting is important but also preprocessing.

Another challenge is how to find requested information from massive data, especially as the volume of both data and users are increasing sharply. According to recent statistics, by August 2014, Google Knowledge Graph had contained 1.6 billion labeled entities [1] [2]. As of January 2014, Freebase had approximately 44 million topics and 2.4 billion facts [3] [4]. To make use of such databases, many researchers focus on algorithms of data processing and analyzing. Topics include, for example, how to improve accuracy, how to increase efficiency, and how to reduce computation cost.

1.2 Motivation

A query system refers to an implementation that aims to answer queries on a database. Such applications have been widely applied in the areas of search engine, social network, e-commerce, and etc. In practical applications, query systems may be queried by more than one user at the same time, therefore, they are supposed to process multiple queries concurrently. The job execution logs from a large Chinese social network show that at peak time, there are more than 20 jobs submitted to the platform at the same time [5]. However, some developing memory-based query systems are inherently designed to evaluate the performance in answering a single query and are difficult to be extended to process multiple queries. Therefore, although such query systems are efficient when processing a single query, they require huge memory usage and long processing time when they process a number of queries concurrently. This is because they cannot support multiple query processing jobs to share in-memory data and each job has to keep an exclusive copy of the same data set, which results in a serious waste of time and memory.

This thesis aims to seek an approach to enable such systems to answer multiple queries concurrently by sharing sharable data among different queries. This approach should ensure 1) a query system uses only one copy of sharable data when it processes multiple queries, 2) the processing time of one query will not be affected by processing other queries, and 3) this approach should be easily used by different query systems.

1.3 Contribution

This thesis introduces a memory-efficient approach, ParQ, to enable memory-based query systems to answer multiple queries concurrently by sharing data among different query jobs. In this thesis, the sharable data is the dataset from which a query system finds the answer of a query.

The ParQ system offers a standard interface. It provides the ability to automatically process data in different formats as long as the formats conform to ParQ's requirements, which allows ParQ to be easily used by many query systems with a little manual work.

Besides the applications of such systems, ParQ could also apply to other similar situations where different processes require the same data.

As case studies, we apply the ParQ system to several existing query systems. A series of experiments are performed on a real computer cluster and ParQ shows good performance. It achieves approximately *n* times less memory usage to answer *n* queries concurrently than the original systems. When there is limited memory, ParQ also enables more concurrent jobs and uses less processing time.

1.4 Thesis outline

In Chapter 2, we give an explicit problem definition. Chapter 3 first describes the overall design of the proposed approach, then gives a detailed explanation of each method provided, and briefly introduces how to use the ParQ system. In Chapter 4, we apply ParQ to several real query systems. In Chapter 5, we design and perform a series of experiments to evaluate the performance when using ParQ. Chapter 6 gives the introduction to related work, and Chapter 7 concludes the thesis.

CHAPTER 2

PROBLEM DEFINITION

With the great increase of data volume in information area, more and more applications focus on mining interesting information from massive data. Massive data sets are normally stored into structured datasets to be further used. For example, Freebase is an online collection of structured data. It is a global resource, which allows people to access information from it. A query is a request for information on a target dataset. In the example of Freebase, a query on it can be "when is the date of Kennedy's birthday?" A query system is an implementation that adopts a specific data processing algorithm and aims to answer queries on a target dataset. For an implementation, a job refers to a process that is responsible for answering a single query. In the process of answering queries on the same dataset, the data used can be divided into two parts: static data and dynamic data. Static data is used but not changed during computations. In this thesis, static data refers to the target dataset, because almost all jobs are executed on the same target dataset. For example, Facebook performs most computations on the same friendship graph [5]. Dynamic data refers to the data generated during computations. It is query-specific and constantly updated. For example, the rank score of a candidate answer is dynamic data. Therefore, a query answering process could be viewed as a computation using a set of static data and a set of dynamic data, as shown in Figure 1.

Traditionally, large data is stored in disk, such as database. However, in order to read and update data faster, a number of query systems store static data in memory. Since many query system frameworks are inherently designed for evaluating the performance of answering a single query, they usually tightly combine static data and dynamic data together. Therefore, they do not allow multiple jobs to share the in-memory static data and each individual job has to maintain an exclusive copy of the static data in memory even if the static data is the same. Such query systems

are inefficient when they try to process multiple queries. The inefficiencies mainly fall in two aspects: longer job completion time and large memory usage.

To be more specific, there are two approaches to answer *n* concurrent queries. First, a query system can keep one copy of the static data in memory and process the *n* queries in serial. In this situation, if the running time for completing one query is *t*, the total running time will be *t***n*. Second, the system can also keep *n* copies of the static data in memory and start *n* jobs to answer *n* queries in parallel, as shown in Figure 2. In this case, if the memory usage for completing one query is *m*, the total memory usage for completing *n* queries will be *m***n*, which could be a huge number. When there is limited memory, the number of running jobs is also limited and the large memory usage can result in longer running time.

The objective in this thesis is to seek a memory-efficient approach to enable a memory-based query system to answer multiple queries concurrently. One possible way is to share static data among different jobs. This approach should also ensure that 1) a query system keeps only one copy of the static data among different jobs, 2) in the ideal situation, the processing time of one job will not be affected by processing other jobs, and that 3) it can be adopted by different query systems where datasets, queries, and implementations are all different.

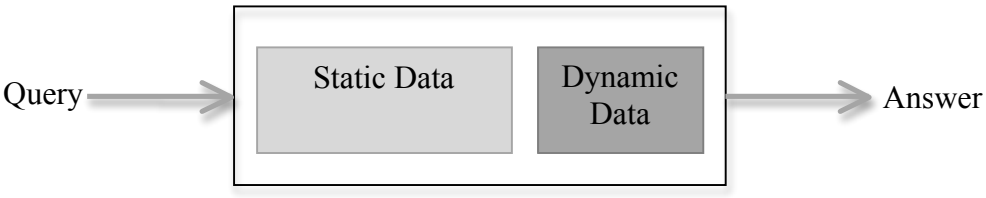


Figure 1: A job of a query system

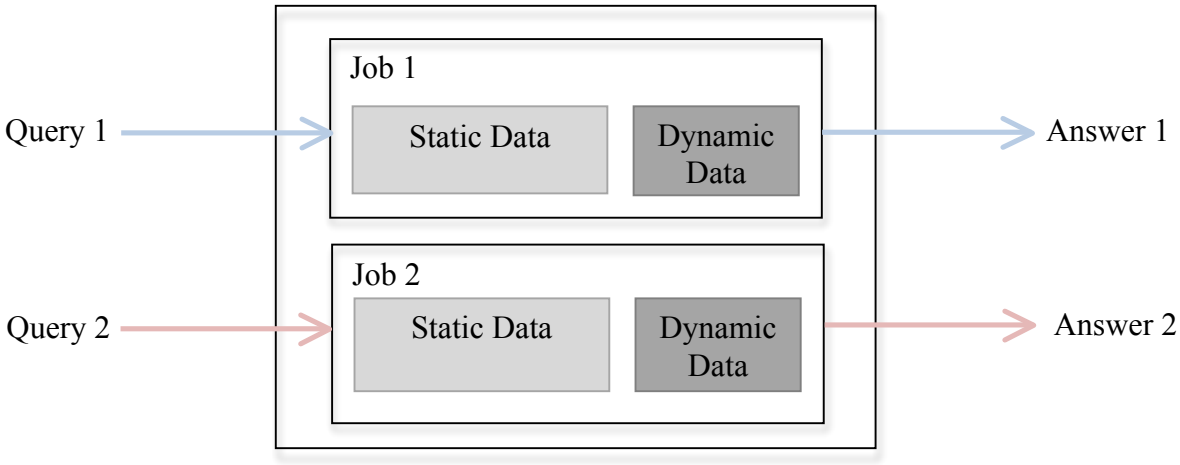


Figure 2: Answering concurrent queries with existing systems

CHAPTER 3

DESIGN AND IMPLEMENTATION OF PARQ

3.1 Overall design

The objective in this thesis is to seek a memory-efficient approach to enable a query system to concurrently answer multiple queries. Since almost all concurrent jobs use the same static data, the main idea of the proposed approach, the ParQ system, is to create a shared memory to realize static data sharing among concurrent query processing jobs.

