PARALLELIZATION OF BACKWARD DELETED DISTANCE CALCULATION IN GRAPH BASED FEATURES USING HADOOP

by

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Abstract

The current project presents an approach to parallelize the calculation of Backward Deleted Distance (BDD) in Graph Based Features (GBF) computation using Hadoop. In this project the issues concerned with the calculation of BDD are identified and parallel computing technologies like Hadoop are applied to solve them. The project introduces a new algorithm to parallelize the APSP problem in BDD calculation using Hadoop Map Reduce feature. The project is implemented in Java and Hadoop technologies.

The aim of this project is to parallelize the calculation of BDD thereby reducing GBF computation time. The process of BDD calculation is examined to identify the key places where it could be parallelized. Since the BDD calculation involves calculating the shortest paths between all pairs of given users, it can viewed as All Pairs Shortest Path (APSP) problem. The internal structure and implementation of Hadoop Map-Reduce framework is studied and applied to the process of APSP problem. The GBF features are one of the features set used in the Ontology classifiers. In the current project, GBF features are used to predict the friendship relationship between the users whose direct link is deleted. The computation involves calculating BDD between all pairs of users. The BDD for a user pair represents the shortest path between them when their direct link is deleted. In real terms, it is the shortest distance between them other than the direct path. The project uses train and test data sets consisting of positive instances and negative instances. The positive instances consist of user pairs having a friendship link between them whereas the negative instances do not have any direct link between them. Apache Hadoop is a latest emerging technology in the market introduced for scalable, distributed computing across clusters of computers. It has a Map Reduce framework used for developing applications which process large amounts of data in parallel on large clusters.

The project is developed and implemented successfully and has the best time complexity. The project is tested for its reliability and performance. Different data sets are used in this testing by considering various factors and typical graph representations. The test results were analyzed to predict the behavior of the system. The test results show that the system has best speedup and considerably decreased the processing time from 10 hours to 20 minutes which is rewarding.

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Acknowledgements

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Chapter 1 - Introduction

In the recent years there is a significant growth of social media and its awareness among the people. It has made a great impact on social interaction of internet users. Though the primary use of it is to make networking with online users, there have been lots of other uses associated with it. It has showed its effect on the business world also. Many companies are interested in finding out the user interests to increase their sales and improve business productivity. Different business individuals use social media to make connections and listen to the customers. This revolution lead to a research in the area of social media called social network analysis. The graph theory is used for modeling social networks. With the increase in social networking sites there grew a need for better algorithms in the area of graph theory to improve the methodologies for social network analysis. The analysis mainly involves graph search problem computations. The current project tries to deduce a solution to one of the graph search problems of social network analysis.

The importance of this project comes from the fact that the graph search problems are also used in other fields like path tracking systems. The Path Tracking and Navigation systems are used predominantly worldwide by many individuals and companies. Most of the car drivers are highly depended on the navigation systems software. The path advice demand is growing and there is need for the navigation software to be improved. While it is easy to retrieve the shortest paths using navigation software, most of the data provided by them is pre-calculated. Sometimes it is necessary to calculate the all possible shortest paths and these computations last very long. The routes and road paths will be changing from day to day and there is need for the navigation software providers to update their systems very frequently. Because these calculations take very long time, there is need for a better system to compute the shortest paths with in a real time. As the calculations are in quadratic to the number of nodes, the systems memory may not be capable holding the whole data. We need a system which can deal with the graph theory problems effectively.

1.1 Problem Description

The current project deals with friendship prediction problem in social network analysis. The following describes the problem context for the current project. Social network analysis deals with different approaches in analyzing and visualizing the social networks. Some of the sub tasks include: finding user interests, determining trustworthiness of user generated content, object classification, link prediction and friendship prediction. The task of friendship prediction uses different types of features sets and Graph Based Features (GBF) are one of them. The GBF features are found to be quite effective in predicting the friendship for a given user pair in a social network. Live Journal social network data is one of the data set used for GBF computation. The specialty of Live Journal social network is that it lays emphasis on user interaction [10].

The problem faced by the current researchers in GBF computations is that it takes lot of time to compute the GBF features. A GBF computation includes the calculation of Backward Deleted Distance (BDD), which is the area where it takes a lengthy time. The BDD calculation involves finding the minimum alternative distance between all pairs of users in the reverse direction, ignoring the direct path if exists. It actual terms it is an All Pairs Shortest Path (APSP) problem. Though there are many existing solutions for the APSP problem they are not that effective and do not provide a better approach. Some of the existing solutions for All Pair Shortest Path problem are Parallel Dijkastras APSP [8], Simple Parallel Floyd Warshall APSP [7], Blocked Parallel Floyd Warshall APSP [5] and Phased Parallel Floyd Warshall APSP [6]. These current existing systems do not provide any effective solution for dealing with the APSP problem.

The existing systems are not capable of extracting true parallelism for the APSP problem. They are not capable of utilizing the resources effectively. The existing approaches have algorithms to compute for a complete network graph in distributed environment, but there are no efficient algorithms to compute for the incomplete network like disconnected graphs and directed graphs in distributed environment. Most of the algorithms are designed for a uni-processor environment. Though there are some solutions for distributed environment they are not capable of handling the parallel APSP problem effectively. Most of the existing systems computing are based on the in-memory representation of the graph. They cannot handle if the graph size or its corresponding data is large. Most of them are not scalable. They cannot provide node level granularity in their computation.

1.2 Motivation

A keen interest in developing a distributed application for a better cause led me to develop the current project. The project is interesting as it presents real world situations for developing highly scalable applications. It has gained an importance as the APSP graph search problem is used in many other fields. The All Pairs Shortest Path computation involves independent asynchronous calculations. The motivation for the current project comes from the idea of deducing a parallel implementation for those asynchronous calculations. A Hadoop tutorial showing parallel implementation of Breadth First Search [12] provides an insight into the current project. The tutorial gives an idea of representing graphs using colors and distances along with adjacency list which motivates us to design a better format for representing the graphs and designing a solution for the APSP problem.

1.3 Proposed System

The current project deals with examining the Graph Based Features computation and identifies the key areas where it takes a lot of time and tries to reduce them by applying parallelization, different techniques and approaches. It mainly deals with parallelization of the APSP problem in Graph based features BDD calculation. The current project introduces a new algorithm for implementing the APSP problem in parallel. It uses Hadoop, an emerging technology for scalable distributed computing with high throughput. In the current project Hadoop map reduce feature is used for parallelizing the computation. The project explores different ways for implementing node level parallelism and introduces new technique for the APSP computation. It investigates different ways of computing for directed and disconnected graphs in distributed environment. In one line to say the project presents a highly scalable and parallel computing approach for the APSP problem. It solves the Graph Based Features computation by solving for APSP problem. It also tries to reduce the time in building the graph from the given social network data.

The System is implemented mainly in two modules: Building Adjacency Graph and Running Parallel APSP Map Reduce Algorithm. They are as follows:

- **Building Adjacency Graph** – In this module, the given friendship links of the social network are transformed into an Adjacency List with Trio Sets Format (ALTS) using Hadoop Map Reduce.

- **Running Parallel APSP Map Reduce Algorithm** – In this module, Parallel APSP algorithm is run on the ALTS node format list graph to compute All Pairs shortest Paths for all the nodes.

The Characteristics of the current project are as follows:

- Highly scalable
- provides node level parallelism
- Redundancy and Failure Recovery
- Less usage of Heap memory
- Low Bandwidth
- High Throughput
- High Speedup
- Optimal Time complexity
- Cost effective
- Flexible and Fault tolerant

The rest of the paper first discusses related work with background and system analysis in Section 2. In Section 3, a detailed implementation and architecture of the system is presented. Section 4 describes how the system is evaluated and presents the results. Section 5 presents our conclusions and describes future work and limitations.

Chapter 2 - Related Work

2.1 Background

The current section gives a brief description about the background of the system by explaining the terminology used in the project. The different terms related to this project are Social Network Analysis, Live Journal Data, Graph Based Features, Backward Deleted Distance and Parallel APSP Problem. The following discussion briefly elaborates them.

2.1.1 Social Network Analysis

The Social Network Analysis is used for unveiling the hidden links or relationships with the use of network model. It views social relationships in terms of the network theory, which consists of nodes representing users and ties representing relationships between users. These are represented using points and lines in network theory. It maps and measures the relationships and flows between people, groups and entities in a social network. It is mainly used to analyze and visualize social network. It includes different tasks like finding user interests, predicting friendship relationship, kinship, link prediction, object classification and analyzing user generated content. They use this knowledge discovered as input for modeling social network and explore further information. The analysis of the social networks is done with the use of ontologies for varied reasons. There are different types of ontologies used for analyzing social networks like domain ontologies, reasoning ontologies and inference ontologies. These ontologies use different types of features for modeling the social network ex: interest based features and graph based features. These features computation requires social network data consisting of user generated content. There are different online services available for providing the network data and Live Journal is one of them. The current project uses the live journal network data as the input Train data.

2.1.2 Live Journal Social Network

Live Journal is an online journal service with an emphasis on user interaction [10, 11]. In the Live Journal social network, users can tag other users as friends and share their interests. It can be represented using a network graph, where nodes of the graph represent the users and the edges between the nodes represent the friendship links between the users. It has 10 million on-line users and provides a free service.