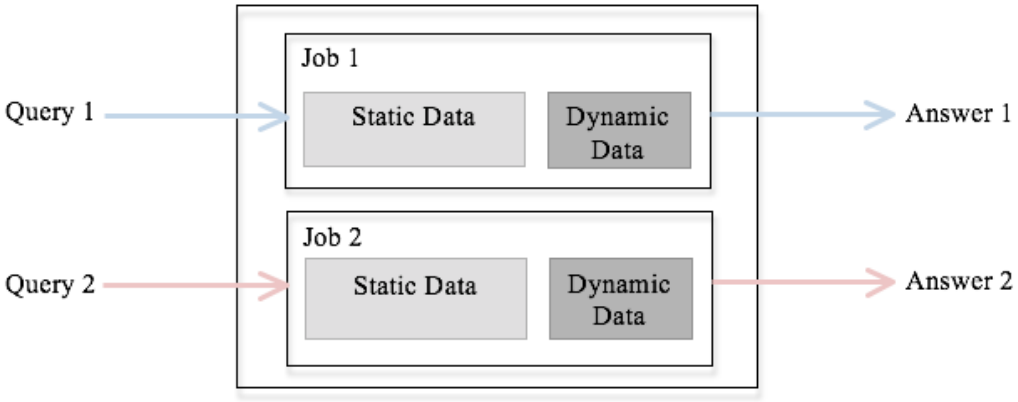
As explained in Chapter 2, a query system can start *n* jobs to answer *n* queries in parallel with *n* copies of the static data in memory. As shown in Figure 3 (a), when a query system processes two queries on the same static dataset at the same time, two jobs are started and each job is responsible for one query. Each job accepts a query, loads one copy of the static data, performs computations, returns answers, and terminates. As a result, the query system has to keep two copies of the static data in memory.

In order to share static data, the design of ParQ splits the task in the original job into two parts: data loading and query processing. A job of data loader creates a shared memory and stores the static data into the memory. A job of query processor accesses the shared memory and fetches requested data from it. ParQ starts *n* jobs of query processor to process *n* queries. Consider Figure 3 (b) as the example. When processing two queries on the same static dataset, ParQ first starts a job of data loader, Job 0, to create a shared memory and store the static data in it. Then, ParQ starts two jobs of query processor, Job 1 and Job 2, to handle the queries. Job 1 and Job 2 connect to the shared memory to get needed data. In this way, ParQ only needs to keep one copy of the static data in memory.

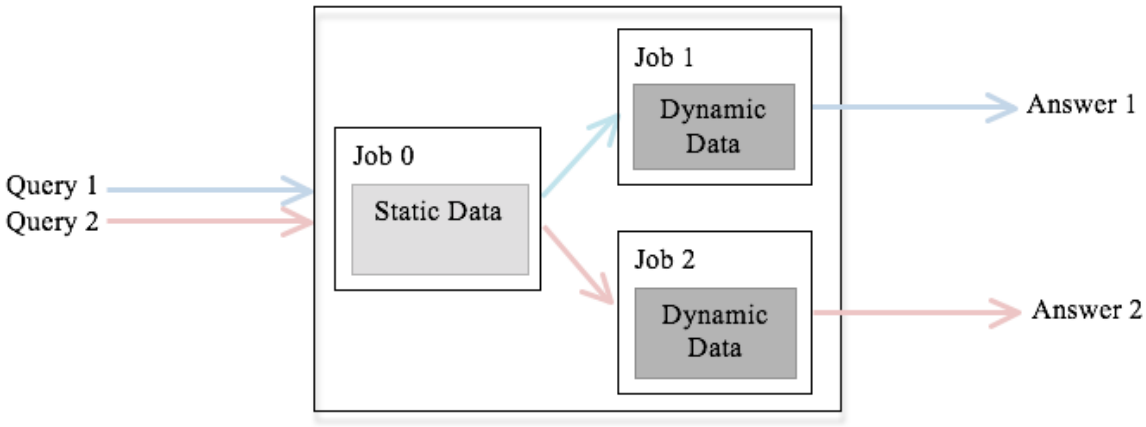
There are two challenges in implementing ParQ. First of all, ParQ should have the ability to adapt to different query systems where datasets, queries, and implementations are all different.

Different datasets are in different data structures. ParQ should support diverse data structures in order to be applied to different query systems with little manual work.

Second, ParQ should be able to work in a distributed environment. The shared memory storing static data may be maintained by more than one machine. Therefore, the segments of the shared memory should be indexed properly to avoid potential errors.



(a) An existing query system keeps *n* copies of the static data



(b) ParQ keeps one copy of the static data

Figure 3: Processing two concurrent queries

The ParQ system contains two classes, one for implementing data loaders and the other one for query processors. It can be applied to different query systems and is able to work in a distributed

environment. The following sections will introduce the API provided by ParQ, including the implementation and usage.

3.2 System implementation

As described in the last section, a data loader of a ParQ program enables static data sharing among different jobs. Each query processor of ParQ is responsible for one job and can connect to the shared memory to get needed data.

This section introduces the implementation of the data loader and the query processor, and explains how to use ParQ.

3.2.1 API for data loading

A data loader creates a shared memory and stores the target static data in this memory. It stores every data item in a specific data type and assigns one name to each. It can support different data formats as long as the formats conform to several requirements.

The ParQ system provides the *DataLoader* class, which is shown as

Figure 4. Given the input file path, the method *loadData(string path)* will process all data in the file under the input path.

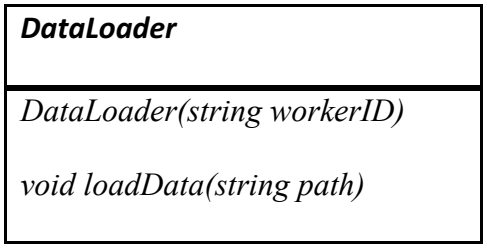


Figure 4: The *DataLoader* class

In order to automatically process different files, ParQ requires the input file to be in a specific format. First, the data in different lines should be organized in the same sequence, namely, the data in the same column should have the same meaning and the same data type. The data items in the first column present the indices. An index is an integer and specifies one line. The data in the following columns can be any supported data type. At present, the ParQ system supports all primitive types and vectors of primitives, such as “int” and “vector<int>”. For a vector, its items are separated by spaces.

Second, users should complete a configuration file shown as

Figure 5. In the configuration file, users will assign a label and specify a data type to each column, while the data in the first column defaults to integer indices.

Index (Default)	Column Name (Optional)	Column Name (Optional)
int (Default)	Data Type	Data Type

Figure 5: Configuration file

For an input file that meets all the requirements, the data loader of ParQ will store every data item in the specific data type and name the data by its index and label. For example, given an input file demonstrated in Figure 6, ParQ will store “-32959029” as an integer in the shared memory and name it as “476-NodeType”.

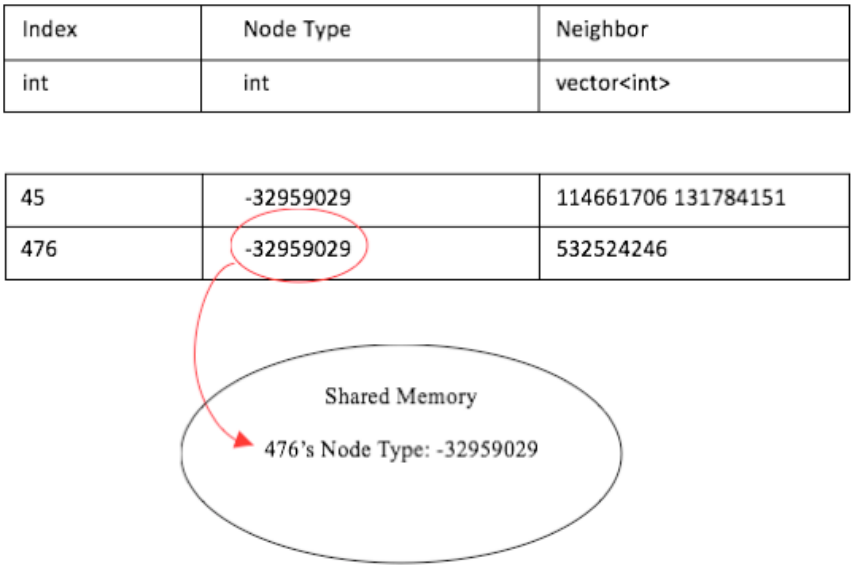


Figure 6: Storing a data item into the shared memory

3.2.2 API for query processing

After loading the static data, users can start query processors to process queries. The ParQ system provides the *QueryProcessor* class, as shown in

Figure 7, for implementing query processors to access the shared memory and fetch needed data.

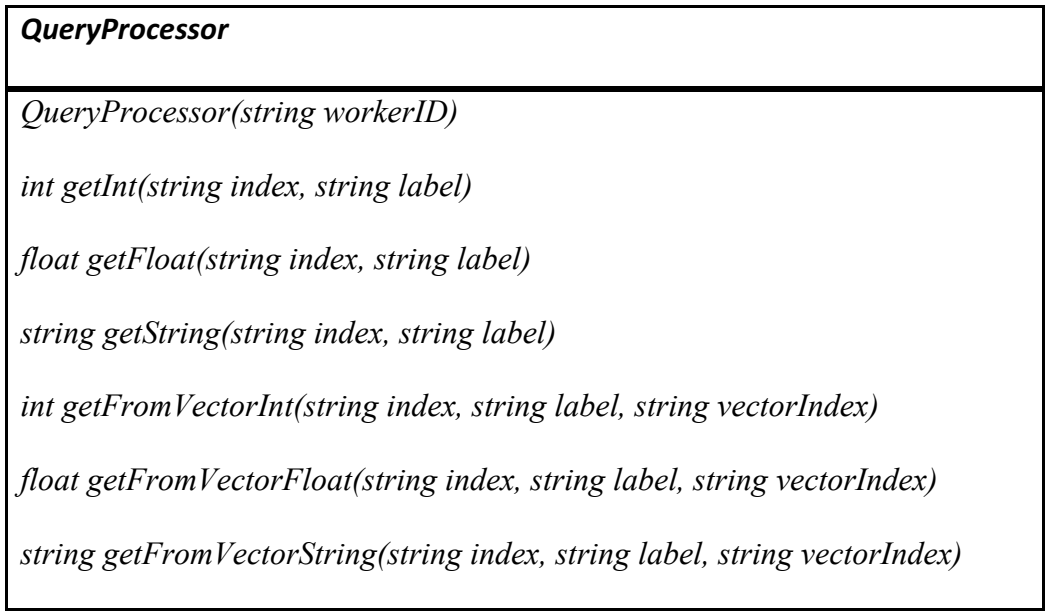


Figure 7: The *QueryProcessor* class

To fetch a target data, the user needs to provide the data type, the index, and the label. Consider the input file shown in Figure 8 as the example. If a user tries to fetch the node type of node 476 from the shared memory, he/she should provide the data type and the label of the target. Since the data type is integer, the label is "NodeType", and the index is 476, the user can call the method *getInt("476", "NodeType")*. This method will connect to the shared memory, search for the data item, and return "-32959029'. Similarly, the user can get a float, or a string from the shared memory by using corresponding methods.

If the target data is in a vector, the user should also provide the vector index. For example, if a user wants to get the first neighbor node of node 476, he/she should call method *getFromVectorInt(string index, string label, string vectorIndex)*, namely *getFromVectorInt("476", "Neighbor", "1")*. Similarly, the user can get an item for a vector of floats, a vector of doubles, or a vector of strings in the same way.

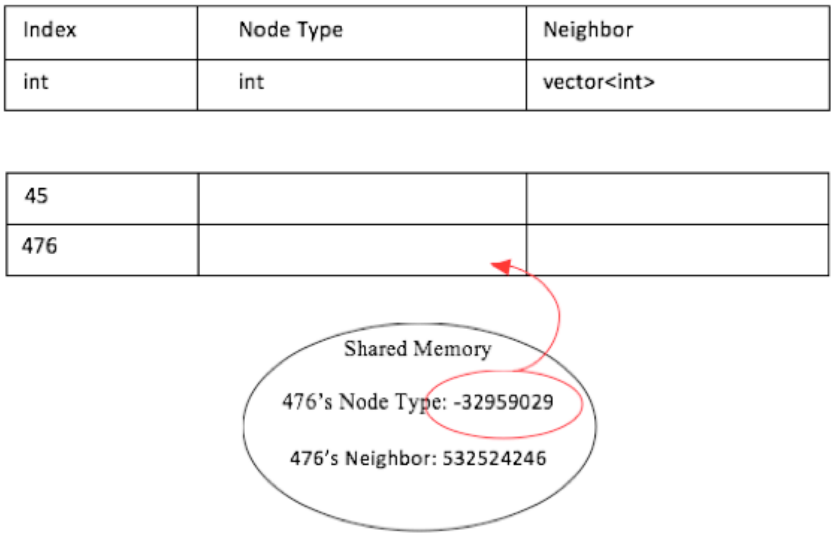


Figure 8: Fetching a data item from the shared memory

3.2.3 Ability to adapt to a distributed environment

The ParQ system starts a data loading job and *n* query processing jobs to process *n* queries. In a distributed model, a job initializes a master and a certain number of workers. The master is responsible for worker scheduling and the workers share the tasks of the job.