2.1.3 Graph Based Features

The Graph Based Features (GBF) is one of the features set used for analyzing the social networks. They are mainly used for *predicting the friendship relationship* and *predicting the interests*. The GBF features are found to be quite effective in predicting the friendship for a given user pair in a social network [11]. The Figure 2.1.3 shows the GBF features for sample graph. For two given users A and B, the graph based features that are derived from a graph are In-degree of A, In-degree of B, Out-degree of A, Out-degree of B, Forward Deleted Distance between A and B and *Backward Deleted Distance* between A and B.

- In-degree of A: The number of links that end at A.
- In-degree of B: The number of links that end at B.
- Out-degree of A: The number of links that start at A.
- Out-degree of B: The number of links that start at B.
- Forward Deleted Distance between A and B: The shortest distance apart from the direct shortest path if exists from A to B.
- Backward Deleted Distance between A and B: The shortest distance apart from the direct shortest path if exists from B to A.

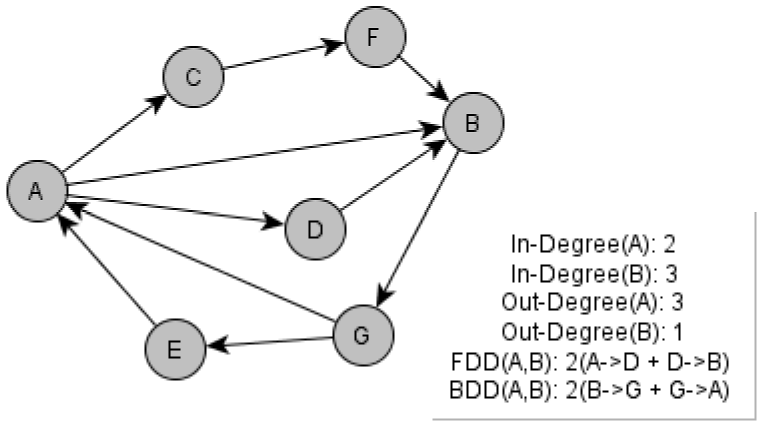


Figure 2.1.3 A Sample Graph showing GBF features

2.1.4 Backward Deleted Distance

For a given graph and two users A and B, the backward deleted distance between A and B is the shortest path from B to A apart from the direct path. In the above sample graph, the BDD from A to B is the path from B to A i.e., the path from B to G and G to A, and the BDD distance is 2.

2.1.5 Parallel APSP Problem

The current project is based on the concept of "Predicting friendship links in incomplete social networks". A Social network is said to be incomplete if two users A and B in the social network are friends in real world but they have not tagged each other as friends in social network, then the friendship link between those two users A and B will not be there in network graph [10]. The current project tries to predict such friendship relationship, using graph based features by calculating backward deleted distance between all pair of users for a given network data and train data. One of the problems faced by the BDD computation is that it consumes a lot of time because of its serial execution which has a time complexity of $O(n^4)$. Since the BDD calculation between all pairs of users involves computing the shortest alternative distance between them, it can be visualized as an All Pairs Shortest Path (APSP) problem. An APSP problem refers to calculation of shortest paths between all pairs of users in a network graph. Floyd-Warshall algorithm was the first approach which tries to solve APSP problem with a time complexity of $O(n^3)$. It is efficient for small size graphs which can be represented in system memory. It cannot handle large graphs. Because of its serial execution it is not as effective as desired. As the APSP computation involves asynchronous and independent calculations, we can come up with an idea of computing those asynchronous calculations in parallel. This approach for solving APSP in parallel can be referred as *Parallel APSP Problem*. There are many existing algorithms for the Parallel APSP problem but most of them do not provide effective solution. The current project focuses on solving for Parallel APSP problem by using various methodologies and algorithms.

2.2 System Analysis

The System Analysis Phase involves studying the problem in detail and breaking the problem into sub-modules, identifying the key problematic areas and getting an overview of the problem specifications. In this phase we try to analyze the functional, behavioral and requirements specifications and develop an idea of how we could derive a solution for the current problem. In this phase we try to determine if it is feasible to design the system based on the specifications analyzed. The following gives a brief description about the motivation, goals and specifications for the current system and outlines the methodologies employed.

2.2.1 Goals & Objectives

The problem that is solved in the current project is the prediction of friendship links in incomplete network by using graph based features and calculation of backward deleted distance. When observed carefully the problem reduces to the parallel All Pair shortest path problem (APSP). The goal of this project is to design a system which provides an effective solution for the parallel APSP problem.

The existing system uses heap memory for graph representation in matrix form. It cannot handle if the graph size is out of heap memory limits. The goal for the current system is to find an alternative solution for the matrix representation of graph in heap memory and minimize the usage of heap memory where ever possible.

In the existing system APSP calculation which relates to BDD computation is executed in a serial fashion. This process takes a lengthy time. The goal of this project is to reduce the time consumption where ever possible and try to parallelize the related APSP problem in it using distributed computing software like Hadoop.

The Different objectives set for this project are as follows:

- The time for the GBF computation should be reduced considerably.
- The system should provide a node level granularity.
- The system should be capable of handling redundancy and failures.
- The system should be able to extract and implement high parallelism.
- The system should minimize the usage of heap memory.
- The system should be efficient and error free
- The system should be able to handle large network graphs.

2.2.2 Strategies

The following gives a brief description about the strategies and ideas used for solving the current problem. The problem here is to reduce the related APSP computation time and related BDD calculation time in GBF features computation. The BDD calculation uses the matrix representation of the graph. We can use a text file for representing the graph so as to minimize the usage of heap memory there by making the system capable of handling large graphs.

When coming to All Pairs Shortest Path calculation, it involves computing for the shortest paths between all pair of nodes in the graph. The computation involves checking for the existing edges between pairs of nodes. Since the checking involves both existing edges and non-existing edges, we can try to eliminate checking for the non-existing edges by representing the graph in adjacency list where it only parses the connected edges. The adjacency list is capable of maintaining the direction of edges from source node to reference node as well. We can further reduce the computation time by processing APSP calculation in parallel. We try to use Hadoop for implementing the current project. Hadoop is one of the parallel computing technologies which provide an environment for distributed computing on cluster. It has a distributed file system which provides a high throughput. It has a map reduce feature which lays foundation for parallel computing.

The idea for implementing this project comes from the parallel BFS tutorial provided on the Apache Hadoop website [12]. The tutorial shows how the breadth first search technique can be implemented in parallel. The approach uses adjacency list and a distance, color attached to it. The color represents if the destination node is visited or unvisited. In this technique the nodes that are at one hop are all visited in parallel and color is changed to visited color in the first iteration. For the next iteration all the nodes which are at two hops from source node are processed in parallel and this process continues until all the connected nodes for the source node are visited.

In the current project we try to apply the concept of using the color and maintaining the distance from the source node at each node along with the adjacency list but with a different format and organization. At each source node we try to maintain the set of reachable nodes from it along with the distance and visited/unvisited color using Trio sets. The Trio sets are designed to accommodate the information of reference node along with distance from source node and color to represent if it is visited or unvisited. Apart from general we try to use adjacency list for in-links and Trio sets for out-links. This way we can maintain the information for both in-links and out-links. The Shortest paths are calculated by sending the information to nodes which are at one hop distance from source node. When they receive the information, they update their corresponding trio sets. The process continues until all the nodes are visited. This process provides a node level parallelism and hadoop handles it effectively when compared to other technologies.

2.3 Requirement Analysis

In Requirement analysis phase we try to analyze different hardware and software requirements for implementing the current project. These requirements are categorized into two modes: pseudo distributed mode and fully distributed mode. A Pseduo-distributed mode represents the installation of single node hadoop cluster on simple CPU machine used for developing, testing and debugging. The Fully distributed mode consists of hadoop installation on large clusters with commodity servers used for deployment and execution. The below configurations are considered when a network graph with size of 5000 nodes or above is computed for fully distributed mode and graph size with 50 to 200 nodes for pseudo distributed mode.

2.3.1 Software Requirements

For a pseudo distributed mode we can use Windows 7 operating system with cygwin (includes ssh, sshd) or we can use Ubuntu 10.04 or above. Cygwin is required for windows so as perform the unix operations or linux like environment. The project requires hadoop environment with a stable version of Hadoop 1.x installed. To view logs and job tracker history a browser is needed.

	Recommended
Operating System	Windows 7 or above Ubuntu 10.04 or above
Software	Sun Java 1.6 or higher, Hadoop 1.0.3 or higher Cygwin 1.5.0 or higher (with ssh, sshd) for windows
Tools	Eclipse IDE Juno 3.4 or above
Technologies	Java, Apache Hadoop, Map Reduce Framework, Junit Testing framework
Browser	Microsoft Internet Explorer 9.0 or higher, Firefox v10 or higher, Google chrome

Table 2.3.1.1 Software Requirements - Pseudo Distributed mode

For this purpose Internet explorer 9.0 or above is preferable. Since hadoop is a java based system, the operating system should have java installed with Sun Java 1.6 or above. To execute on a server, a robust operating system like Red Hat Enterprise Linux (RHEL) v5.x (64-bit) is preferred. The Table 2.3.1.1 gives the software requirements for pseudo-distributed mode and Table 2.3.1.2 gives the software requirements for fully-distributed mode.