Consider Figure 9 as the example, there are two workers for each job. Job 0 is a data loading job and aims to load static data. Each worker of Job 0 maintains a part of the static data. Job 1 and Job 2 are query processing jobs and aim to process queries. The workers of Job 1 or Job 2 share the computations and keep a portion of the dynamic data. The dynamic data is generated during computations.

In a distributed model, a large static dataset is split into several partitions based on partitioning strategies. Workers with the same ID are responsible for the partitions with the corresponding ID. To be more specifically, let *I* represent a specific ID number, if Worker *I* of the data loader creates a shared memory on a physical machine and loads Part *I* into this memory, then each Worker *I* of the query processors must be on the same physical machine to access Part *I*. As shown in Figure 9, A,

C, and E must be on the same physical machine, so that C and E can access the shared memory created by A. ParQ ensures that every Worker *I* is assigned to the same machine by creating a map between worker IDs and machine IDs.

All workers with the same ID will be assigned to the same physical machine, while it is possible that the same physical machine holds workers with different IDs. To handle this case, ParQ gives identifiers to the tasks of the data loader and the query processors based on their worker IDs, which ensures that every Worker *I* of the query processors connects to the shared memory created by Worker *I* of the data loader. Consider Figure 9 as the example, A, B, C, D, E, and F are assigned to the same physical machine. The memory created by A is named "1" and the memory created by B is named "2". The query processing tasks on C and E are given "1" identifiers, so that C and E know they should connect to the shared memory "1" rather than "2".

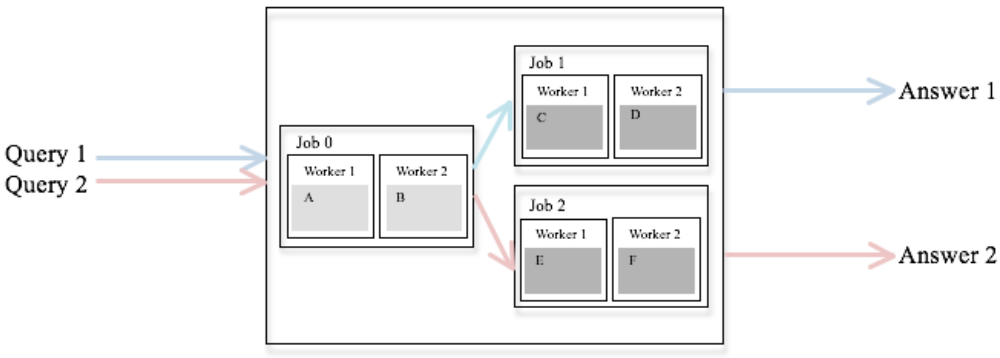


Figure 9: Processing two jobs in a distributed model when ParQ applied

3.3 Instructions for application

The ParQ system can be easily used by many query systems with a little manual work. The input static data of an implementation should be presented in required format. The task in an

original job will be split into two: data loading and query processing. A job uses an *if* statement to determine whether it is a data loader or a query processor. If it is a data loader, it will create a shared memory and call corresponding methods to store the static data. If it is a query processor, it will access the shared memory, call corresponding methods to fetch requested data, and perform computations. The following application examples will show how ParQ can be applied to real query systems.

CHAPTER 4

APPLICATION ON EXISTING SYSTEMS

4.1 Application on the top-*k* personalized PageRank system

The ParQ system is first applied to the top-*k* PageRank system [6]. In the following sections, after a brief introduction of the top-*k* PPR system, we will show how to apply ParQ to it.

4.1.1 System specification

PageRank [7] was first proposed by Google. It is an algorithm used to rank websites for the results of their search engine. PageRank works by counting the number and measuring the quality of links to a page to get a rough estimate of how important the website page is. PageRank assumes that a more important website page is likely to receive more links from other websites [8].

Personalized PageRank is an algorithm used to obtain the items that are highly-relevant to a given set of facts. It has been widely used in various applications. For example, some social networking sites adopt personalized PageRank to give recommendation and relationship prediction.

The top-*k* PPR system makes personalized recommendation by implementing the Personalized PageRank computation. It aims to find *k* items that are the most relevant to a query set from an item graph. The query item set is formed based on known personal preferences. Personalized PageRank is used to measure the relevance of candidates by computing the stationary distribution of a random walk. In each computing step, the random walk reaches a random out-neighbor with probability *d* or jumps to a query node with probability *1 – d*.

The top-*k* PPR system is an extension of the Maiter framework [9]. In this system, relevance score is computed by accumulative computation in an asynchronous manner. A fraction of nodes are selected to update their scores in each pass. The chosen nodes will update its value and

propagate the change of value to their neighbors. The top-*k* PPR system uses score bounds to speed up the computation.

To process a query, the top-*k* PPR system will start a process，or job, that loads the graph into memory and performs an accumulative computation on the in-memory graph to measure the relevance of candidates. The computation is performed until the top-*k* answers are obtained.

4.1.2 Implementation process

As descripted in the last section, the top-*k* PPR system starts a process, or job, to process a query. The job loads the graph into memory and performs an accumulative computation on the in-memory graph to measure the relevance of candidates. The computation is performed until the top-*k* answers are obtained.

When answering multiple queries on the same graph, the item graph used is static and can be shared among different jobs. Therefore, we apply the ParQ system to enable in-memory data sharing among query processing jobs.

First,

Figure 10 shows how an item graph should be represented in a text file to use ParQ. Each line describes one node. A data item in the first column is an integer representing the node name or the node key. The next two are the nodes attributes used in bound computation. The following column lists the node's neighbors. As explained in Section 3.2.1, the data types of the columns except the first column should be specified in the configuration file.

```
        globalScore     incomingDegree  Neighbors
        float   float   vector<int>
0       30.349953       138.460022      11342 824020 867923 891835
1       0.38410074      7.46896818      53051 203402 223236 276233 552600 569212 635575 748615 862566 893884
2       3.7941647       15.35852867     30957 357310 423174 430119 462435 472889 565424 581609 597621 644135 858904
3       0.8809524       2.466473115     87562 131116 262285 290424 298887 449136 456686 718023 789669 812470
```

Figure 10: A part of the static data of the top-*k* PPR system

Second, we write the code of data loader. In the original system, method *read_graph* in *struct PPRGlobalIterateKernel* is responsible for data loading. To apply ParQ, we create an instance of *DataLoader* and pass in the current worker ID as shown in Figure 11. Then, we call the method *loadData* to enable in-memory static data sharing.

```
void read_graph(string& patition_file, TypedGlobalTable<int, double, double, PPRGlobal_data > *table) {
    //..
    DataLoader loader(workerID.str());
    loader.loadData(path);
    //..
}
```

Figure 11: Code segment 1

Third, we write the code for query processing. As shown in Figure 12, we create an instance of *QueryProcessor* in *struct PPRGlobalIterateKernel*. In *struct PPRGlobalIterateKernel*, we define a variable with type *QueryProcessor*, create an instance of *QueryProcessor*, and pass in the current worker ID. The method *g_func* and *dynamic_incbound* are responsible for processing query, where we call corresponding methods to access the shared memory and fetch the requested data.

```
struct PPRGlobalIterateKernel : public IterateKernel<int, double, PPRGlobal_data > {
    //..
    QueryProcessor* processor;
    //..
    PPRGlobalIterateKernel() {
        //..
        processor = new QueryProcessor(workerID.str());
        //..
    }

}

void g_func(const int& key, double& value, double& delta, PPRGlobal_data & data, vector<pair<int, double> >* output) {
    //..
    int neibor_size = processor->get_vecsize(key_str.str().c_str(), "3");
    //..
}
```

```
double dynamic_incbound(const int& key, double dv, double maxdv, double sumdv, double hopbound, PPRGlobal_data & data) {
    //..
    float globalScore = processor->getFloat(key_str.str().c_str(), "1");
    float incomingDegree = processor->getFloat(key_str.str().c_str(), "2");
    //..
}
```

Figure 12: Code segment 2

At last, we add an *if* statement in method *read_graph* to determine whether the present job is a data loading job or a query processing job. As shown in Figure 13, if the current job is responsible for data loading, it will perform the tasks of a data loader. If the current job is for query processing, it will perform the tasks of a query processor.

```
void read_graph(string& patition_file, TypedGlobalTable<int, double, double, PPRGlobal_data > *table) {
    //..
    if(FLAGS_is_dataLoader) {
        DataLoader loader(workerID.str());
        loader.loadData(path);
    } else {
        //Process the query.
    }
    //..
}
```

Figure 13: Code segment 3

With the application of ParQ, we can start a data loader to enable static data sharing and *n* query processors to process *n* queries concurrently.

4.2 Application on the top-*k* star query system

The ParQ system is also applied to the top-*k* star query system [10]. In the following sections, we will first introduce the top-*k* star query system and then present how to apply ParQ to it.

4.2.1 System specification

Massive information networks contain billions of labeled entities. For example, Freebase, a real-life knowledge graph, contains a lot of labeled entities representing people. Star query is an

approach used to identify an unknown entity, based on its relationship with other known entities. For example, in Freebase, star query algorithm can be used to search for an actor in the movie Cloud Atlas who has worked with the director Steven Spielberg.

An implementation of star query, the top-*k* star query system, answers pattern match queries in massive information networks [11]. A massive information network describes labeled entities and the relationships among the entities. An entity can be a person or a thing with one attribute, type. On a massive information network, a star query aims to identify an unknown entity based on known facts. When representing the network as a graph, the star query problem can be modeled as a pattern matching problem.

In this problem, a query describes a known node, the type of an unknown node, and their relationship. The top-*k* star query system aims to find the best *k* answers for a query from a graph. The candidates are ranked by their relevance to the known nodes. The relevance score between two nodes is computed by

$$\varphi(u,v) = \begin{cases} 1 & u = v \\ \min\{N, n_{u,v}\} \cdot \alpha^{l_{u,v}} & otherwise \end{cases},$$

where α is a damping factor having the value between 0 and 1. $l_{u,v}$ is the length of the shortest path between node *u* and *v*. $n_{u,v}$ is the number of the shortest paths. *N* is a constant used to bound the value of $n_{u,v}$. That is, the relevance between two nodes is quantified by the length of the shortest path and the number of the shortest paths between them. The top-*k* star query system uses breadth-first search to traverse a target graph to compute $n_{u,v}$ and $l_{u,v}$. It also adopts a bounding technique to speed up the computation. The bounding technique can detect the top-*k* answers without having to compute converged scores.

To answer a query, the top-*k* star query system will start a process, or job, that loads the graph into memory and performs multiple BFSs on the target graph to measure relevance scores of candidates until the top-*k* answers are obtained.

4.2.2 Implementation process

As descripted in the last section, the top-*k* star query system starts a job to answer a query. The job loads the target graph into memory and performs BFS on the in-memory target graph to measure relevance scores of candidates until the top-*k* answers are obtained.

When answering different queries on the same target graph, the graph is static and can be shared among different jobs. Therefore, we apply the ParQ system to the top-*k* star query system to enable in-memory static data sharing.

First, we represent the target graph in the requested format, as shown in

Figure 14. All information of one node is represented in one line. A data item in the first column is an integer representing the node name or the node key. The data in the second column is the node type. The third column lists the node's neighbors. As explained in Section 3.2, the integers in the first column will be used as indices. The labels and the data types of the following columns are specified in the configuration file.

```
        type    neighbors
        int     vector<int>
3177    -100    3098 2407 3052 5437 2073 3310 4382
3173    -100    3172
3169    -100    2441 3973 4194 6805 3702 3874 3900 5962 1746 4454 1445 6860 3168 2212
3097    -100    3096 3205 3009 4669 6430
```

Figure 14: A part of the static data of the top-*k* star query system

Second, we modify the code for data loader. Method *initDataGraph* in class *BoundWorker* is responsible for graph initializing. As shown in Figure 15, in this method we create an instance of *DataLoader* and pass in the current worker ID. Then, we call method *loadData* to create a shared memory and load the static data into the memory.

```
void BoundWorker::initDataGraph(){
    //..
    DataLoader loader(workerID.str());
    loader.loadData(path.str());
    //..
}
```

Figure 15: Code segment 1

Third, we write the code of query processor. Method *runIter* in class *BoundWorker* is responsible for computations. As shown in Figure 16, we define a variable with type *QueryProcessor* in the header file *DBRWorker.h*. We create an instance of *QueryProcessor*, pass in the current worker ID got from *setMaiter*, and call methods in *runIter* to connect to the shared memory and get requested data.

```
class BoundWorker : public DSMKernel, public NetworkController{
    //..
    QueryProcessor* processor;
    //..
};

void BoundWorker::setMaiter(MaiterKernel<uint, BoundList, TargetNode*>* inmaiter) {
    //..
    processor = new QueryProcessor(workerID.str());
    //..
}

void BoundWorker::runIter(int tabId, const uint& k) {
    //..
    QueryProcessor* p = this->processor;
    int node_type = p->get_int(key.str().c_str(), "1");
    int neibor_size = p->get_vecsize(key.str().c_str(), "2");
    //..
}
```

Figure 16: Code segment 2

At last, as shown in Figure 17, we add an *if* statement in method *Run* to determine whether the current job is a data loader or a query processor. If the current job is a data loader, it will load the static data then terminate. If the current job is a query processor, it will skip data loading and start to process query.

```
void DBRMaster::Run(Master* master){
    //..
    if(FLAGS_is_dataLoader){
        //Load the static data.
    }else{
        //Process the query.
    }
    //..
}
```

Figure 17: Code segment 3

Now with the application of ParQ, we can start a data loading job and *n* query processing jobs to process *n* queries concurrently.

4.3 Application on the belief propagation system

In order to further study the performance of the ParQ system, we also applied it to the belief propagation system [12]. The following sections give the introduction of that system and present how to apply ParQ to it.

4.3.1 System specification

Belief propagation was first used in artificial intelligence and information theory and has demonstrated great use in many other areas. For example, belief propagation can be used to predict the probability of one event based on the probabilities of related events, given the probabilistic interactions between them.

The belief propagation system performs approximate inference on probabilistic graphical models. Probabilistic graphical models use a graph-based representation to capture uncertainty in real-world applications. In this graphical representation, the nodes correspond to the variables in the

real world. The edges represent direct probabilistic interactions between them. A query describes a set of variables.

In this example, we consider a typical probabilistic graphical model, factor graph, since any other graphical models can be converted to a factor graph. There are two types of nodes in factor graphs: variable nodes and factor nodes. Each variable node represents a random variable and each factor node describes a specific function that maps variable nodes to non-negative real-valued numbers.