	Minimal	**Recommended**
Operating system	Red Hat Enterprise Linux v5.x(64-bit) CentOS v5.x or 6.x (64-bit) SUSE Linux Enterprise Server (SLES) 11, SP1 (64-bit)	Red Hat Enterprise Linux v5.x(64-bit)
Software	Sun Java 1.6 or higher Hadoop 1.0.3 or higher	,,
Packages	yum, rpm, scp, curl, wget, pdsh, ssh, sshd	,,
Browser	Microsoft Internet Explorer 9.0 or higher Firefox v10 or higher Google chrome	,,

Table 2.3.1.2 Software Requirements - Fully Distributed mode

2.3.2 Hardware Requirements

A pseudo distributed mode computing may not be capable of utilizing all the cores of a processor. There is no need for a high end hardware configuration as it is mostly used for developing and debugging the code. For a pseudo distributed mode a normal hardware configuration like dual core processor with 4 GB RAM and 500GB hard disk with processor speed of 2 GHz would be sufficient. In a fully distributed mode there are different types of processing environments like light weight, balanced and heavy computation. Each of them has different hardware requirements. For light weight processes a hardware configuration with 2 quad cores and 8GB RAM with 1Gbps Ethernet would be sufficient. For a balanced and heavy weight processes 2 quad core processors with 16-24GB RAM and 2Gbps Ethernet is required. The Table 2.3.2.1 gives the hardware requirements for the pseudo-distributed mode and Table 2.3.2.2 gives the hardware requirements for the fully-distributed mode.

	Recommended
CPUs	1 Dual core
Processor speed	>2Ghz
Memory/RAM	4GB
Hard Disk	500GB
Ethernet	1 Mbps

Table 2.3.2.1 Hardware Requirements - Pseudo Distributed mode

	Minimal	Recommended
CPUs	2 Quad core	2 Quad core
Processor speed	>2Ghz	>2Ghz
Memory/RAM	8GB	16-24GB
Hard Disk	4 disk drives(1 TB)	4 disk drives(2 TB)
Ethernet	1Gbps	>2Gbps

Table 2.3.2.2 Hardware Requirements - Fully Distributed mode

2.4 Technologies Description

2.4.1 Hadoop Software Framework

Hadoop is an Apache Software Foundation project. It is an open source framework written in java for handling large scale distributed applications. It is used for developing and running data intensive distributed applications on large commodity clusters [1]. It is designed to handle large number of servers with high degree of fault tolerance. It is composed of mainly composed of two main components. They are Hadoop Distributed File System (HDFS) and Map Reduce computational model. It can process vast amount of data on an order of magnitude of petabytes which is larger than the existing systems. There have been lot of existing systems performing computation on large volumes in a distributed environment, but what unique about hadoop is that it has got a simplified programming which makes the programmers to develop and test the code for distributed applications easily. It is very efficient, distributes the work and data across different processing machines automatically. It fully utilizes the parallel computing power of the processing machines CPUs.

2.4.2 Hadoop Distributed File System

Hadoop Distributed File System (HDFS) can store large files across different machines in a reliable and efficient manner. It handles fault tolerance, network errors and provides high throughput. It has master/slave architecture with one single master ‘Namenode’ managing namespace, file access and several worker ‘Data nodes’. It splits the large data files into small size chunks, each managed by different nodes of the cluster. Data is replicated across several machines so that in the event of individual machine failure data will be still available. All these chunks are stored under a single namespace. As the files are spread across different machines as chunks, each node operates on a part of the data. This alleviates the burden of network transfers there by achieving high data locality, high performance and throughput.

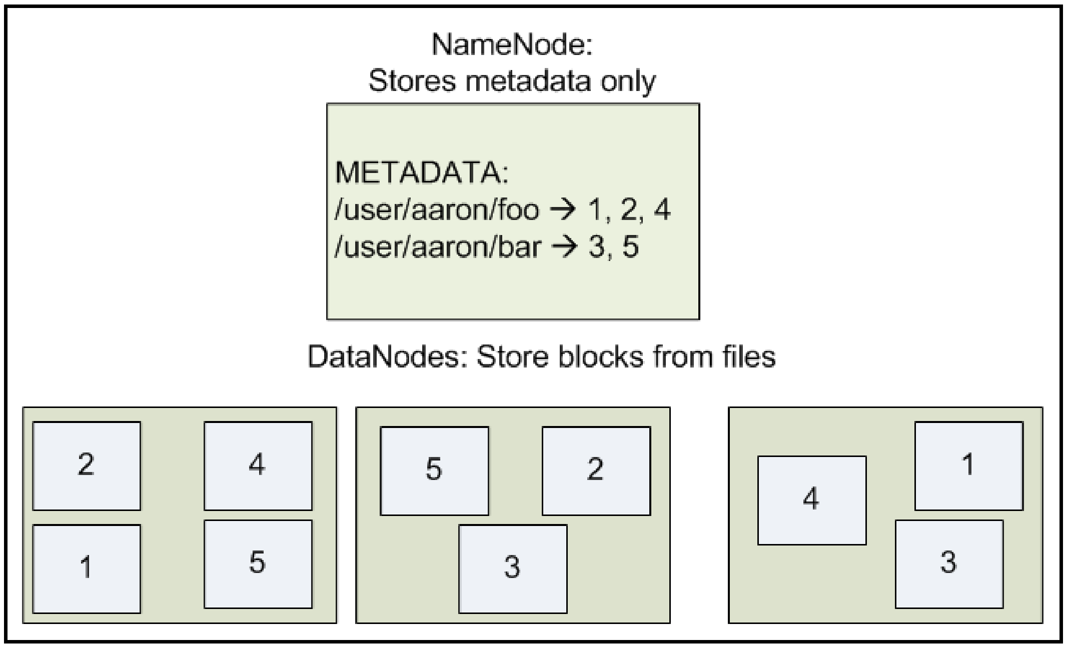


Figure 2.4.2 Datanode and Namenode managing files in the form of blocks [9]

2.4.3 Hadoop Map Reduce Framework

Hadoop map reduce framework is a programming model designed to process large volumes of data in parallel. It runs only those programs which conform to the map reduce programming model. It has two phases of execution: mapping phase and reducing phase. Each phase has an input and output data set of key and value pairs. In the mapping phase, it splits the input data into a large number of data fragments and distributes them across different machines.

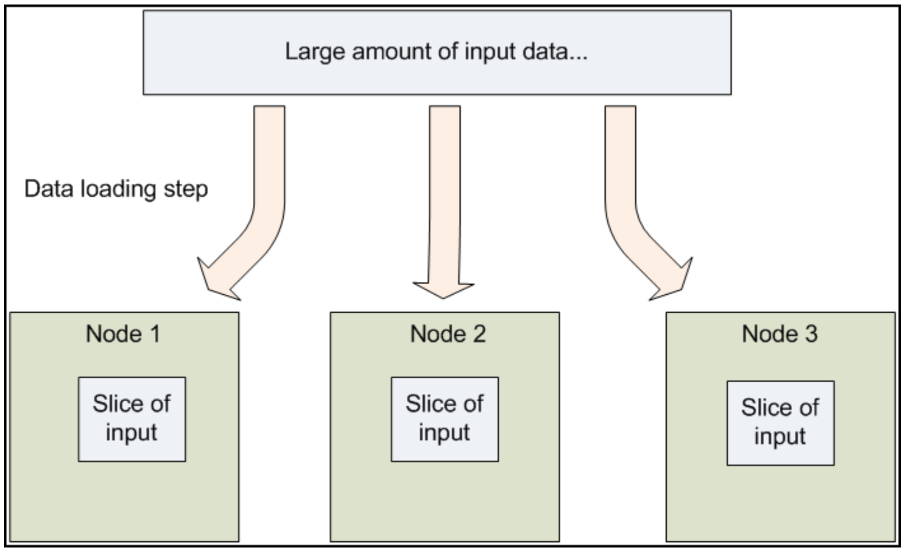


Figure 2.4.3.1 Distribution of data across different nodes [9]

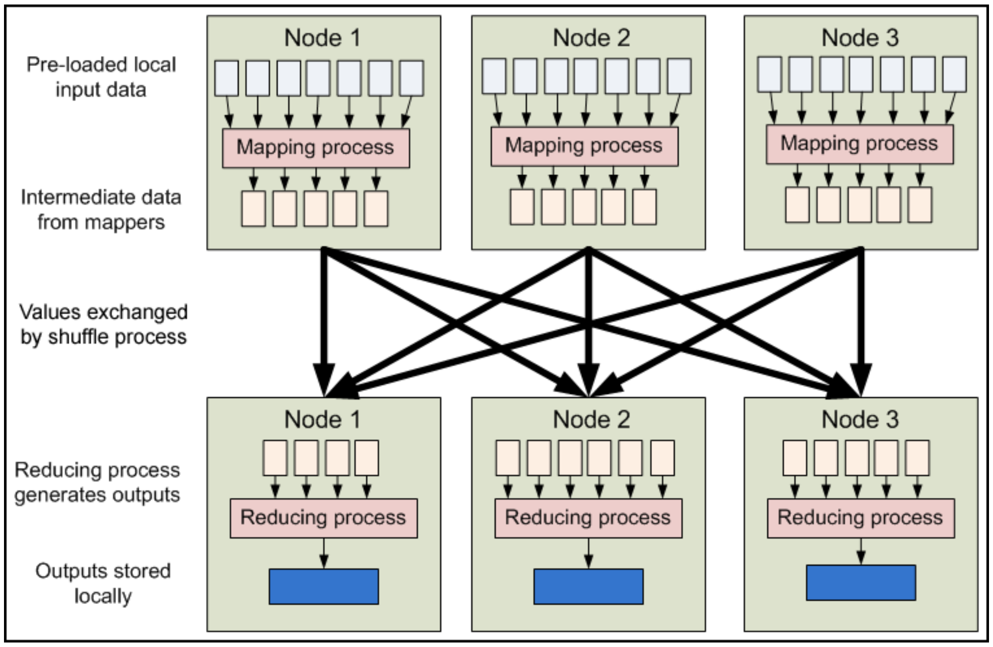

Pre-loaded local input data
Intermediate data from mappers
Values exchanged by shuffle process
Reducing process generates outputs
Outputs stored locally
Node 1
Node 2
Node 3
Mapping process
Reducing process

Figure 2.4.3.2 Map Reduce pipeline on different nodes [9]

Each data fragment is assigned a map task. All the map tasks are executed in parallel which takes the input data and transforms them into set of intermediate key/value pairs using a user defined function. After this phase the intermediate values are sorted, merged and distributed into different fragments across different machines depending on the number of reducers and presented as input to the reducing phase. Each fragment is assigned a reduce task which processes the data fragment into output key/value pairs depending on the user defined function. The output data of reducing phase is stored to the local machine. The map reduce framework consists of different nodes with a master/slave architecture having single master Jobtracker node and several slave Tasktracker nodes. All the map reduce jobs are added to the queue of pending jobs managed by Jobtracker. Jobtracker handles the entire map-reduce tasks and assigns them to the task trackers which execute tasks according to the instructions.