The belief propagation system here adopts the sum-product algorithm, which answers query by computing marginal probabilities of factor graphs. In order to reduce scheduling cost, the belief propagation system calculates the priority of nodes and selects a set of messages to update at a time via the priority. In each step, from the chosen nodes, the computation reaches their out-neighbors. It keeps propagating messages in both directions along edges until a stable situation is reached.

The belief propagation system extends the Maiter framework [9]. In this system, the message is computed by accumulative computation in an asynchronous manner. A fraction of nodes are selected to update their scores in each step. The chosen nodes will update theirs values and propagate the change of values to their neighbors.

To process a query, the belief propagation system will start a process, or job, that loads the factor graph into memory and performs an accumulative computation on the in-memory graph to measure the values of variables. The computation is performed until it reaches a stable situation.

4.3.2 Implementation process

As descripted in the last section, the belief propagation system starts a job to perform approximate inference on probabilistic graphical models. The job loads the target graph into memory and performs an accumulative computation on the in-memory graph to measure the values of variables until the values reach a stable situation.

When answering different queries on the same target graph, the graph remains the same, or static, and can be shared among different jobs. Therefore, we apply the ParQ system to the belief propagation system to enable in-memory static data sharing.

First, we represent the target graph in a requested format, as shown in Figure 18. All information of one node is represented in one line. The data in the first column is an integer representing the node name or the node key. The second column lists the node's neighbors. As explained in Section 3.2, the integers in the first column will be used as indices. The labels and the data types of the other columns are specified in the configuration file.

```
void read_data() {
        //..
        DataLoader loader(workerID.str());
        loader.loadData(path.str());
        //..
}
```

Figure 18: Code segment 1

Second, we modify the code for data loader. Method *read_data* is responsible for graph initializing. As shown in Figure 19, in this method we create an instance of *DataLoader* and pass in the current worker ID. Then, we call method *loadData* to create a shared memory and load the static data into the memory.

```
QueryProcessor* p = this-> processor;
int node_type = p->get_int(key.str().c_str(), "1");
int localstatenum = p->get_int(key.str().c_str(), "2");
int outstatenum = p->get_int(key.str().c_str(), "3");
int neibor_size = p->get_vecsize(key.str().c_str(), "4");
```

Figure 19: Code segment 2

Third, we write the code of query processor. Method *c_fun* and *u_fun* are responsible for computations. We call methods in *runIter* to connect to the shared memory and get requested data.

At last, we add an *if* statement in the method *Run* to determine whether the current job is a data loader or a query processor. If the current job is a data loader, it will load the static data and then terminate. If the current job is a query processor, it will skip data loading step and start to process query.

With the application of ParQ, we can start a data loading job and *n* query processing jobs to process *n* queries concurrently.

CHAPTER 5

EVALUATION

5.1 Overview

The ParQ system has been applied to the top-*k* personalized PageRank system, the top-*k* star query system, and the belief propagation system. In order to examine the performance, we design and perform a series of experiments, which includes measuring running time and memory usage. For one query system that uses ParQ, multiple queries can be processed in parallel with one in-memory target graph. We compare ParQ with the original system running in two ways. First, the original system can process multiple queries in serial with one target graph in memory (or "Serial/single" for short). Alternatively, it can process queries in parallel but with multiple graphs in memory (or "Parallel/duplicated" for short).

5.2 Performance of the top-*k* personalized PageRank system using ParQ

We first evaluate the performance of the top-*k* PPR system adopting ParQ. In the following sections, an experiment overview is given and the experimental results are presented.

5.2.1 Experiment settings

We perform the experiments on a local computer cluster. The local cluster consists of four machines connected by an 1Gb Ethernet switch. Each machine has 16GB RAM and one 1.86GHz CPU.

We use a set of queries on a 916K-line graph. The graph is a web graph that shows the directed links between webpages. The queries describe the personal preferences.

5.2.2 Running time

Figure 20 shows the comparison of the running time of the approaches for completing queries. First, it can be seen that for ParQ and Parallel/duplicated, as the number of queries increases, the running time increases slightly. This is because that there is enough free memory as shown in Figure 21, since the top-*k* PPR system requires less memory to process one query.

Second, the results show that the running time of ParQ is less than Serial/single. The first reason is that ParQ processes the queries concurrently while Serial/single processes queries in serial. The second reason is Serial/single uses a long time to load the static data before processing each query, while ParQ can directly use the static data in the shared memory.

Third, the results also show that the running time of ParQ is less than Parallel/duplicated. This is because of limited free memory. In order to process *n* queries concurrently, Parallel/duplicated keeps *n* copies of the static data in memory. When there is limited free memory, the running time of Parallel/duplicated increases due to increased workload. The second reason is that Parallel/duplicated also takes a long time to load the static data before handling each query.

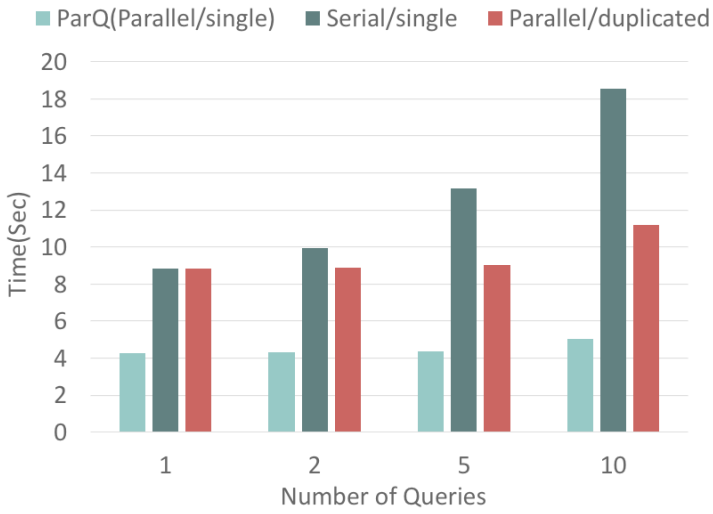


Figure 20: Running time for completing all queries

5.2.3 Memory usage

Figure 21 shows the comparison of the memory usage of the three approaches. First, the results show that ParQ requires less memory than Parallel/duplicated, because ParQ keeps only one copy of the static data in memory while Parallel/duplicated needs *n* copies to process *n* queries.

Second, it can be seen that ParQ requires more memory than Serial/single. Since each query job needs to maintain a set of dynamic data generated during computations, ParQ keeps *n* sets of dynamic data in memory, while Serial/single keeps only one set of dynamic data at a time because it processes *n* queries in serial.

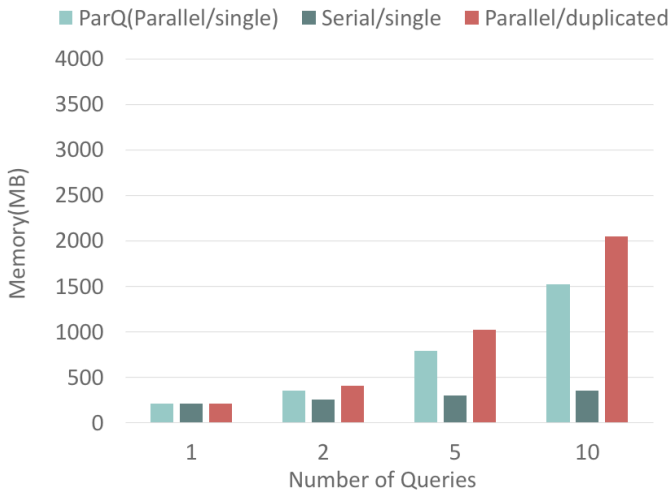


Figure 21: Memory usage

5.3 Performance of the top-*k* star query system using ParQ

The proposed approach is also applied and evaluated on the top-*k* star query system. What shall be introduced in later sections includes an experiment overview and the experimental results.