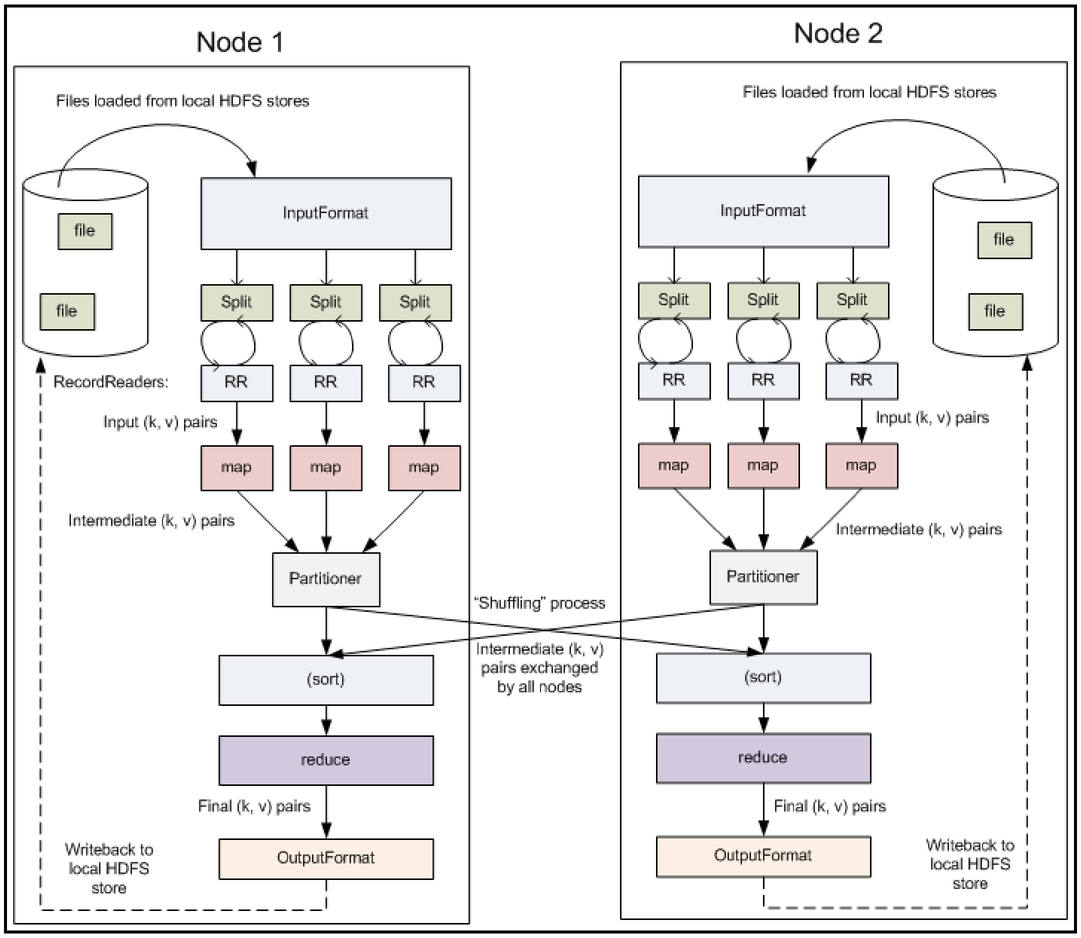


Figure 2.4.3.3 Internal Structure of Map Reduce data flow [9]

Hadoop implicitly handles the communication from node to node there by making it reliable. It tags the data fragments with key names so that it knows how to send data to the common destination node. It manages the data transfer and cluster configuration internally. It is very robust when concerned with the data congestion issues. In the case of a node failure it restarts the tasks on other processing machines.

Hadoop has some disadvantages like the input data elements cannot be updated. It does not provide any security model or safe guards. As it consumes some time to start the map reduce tasks it may not show optimal performance with a small quantity of data processed over a small number of nodes.

2.5 Why Hadoop?

There are several existing softwares for distributed computing like MPI, CUDA and Apache Pig but they do not fit into criteria of the current project. The below discussion tell us why Hadoop is chosen for this project.

MPI consists of a message passing model. The threads of mpi system are independent to one another. The communication between all the machines is done through message passing over the network. The current project includes processing large number of small elements. If the MPI approach is used for the current project it uses a high amount of network bandwidth and very low CPU utilization which is not ideal.

CUDA is distributed computing software where it uses GPU for its computation. It is implemented using SMT paradigm. The execution of instructions is similar to the SIMD model. Here the amount of global memory and shared memory used in a GPU are limited. The current project consists of processing a large network graph which may not fit into the memory. Since the instructions are executed in a lock step fashion it may block the resource which is not ideal. For this reason CUDA is not used in the current project.

Apache Pig is highly scalable distributed computing software developed on hadoop map/reduce fundamentals. It reduces the lines of code need to be written for map/reduce jobs It uses data flow operations and creates a series of map reduce jobs for them automatically. The current project prototype does not fit here since the executions are done in a non-serializable fashion and most of the computations get repeated. It cannot check the convergence. The graph algorithms with Pig are generally very slow.

When compared with the above technologies Hadoop map-reduce use parallel tasks execution with different phases and has convergence of all the intermediate results between each map and reduce job. This is ideal and required for the current project.

2.6 Discussion – Other approaches

There are several algorithms developed for computing the all pairs shortest path problem. Most of these algorithms are designed from two basic algorithms: Dijkastras algorithm [4] and Floyd-Warshall Algorithm [3]. Dijkastras algorithm solves for shortest path from single source to all other vertices. This can be used for computing APSP problem by iterating it over all the vertices. The Floyd-Warshall algorithm solves for the APSP problem by saving the computed shortest distance of intermediate paths for each pair at each step. The following discussion presents some of the approaches developed for solving the Parallel APSP problem in distributed mode. The discussion uses the term *'relax'* to specify the shortest path calculation for a single graph node.

2.6.1 Parallel Dijkastras APSP

A Parallel Dijkastras APSP computation is done by executing each Single source shortest path on each of the processors. For this approach, the adjacency matrix is to be replicated on to all the processors. This approach supposes that there are enough processors, one for each node. The execution is done in an independent fashion with no much of inter process communication between processors. It takes same time as that of computing it for Single source shortest path SSSP. This has a run time complexity of $O(n^2)$, with a given '*n*' number of vertices.

Another version of Parallel Dijkastras scheme [8] is to partition the number of vertices and execute each partition on a separate processor. In distributed mode for a given *p* processors, each of SSSP is executed on the *n/p* processors. The nodes in each partition uses Dijkastras algorithm to solve for the shortest path. It has a time complexity of $O(n^3/p)+O(n \log p)$.

The speed ups for these two versions are almost equal to '*p*'. The pros of this approach are optimal time complexity; low bandwidth, easy to compute, no underlying complexity involved and no inter process communication whereas the cons are: it requires the number of processors equal to the number of vertices, no node level parallelism and adjacency matrix should be replicated on each of the processors.

2.6.2 Simple Parallel Floyd Warshall APSP

The Simple Parallel Floyd Warshall APSP [7] scheme uses the Floyd Warshall algorithm. In this scheme, the initial adjacency matrix is distributed among different processors each sharing some portion of the rows like *1..k* of the initial adjacency matrix rows of *1..n,* where $1<k<n$. Each

processor owning a row *'k'* broadcasts the whole row over the network to the other processors. Each processor receives rows broadcasted by other processors and relaxes them with the rows owned by them. In this cost of communication depends on broadcast latency, bandwidth and time taken to relax single entry. For a given '*p'* processors and *'n'* number of vertices, the time complexity of this scheme is $O(n^3/p)+O(n^2)+O(n)$.

The pros of this scheme are low bandwidth, good load balancing and efficient CPU utilization. The cons of this scheme are poor cache performance, requires matrix representation of graph in heap memory.

2.6.3 Blocked Floyd Warshall APSP

The Blocked Floyd Warshall APSP [5] scheme considers the adjacency graph is partitioned into blocks. If '*n'* is the size of the matrix and '*b'* is the size of the block, then the number of blocks is N^2, where $N=n/b$. For this algorithm if there are '*p'* cluster nodes, then the block size is $b=n/p$. Each cluster node is assigned one complete row of blocks.

In this approach processors broadcast their pivot row blocks over the network. Each processor receives and computes pivot row block and pivot column block sent by other processors and relax their own pivot blocks and then other non-pivot blocks. The relaxing of blocks is done in an order. It then broadcasts them for the next iteration.

This approach has a time complexity of $O(n^3/p)+O(n^2)$. The pros of this approach are low bandwidth, good load balancing and efficient CPU utilization. The cons of this approach are computation is complex, needs adjacency matrix representation of graph, no failure recovery methods, inefficient for medium sized graphs and nodes have to wait for the relaxation step and till the broadcast of the next iteration.

2.6.4 Parallel Map Reduce APSP

This is the current algorithm used in our project. It is done in two phases: Building Adjacency Graph and Running Parallel APSP Map Reduce. In the first phase of building adjacency graph, adjacency list with trio sets are created from the input links. In the next phase of running parallel apsp map reduce, the algorithm makes use of the adjacency list representation of the graph in a specific format. Each node is represented using adjacency list and trio sets. Each Trio set for a node consists of the destination node, shortest distance to the destination node and color to check if the destination node is visited or unvisited. The process involves a Map phase and a Reduce phase iterated over a Stopping condition.

The map phase consists of processing all the nodes with the ALTS format. For each node it checks if there is any trio set with an unvisited color. It sets the stopping condition flag to false. It emits the original source node as key and the trio set with color changed to visited color. It also emits each of the adjacent nodes of original source node as key and the trio set with distance increased by '1' in it. This process of mapping continues until the stopping condition is true. In the reducer phase, the nodes that are emitted by the mapper phase are continued. For each node emitted by the Mapper, the values of the trio sets are checked for least distance and darkest color of the destination node and the list of triosets for each node are updated. This process of map reduce iterations continues until the stopping condition is set to true.

For a graph with size *‘n’*, M mappers, R reducers and T threads for each map/reduce task. The Buidling Adjacency Graph phase has a time complexity of $O(n^2/MT)+O(n^2/RT)$ and Running Parallel APSP Map Reduce phase has a time complexity of $O(n^3/MT)+O(n^3/MT)$. For a given system with *‘p’* number of processors $MT >> p$, $RT >> p$ i.e., MT and RT values are much greater than *‘p’*. This implies that the current algorithm has the best time complexity when compared to other existing approaches. For an average case, assuming the longest shortest path will be a constant *‘k’* << *‘n’*, the average time complexity will be $O(n^2/MT)+O(n^2/RT)$. This shows that the system can perform in an order of *‘n2’* time complexity for average case, which is the least time complexity when compared to that of existing systems.

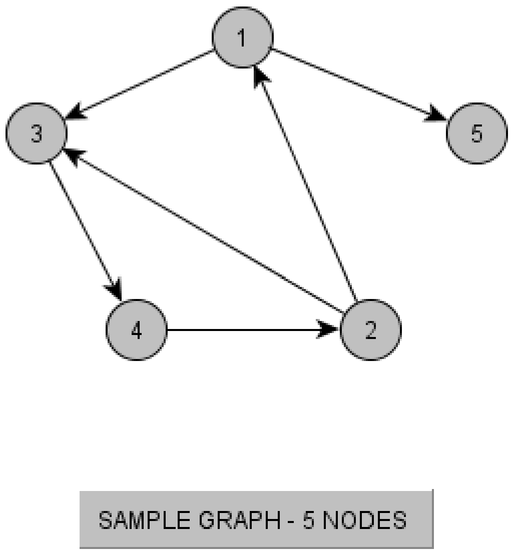
The pros of this approach are mapper phase has an efficient CPU utilization when compared to other existing systems, fault tolerant, optimal time complexity, provides node level parallelism, good load balancing, high throughput and less inter process communication.

The cons of this approach are reducer phase has to wait till all the intermediate values are sorted and merged, requires hadoop cluster system environment, initialization of map reduce tasks take time.

Chapter 3 - Implementation

Before we implement the system we try to develop a pseudo code and understand the working of it; we try to devise a plan and implement it accordingly to develop the system. The following section discusses about the pseudo code and working for the two algorithms developed for this project.

The following Sample graph shown in Figure 3.1 with 5 nodes is used to describe the working of the two algorithms.



Input Node Links
1 -> 5
1 -> 3
2 -> 1
2 -> 3
3 -> 4
4 -> 2

Figure 3.1 Sample 5-Node Graph

3.1 Modules

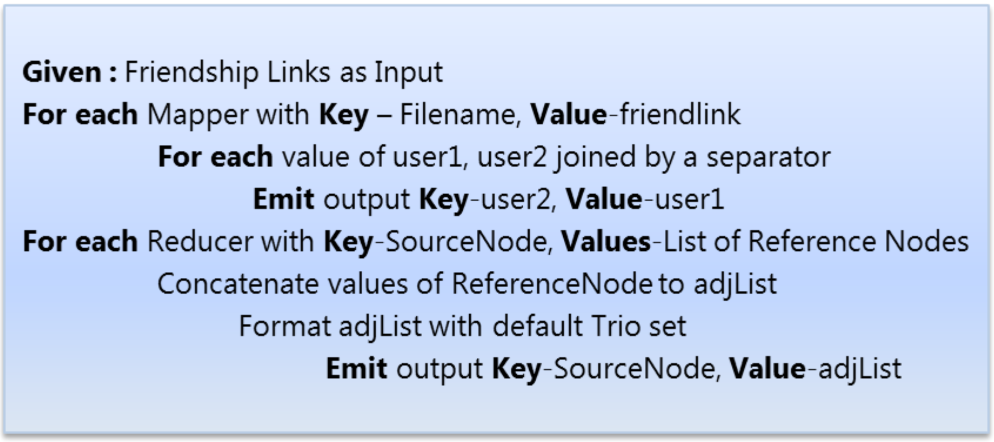
The project is implemented in two main modules. They are Build Adjacency Graph from the given network data and running Parallel APSP Map Reduce on the Adjacency Graph.

3.1.1 Build Adjacency Graph

The “Build Adjacency Graph” module includes extracting the links from the network data file, transforming the links into adjacency list, formatting the output by adding default trio set and writing it to a file. The users and their links are extracted from the file. The extracted user pairs are then joined with the first user as the key and the list of users attached to the user as adjacency list separated by a tab. The process of extraction and transformation uses the map reduce paradigm which processed all the links in parallel in mapper phase. The reducer phase waits for the completion of mapper phase and formats the adjacency list derived. The output graph format will have the information for both the in-links and reachable nodes from out-links.

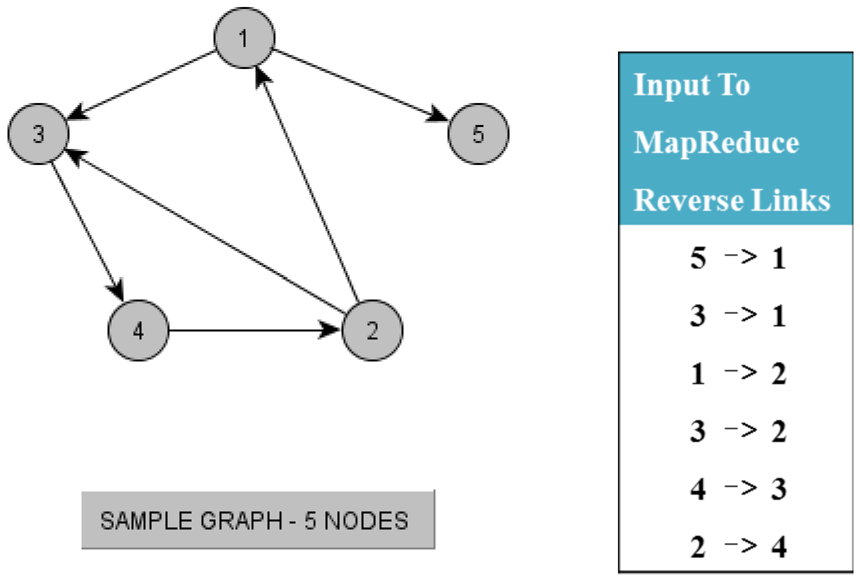
Pseudo code for Building Adjacency Graph

The following Figure 3.1.1 gives the Pseudo code for Building Adjacency Graph module.



```
Given : Friendship Links as Input
For each Mapper with Key – Filename, Value-friendlink
        For each value of user1, user2 joined by a separator
              Emit output Key-user2, Value-user1
For each Reducer with Key-SourceNode, Values-List of Reference Nodes
        Concatenate values of ReferenceNode to adjList
              Format adjList with default Trio set
                    Emit output Key-SourceNode, Value-adjList
```

Figure 3.1.1 Pseudo code - Building Adjacency Graph



Input To MapReduce Reverse Links
5 -> 1
3 -> 1
1 -> 2
3 -> 2
4 -> 3
2 -> 4

Figure 3.1.1.1 Sample Input Graph - Building Adjacency Graph

Working

The input for this algorithm is the sample network graph data shown in Figure 3.1.1.1 which consists of friendship links separated by a 'separator'. The user1 and user2 from each link are extracted and emitted by each map task. For example for link *3->4*, the user *'3'* and user '*4*' are extracted and emitted as key=4 and value=3. This is done for all the values. The intermediate values are aggregated over the emitted key values. In the sample graph, for key *'1'* the values aggregated will be *3*, *5*. These values represent the adjacent nodes for the key node *'1'*. The reducer tries to join all the key values emitted by the mapper and write it to a file. While writing it to a file we also add a trio set at the end of it consisting of the source node and distance as *'0'* and color as *'G'* which will be used in running parallel APSP map reduce phase. For the current example key-*'1'* and value-*'2|1,0,G'* is emitted as the output of the reducer. The following Figure 3.1.1.2 gives the output of the reducer phase for the sample graph. This format of graph has the in-links as adjacency list and trio sets as out-links.