5.3.1 Experiment settings

We perform the experiments on the same local computer cluster. The local cluster consists of four machines connected by an 1Gb Ethernet switch. Each machine has 16GB RAM and one 1.86GHz CPU.

We use a set of queries on a 548K-line graph. The graph describes the collaboration among authors. The queries consist of a known node set, an unknown node, and their relationship.

5.3.2 Running time

Figure 22 shows the performance comparison of the three approaches, focusing on the running time for completing various numbers of queries. First, the results show that for ParQ and Parallel/duplicated, as the number of queries increases, the running time increases as well due to increased workload.

Second, it can be seen that the running time of ParQ is less than Serial/single. This is because ParQ processes the queries concurrently while Serial/single processes the queries one by one.

Third, the results show the running time of ParQ is also less than Parallel/duplicated. When there are 10 queries, the running time of Parallel/duplicated is large. The reason is that although Parallel/duplicated processes 10 queries concurrently, it keeps 10 copies of the static data in memory. When there is limited free memory, the running time of Parallel/duplicated increases sharply.

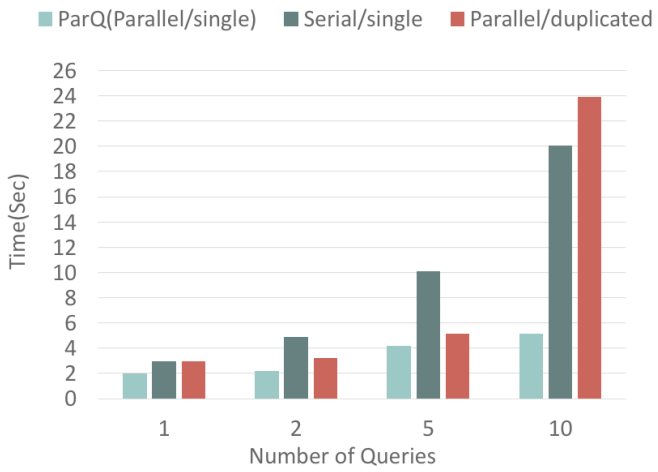


Figure 22: Running time for completing all queries

5.3.3 Memory usage

Figure 23 shows the performance comparison of the approaches, focusing on the memory usage for completing different numbers of queries. First, the results show that ParQ uses less memory than Parallel/duplicated, because ParQ keeps only one copy of the static data in memory while Parallel/duplicated requires *n* copies to process *n* queries.

On the other hand, the results show that ParQ requires more memory than Serial/single. Each query job needs to maintain a set of dynamic data generated during computations. Since ParQ processes *n* queries concurrently, it keeps *n* sets of dynamic data in memory, while Serial/single keeps only one set of dynamic data at a time because it processes *n* queries in serial.

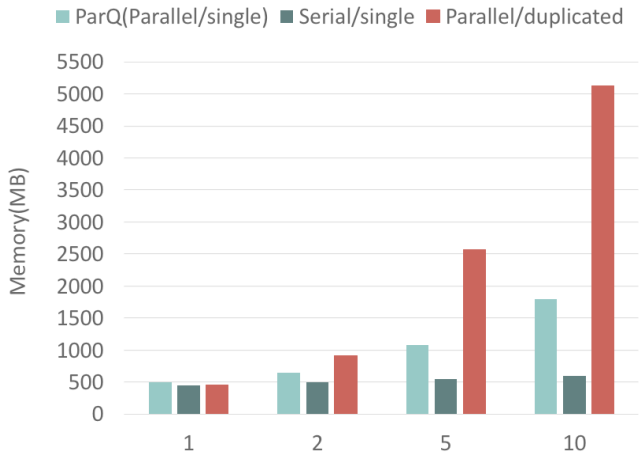


Figure 23: Memory usage

5.4 Performance of the belief propagation system using ParQ

At last, the proposed approach is applied and evaluated on the belief propagation system. What shall be introduced in later sections are an experiment overview and the experimental results.

5.4.1 Experiment settings

We perform the experiments on the same local computer cluster. The local cluster consists of four machines connected by an 1Gb Ethernet switch. Each machine has 16GB RAM and one 1.86GHz CPU.

We use a set of queries on a 908K-line graph. The graph describes direct probabilistic interactions between given real facts.

5.4.2 Running time

Figure 24 shows the job completion time comparison of the three approaches. First, the results show that for ParQ and Parallel/duplicated approach, as the number of queries increases, the running time increases as well due to increased workload.

Second, it can be seen that the running time of ParQ is less than which of Serial/single. The reason is that ParQ processes the queries concurrently while Serial/single processes queries one by one.

Third, the results also show that the running time of ParQ is less than Parallel/duplicated as well. Especially when there are 10 queries, the running time of Parallel/duplicated is large. The reason is that although Parallel/duplicated processes 10 queries concurrently, it keeps 10 copies of the static data in memory. When there is limited free memory, the running time of Parallel/duplicated increases sharply.

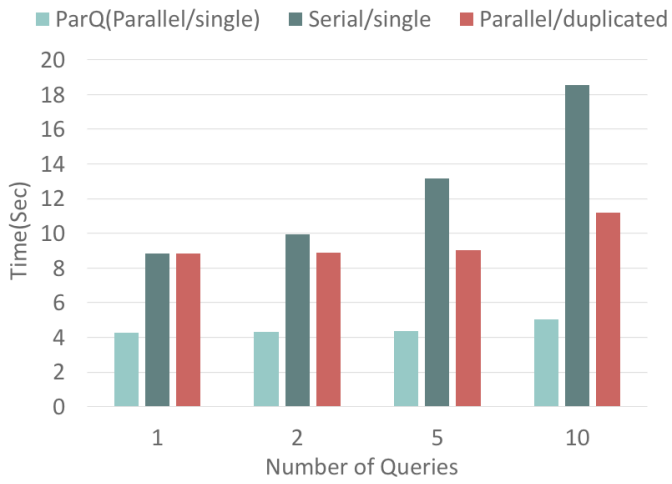


Figure 24: Running time for completing all queries

5.4.3 Memory usage

Figure 25 shows the performance comparison of the approaches, focusing on the memory usage for completing different numbers of queries. Similarly, first, the results show that ParQ uses less memory than Parallel/duplicated, because ParQ keeps only one copy of the static data in memory while Parallel/duplicated requires *n* copies to process *n* queries.

On the other hand, the results show that ParQ requires more memory than Serial/single. Each query job needs to maintain a set of dynamic data generated during computations. Since ParQ processes *n* queries concurrently, it keeps *n* sets of dynamic data in memory, while Serial/single keeps only one set of dynamic data at a time because it processes n queries in serial.