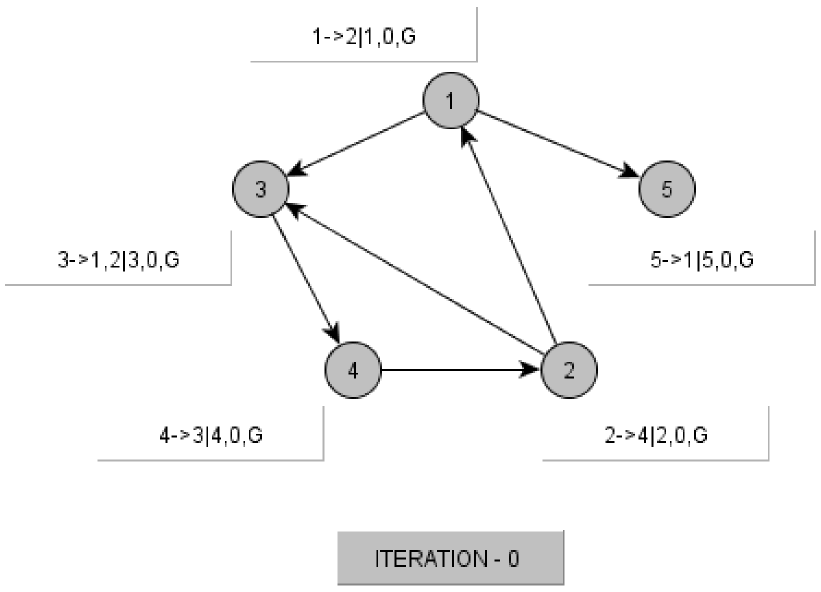


Figure 3.1.1.2 Output Graph of Building Adjacency Graph using Map Reduce

Time Complexity

The time for processing the Mapping phase consists of initializing the map tasks and processing all the mappers in parallel. Considering there are a total of n_m tasks in the mapping phase with M number of map tasks and T number of threads per each task. Let t_{im} be the time taken to initialize a single mapper. The total time taken to initialize all the map tasks would be Mt_{im}. Apart from the initialization of map tasks the time taken to process the whole mapping phase will depend on the time taken to process each single map task. Each mapper consists of n_m/M tasks. If t_m is the time taken to process each single task, the time taken for a single mapper execution will be $n_m t_m/M$. As each map task has *'T'* threads processing it, the time taken will be $n_m t_m/MT$. Since all the mappers are processed in parallel the total time for all the mappers will also be $n_m t_m/MT$. Let T_M be the total time for the mapping phase then

$$T_M = Mt_{im} + n_m t_m/MT$$

The Reducer is also processed in a similar fashion.

$$T_M = Rt_{ir} + n_r t_r/RT$$

The total time taken for building adjacency graph

$$T_{BAG} = T_M + T_R = Mt_{im} + n_m t_m/MT + Rt_{ir} + n_r t_r/RT$$

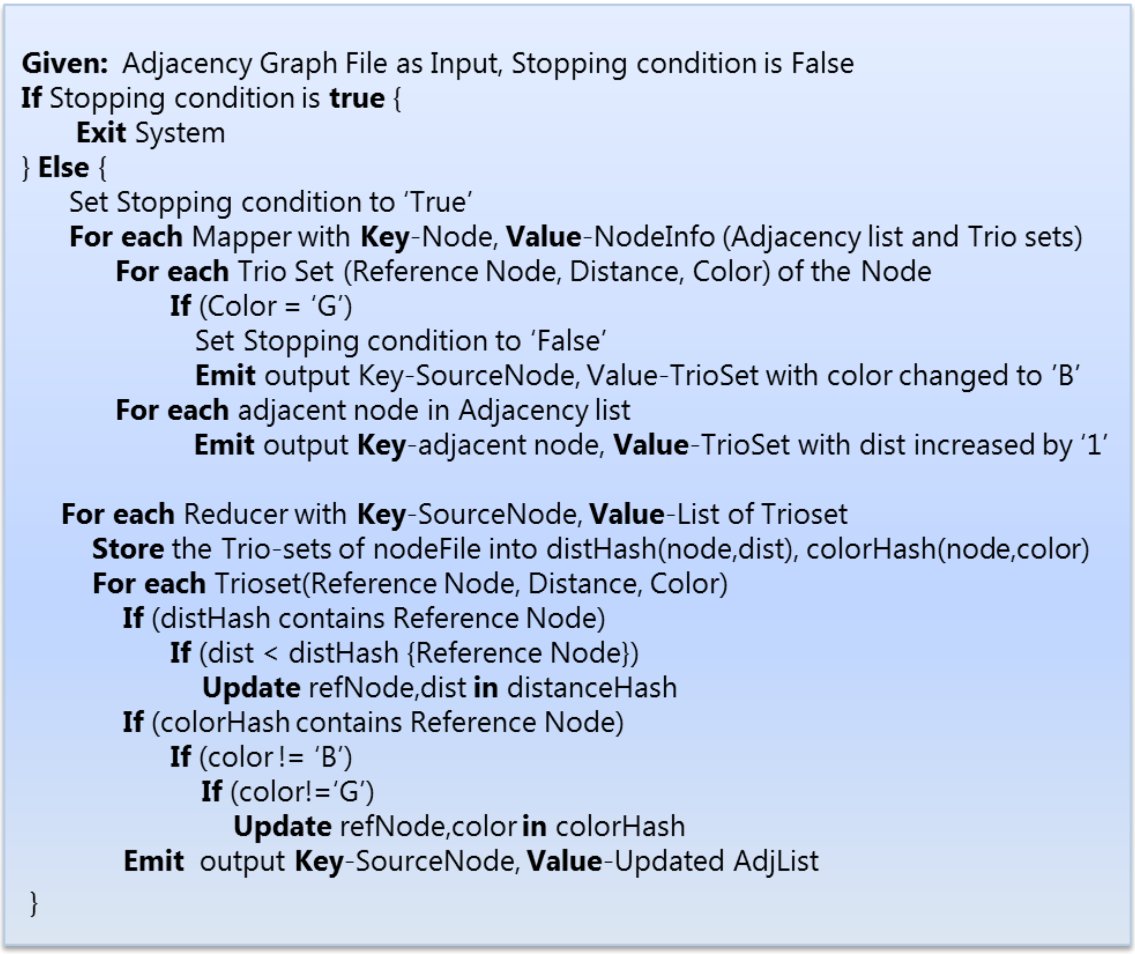
The time complexity is of order of $O(n_m t_m/MT) + O(n_r t_r/RT)$. For a given graph with 'n' number of nodes, nm will be of the order of $O(n^2)$. So, the worst case time complexity of Building Adjacency Graph will be $O(n^2/MT)+O(n^2/RT)$.

3.1.2 Running Parallel APSP Map Reduce

The "Running Parallel APSP Map Reduce" module includes the process of running parallel APSP Map reduce algorithm through iterative phases and calculating the BDD for all pairs of nodes in the network graph. The algorithm is iterated by checking a Boolean flag called stopping condition which determines if there is any next iteration. All the iterations consist of a mapper phase and a reducer phase. The mapper phase includes extracting the trio sets from each node, processing them by their color and distance, sending it to the reducer. The reducer phase tries to evaluate the key value pairs of trio sets emitted by the mapper and process them by checking for least distance and darkest color so as to keep the concept of shortest distance from source node to destination node. The processed nodes are used as input for the next iteration. The process continues until all the nodes are explored and all possible shortest paths are computed.

Pseudo code for Running Parallel APSP Map Reduce

The following Figure 3.1.2.1 gives the Pseudo-code for the Running Parallel APSP Map Reduce module.



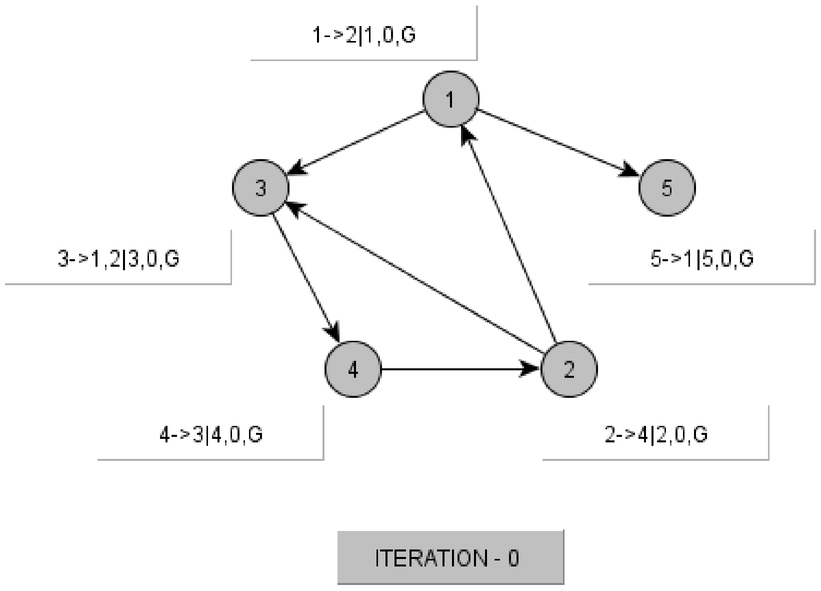
```
Given:  Adjacency Graph File as Input, Stopping condition is False
If Stopping condition is true {
     Exit System
} Else {
    Set Stopping condition to 'True'
    For each Mapper with Key-Node, Value-NodeInfo (Adjacency list and Trio sets)
        For each Trio Set (Reference Node, Distance, Color) of the Node
            If (Color = 'G')
              Set Stopping condition to 'False'
              Emit output Key-SourceNode, Value-TrioSet with color changed to 'B'
        For each adjacent node in Adjacency list
              Emit output Key-adjacent node, Value-TrioSet with dist increased by '1'

   For each Reducer with Key-SourceNode, Value-List of Trioset
      Store the Trio-sets of nodeFile into distHash(node,dist), colorHash(node,color)
      For each Trioset(Reference Node, Distance, Color)
        If (distHash contains Reference Node)
            If (dist < distHash {Reference Node})
               Update refNode,dist in distanceHash
        If (colorHash contains Reference Node)
            If (color != 'B')
               If (color!='G')
                  Update refNode,color in colorHash
        Emit  output Key-SourceNode, Value-Updated AdjList
}
```

Figure 3.1.2.1 Pseudo code for Running Parallel APSP Map Reduce

Working

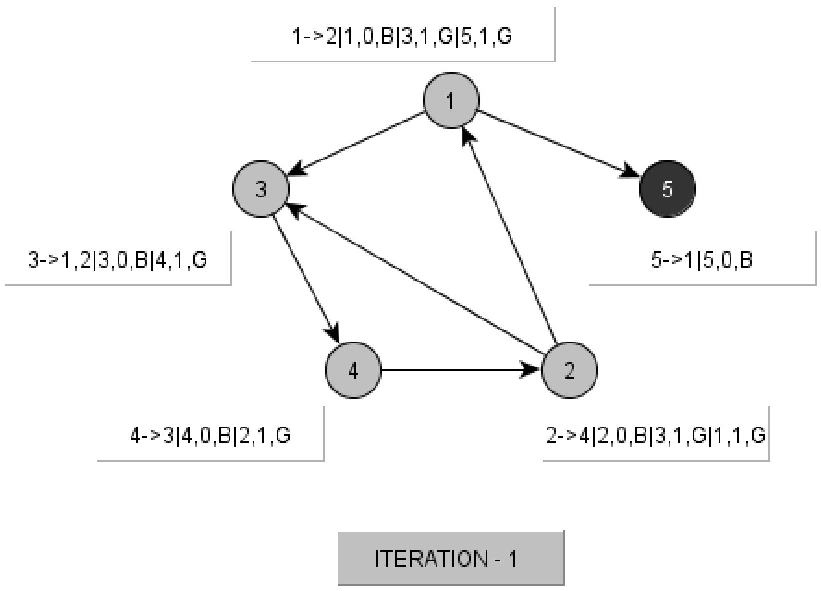
The algorithm requires an adjacency list with trio sets format as input and stopping condition set to false. In the initial step the adjacency list file is the output of the Building Adjacency Graph module. It checks for the global variable 'Stopping condition' at the starting of iteration. If the variable is '*true'* then it exits the system without processing further. If it is '*false'*, then it enters into the iteration. Each iteration consists of a map phase and a reduce phase. In the map phase, the mappers process all the lines with node information in parallel. Each mapper splits the input node information line into adjacency list and trio sets. It checks if there exists color *'G'* in any of the trio sets and updates the Stopping condition variable to '*false'*. The color *'G'* is used to represent the information that the node can be processed further in the next iteration. The trio sets for a source node represent the information of other reference nodes from which it can be reached. The trio sets are generated at the node with the adjacency list and source node. In each iteration they are sent to the connected nodes thereby making the trio sets travel from source node to all of its connected reference nodes one level/hop at a time. In the process of travelling from one node to other connected nodes, the triosets for a node are updated which gives the information of shortest distance from a reachable node to the source node. After the completion of all the iterations, each source node will be having the connected reference node information in the form of trio sets. At last the shortest distances for all the nodes are calculated at the end of iterations.

In the current example, the stopping condition variable is set to *'false'* before the starting of the algorithm so that it can enter into the iteration loop. For the node *'1'* it consists of trio set *(1,0,G)* which has color '*G'*. It sets the stopping condition to false. It then emits the source node *'1'* and trio set *(1,0,B)*. This is to acknowledge that trio set with reference node *'1'* is processed by current map task. It then emits the adjacent nodes as key and the value as trio set *(1,1,G)*. This tells us that the node *'1'* information is sent to the connected nodes which are the adjacent nodes of the source node and the adjacent nodes will be having the node *'1'* with distance *'1'* and color *'G'*. The outputs emitted for node'1' after the first map phase with key-value pairs are :*(1 1,0,B)* and *(2 1,1,G)*. In the reducer phase, the node *'2'* receives the trio set *(1,1,G)* and updates its triosets list. It first checks if the trioset received is having the least distance than the existing trioset for reference node *'1'* in trio set. It then checks for the darkest color and update its corresponding trioset. Similarly all the nodes update their triosets list. In the next iteration i.e., Iteration-1, node *1* and node *2* processes the triosets received from the previous iteration. For node *'1'*, it has *(1,0,B), (3,1,G),* and *(5,1,G)*. It checks the color of each trioset and it forwards triosets with *'3'* and *'5'* to its adjacent node *'2'* as they have their color *'G'*. The values emitted for node *'1'* are *(1 3,1,B), (2 3,2,G), (1 5,1,B)* and *(2 5,1,G)*. In the reducer phase each node receives the triosets forwarded by other nodes and updates their triosets list. In this way the information for received by node *'1'* is forwarded to it in-link nodes at each iteration. All the nodes are processed in the same manner. The process continues for several iterations until there are no trio sets with color *'G'* encountered. At last the node *'1'* will have the triosets *(3,1,B), (5,1,B), (4,2,B)* and *(2,3,B)* representing all the reachable nodes from it. The following figures give the adjacency list with trio sets and key/value pairs emitted for all the iterations.



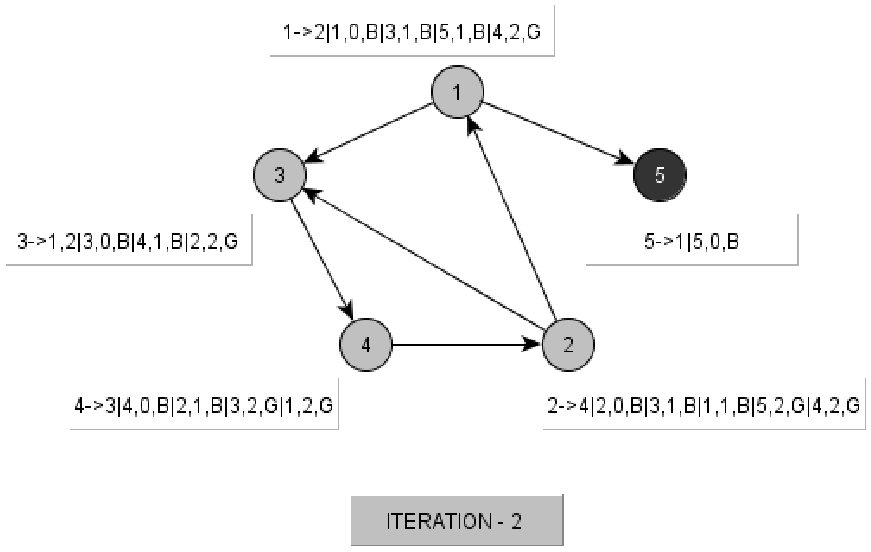
Key	Value
1	1,0,B
2	1,1,G
2	2,0,B
4	2,1,G
3	3,0,B
1	3,1,G
2	3,1,G
4	4,0,B
3	4,1,G
5	5,0,B
1	5,1,G

Figure 3.1.2.2 Iteration-0 Graph - Running Parallel APSP Map Reduce



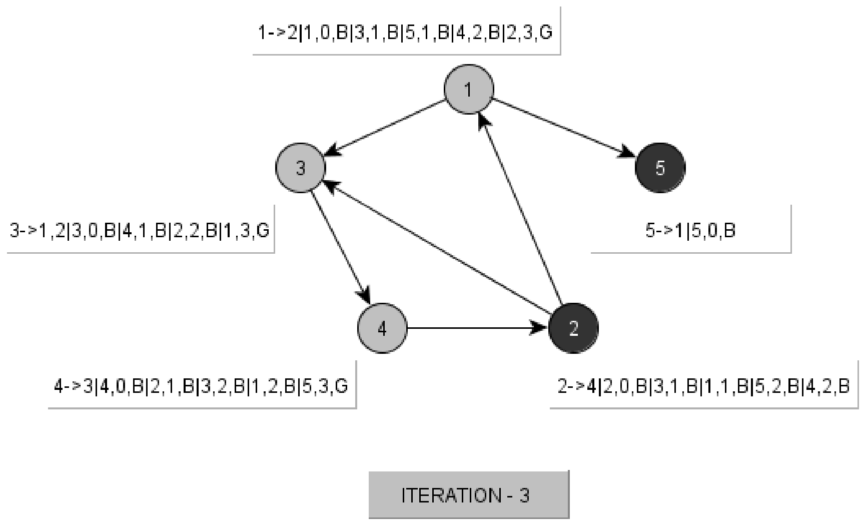
Key	Value
1	3,1,B
2	3,2,G
1	5,1,B
2	5,2,G
2	3,1,B
4	3,2,G
2	1,1,B
4	1,2,G
3	4,1,B
1	4,2,G
2	4,2,G
4	2,1,B
3	2,2,G