However, compared with the performance of the PageRank system and the star query system, ParQ here requires relative much more memory than Serial/single and is only slightly better than Parallel/duplicated. Recall that the belief propagation system calculates the priority of nodes and selects a set of messages to update at a time based on the priority. In each step, from the chosen nodes, the computation reaches their out-neighbors. It will visit all graph nodes before a stable situation is reached while the previous two systems will visit only a small fraction of nodes. The dynamic data of each belief propagation job will be relative much more.

As a conclusion, ParQ is more suitable in the situations when the size of static data is much larger than the size of dynamic data, although it is still useful in the opposite situations in term of running time.

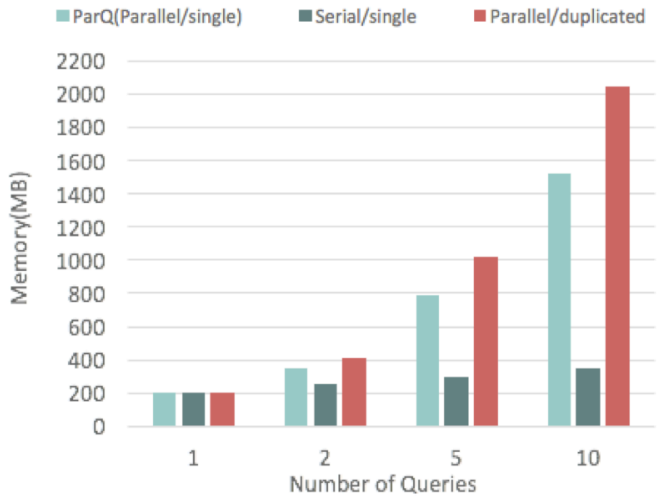


Figure 25: Memory usage

CHAPTER 6

RELATED WORK

As the volume of data increases sharply, more and more researches focus on how to process and analyze large-scale data. Many distributed computing works, such as Dryad [13] [14] and MapReduce [15], have been proposed to process large data in a cluster of physical machines or in a cloud environment. A lot of frameworks have also been designed and implemented for complementing existing functionality and for accelerating computations.

Dryad is a computing framework for general-purpose, distributed, and parallel applications. An application of Dryad generates a dataflow graph by combining computational vertices with communication channels. The Dryad application can make efficient use of the available resources by discovering the size and arrangement of data at run time and modifying the graph during the computation progress.

MapReduce is an implementing model for analyzing and processing big data sets by adopting a distributed and data-parallel algorithm in a cluster of machines or in a cloud environment. A MapReduce program is composed of mapper procedure and reducer procedure [16]. Mapper procedure performs filtering and sorting. For example, in order to count the words in a large file, mapper will sort words by counting into queues, one queue for each word. Reducer performs a summary operation, such as counting the total number of words in each queue and yielding word frequencies. MapReduce has been widely used as a big data processing model and its libraries have been realizing in many programming languages, such as Java and C++. MapReduce also provides different levels of optimization, including scalability and fault-tolerance for a variety of applications.

The competition advantage of MapReduce reflects in reducing running time with multi-threaded implementations. A single-threaded MapReduce implementation is usually not faster than a non-MapReduce one. To design a distributed model, one challenge is how to improve fault-tolerance

and to reduce network communication cost among the physical machines in the cluster. The open-source implementation, Apache Hadoop [17], is a good complementary to MapReduce, which supports optimized distributed operations. Another challenge is how to improve the data processing speed. To address this challenge, a series of frameworks, have been proposed for accelerating computations by adopting large-scale iterative algorithms. What's more, many practical problems concern large graphs. For example, the scale of large graphs, like webpage graphs and social networks, brings up challenges to efficient processing. The significant increasing need to process and analyze large volume of graph-structured data leads to lots of recent researches on parallel frameworks, such as Pregel [18], Giraph [19], GraphLab [20]. Those frameworks are the most advantageous complement to MapReduce in order to process large graph-structured data.

The Pregel framework is similar to MapReduce, but with a natural API and efficient iterative computations over the data graph. It is for synchronous, fault-tolerant, and distributed implementations and is easy to program. Computations of Pregel program are performed as a sequence of iterations, within each iteration a vertex sends messages to its neighbors, receive messages sent in the previous iteration, and update its internal state. This vertex-centric approach applies to varies practical applications.

Giraph is an iterative data graph processing framework designed for improving scalability. Giraph is an important counterpart to Pregel with several advanced features beyond, including master scheduling and edge-oriented computation. Giraph is currently used by Facebook to process and analyze their social network graphs.

The GraphLab framework is for data-parallel and iterative programs. GraphLab was first designed for machine learning tasks, but it has been widely used in varies areas related to data-mining. The implementations of GraphLab usually concern sparse data, iterative algorithms, and asynchronous computations.

MapReduce and other related frameworks introduced above store intermediate results in Hadoop Distributed File System [21], which requires much longer time to access and update data. Therefore, MapReduce framework are not suitable when implementations need to visit intermediate results frequently. In order to solve this problem, many new frameworks are proposed, such as Piccolo [22] and Maiter [9], which store intermediate data in memory instead of disk.

Piccolo is a data-centric programming framework for writing memory-based applications on clusters. It allows computations running on different machines to share mutable and distributed state via an in-memory key-value table. The Piccolo framework is designed for efficient and data-parallel applications. It also provides fault-tolerance and is easy to program.

Maiter is also a data-centric framework that is designed and programmed by modifying Piccolo. It adopts accumulative iterative update algorithm, which accelerates normal iterative computations. Maiter framework contains a master and a number of works. The master schedules the workers and monitors their status. Those workers run in parallel and communicate with each other via MPI [23].

Although the implementations of such systems can process single graph-processing job efficiently, they require high cost when processing multiple concurrent jobs. The reason is that these designs do not allow multiple jobs to share the in-memory graph data, which results in each job needs to maintain their own separate data graph in memory.

There are also many new frameworks proposed to solve that problem. For example, Seraph [5] is designed and realized based on a decoupled model, which allows multiple concurrent jobs to share in-memory graph structured data. Seraph supports good fault-tolerance. Specifically, it adopts a copy-on-write technique to isolate the data change of concurrent jobs and uses snapshots to maintain a static in-memory graph for jobs submitted at different time.

However, Seraph is an independent framework, the implementations of Maiter cannot use it to achieve in-memory data sharing. Therefore, many implementations of Maiter, such as the fast

approach for top-k path-based relevance query [6] and the index-free approach for top-k star queries [10], cannot adopt Seraph to realize query-level parallelism.

CHAPTER 7

CONCLUSION

Query system refers to an implementation that adopts a data processing algorithm to answer queries on a dataset. Many existing query systems are good when processing a single query, but still have problem when processing multiple queries. That is, they do not allow multiple jobs to share the in-memory graph data, which results in large memory usage and longer job completion time.

This thesis aims to design and implement a memory-efficient system, ParQ, which can be adopted by query systems to realize query-level parallelism. The main idea includes constructing a common memory block for maintaining sharable data. By sharing data, ParQ is able to process multiple queries concurrently while reducing memory usage and running time.

ParQ has the ability to work in a distributed environment. We also offer a standard interface. It provides the ability to automatically process data in different formats as long as the formats conform to the system's requirements, which allows ParQ to be easily used by many query systems with a little manual work.

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