Figure 3.1.2.3 Iteration-1 Graph - Running Parallel APSP Map Reduce


1->2|1,0,B|3,1,B|5,1,B|4,2,G
1
3
5
3->1,2|3,0,B|4,1,B|2,2,G
5->1|5,0,B
4
2
4->3|4,0,B|2,1,B|3,2,G|1,2,G
2->4|2,0,B|3,1,B|1,1,B|5,2,G|4,2,G
ITERATION - 2

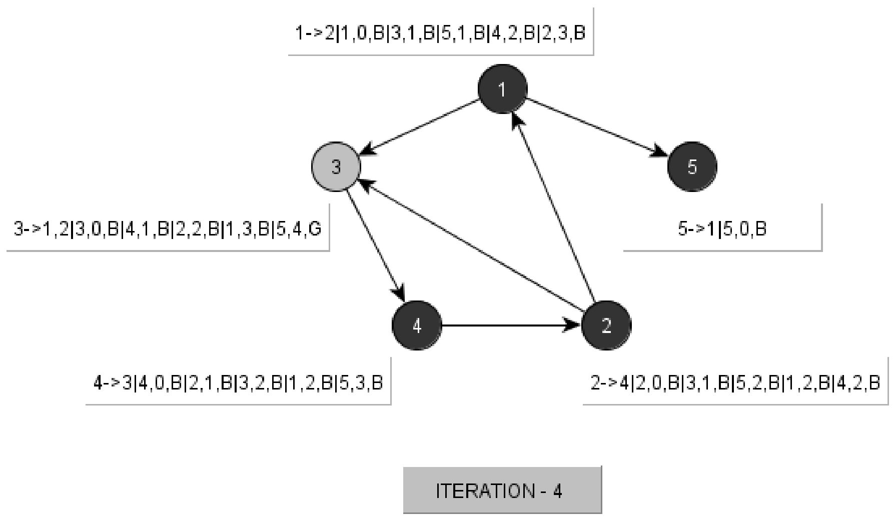
Key	Value
1	4,2,B
2	4,3,G
2	5,2,B
4	5,3,G
2	4,2,B
4	4,3,G
3	2,2,B
1	2,3,G
2	2,3,G
4	3,2,B
3	3,3,G
4	1,2,B
3	1,3,G

Figure 3.1.2.4 Iteration-2 Graph - Running Parallel APSP Map Reduce


1->2|1,0,B|3,1,B|5,1,B|4,2,B|2,3,G
1
3
5
3->1,2|3,0,B|4,1,B|2,2,B|1,3,G
5->1|5,0,B
4
2
4->3|4,0,B|2,1,B|3,2,B|1,2,B|5,3,G
2->4|2,0,B|3,1,B|1,1,B|5,2,B|4,2,B
ITERATION - 3

Key	Value
1	2,3,B
2	2,4,G
3	1,3,B
1	1,4,G
2	1,4,G
4	5,3,B
3	5,4,G

Figure 3.1.2.5 Iteration-3 Graph - Running Parallel APSP Map Reduce


1->2|1,0,B|3,1,B|5,1,B|4,2,B|2,3,B
1
3
5
3->1,2|3,0,B|4,1,B|2,2,B|1,3,B|5,4,G
5->1|5,0,B
4
2
4->3|4,0,B|2,1,B|3,2,B|1,2,B|5,3,B
2->4|2,0,B|3,1,B|5,2,B|1,2,B|4,2,B
ITERATION - 4

Key	Value
3	5,4,B
1	5,5,G
2	5,5,G

Figure 3.1.2.6 Iteration-4 Graph - Running Parallel APSP Map Reduce

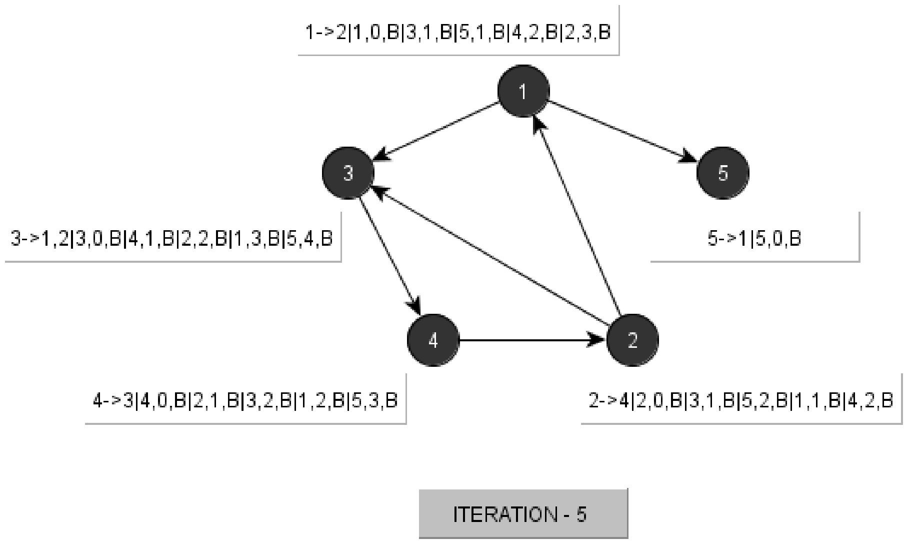

1->2|1,0,B|3,1,B|5,1,B|4,2,B|2,3,B
1
3
5
3->1,2|3,0,B|4,1,B|2,2,B|1,3,B|5,4,B
5->1|5,0,B
4
2
4->3|4,0,B|2,1,B|3,2,B|1,2,B|5,3,B
2->4|2,0,B|3,1,B|5,2,B|1,1,B|4,2,B
ITERATION - 5

Figure 3.1.2.7 Iteration-5 Graph - Running Parallel APSP Map Reduce

Time Complexity

The time complexity for this algorithm depends on tasks of map-reduce phases and the number of iterations of map-reduce phases. Consider there are a total number of n_m tasks in the map phase and M mappers with T number of threads for each map task. Let t_{im} be the time taken to initialize a single mapper. The total time taken to initialize all the map tasks would be Mt_{im}. The time taken to compute a single task depends on the time taken to process the trio sets. Let *nmt* be the number of trio sets processed for each task and t_{mt} is the time taken to process it. The time taken for a single task is $n_{mt}t_{mt}$. The time taken to execute all the tasks in map phase is $n_m n_{mt} t_{mt}/MT$. The total time for the mapping phase will be

$$T_M = Mt_{im} + n_m n_{mt} t_{mt}/MT$$

Similarly the time taken for the Reduce phase is

$$T_R = Rt_{ir} + n_r n_{rt} t_{rt}/RT$$

The total time taken for running the Parallel APSP Map Reduce algorithm is

$T_{PAPSP} = I\ (T_M + T_R) = I\ (Mt_{im} + n_m n_{mt} t_{mt}/M + Rt_{ir} + n_r n_{rt} t_{rt}/R)$, where *'I'* is the number of iterations. The Total Time complexity for Running Parallel APSP Map Reduce is $O(n_m n_{mt} t_{mt} I/MT)+O(n_r n_{rt} t_{rt} I/RT)$. The *'I'* value represents the longest shortest path and in worst case it could be *'n'*. In worst case the number of triosets and number of tasks will be in an order of '*n'*. So, the worst case time complexity of the algorithm is $O(n^3/MT)+O(n^3/RT)$. If we consider an average case, number of triosets and number of tasks will be in an order of *log n*. So, the average time complexity of the algorithm will be $O(n*(\log n)^2/ MT)+O(n*(\log n)^2/RT)$.

3.2 Coding

The coding of the system is done using four different class files: GraphBasesFeaturesTrain, Graph, Variables and Stopwatch. The first java class file GraphBasesFeaturesTrain is actual java class file in which the friendship prediction for the input social network is done using GBF features and BDD calculation. The two other java files were developed to implement the Building adjacency graph and Running parallel APSP map reduce algorithms. Variables and Stopwatch are supporting classes used in other classes.

GraphBasesFeaturesTrain - In GraphBasesFeaturesTrain.java class file, a string variable 'mainDir' is used to set the main folder path, which will be used as the working folder. Using this main directory path other directory paths are set and organized which are used in the further processes. In the map reduce execution the class instance variables get destroyed when they are used for the next phase or iteration. To overcome this problem, the global variables are maintained in the form of files under a directory named 'variables'. The folder 'In' is used as input for building the adjacency graph process. The output adjacency graph will be stored in the directory called 'Out' having file for each node. The folder also contains a combined file which is used as input for the parallel APSP mapreduce process. The process updates the ‘Out’ folder files after each iteration and combines all the files into a single file and uses the file as input for the next iteration.

Graph - The Graph.java class file contains methods to check and organize the directory structure of the file system, map reduce methods for building adjacency graph and running parallel APSP.

Varibles - The Variables.java class file contains methods to set and get the variables, folder paths. These methods are used by the other two java classes. The various variables that are set and used in the class files are *mainDir, dataDir, graphDir, inputDir, inputTrainDir, outputDir, outputTrainDir, tempDir, outputTrainFile* and *stoppingCondition*. Of all these variables *stoppingCondition* is checked at the start of each iteration to check whether there is need to process for the next iteration.

Stopwatch - The Stopwatch.java class file is created to record the amount of time taken for the execution. It contains a method *getelapsedTime*, which returns the elapsed time since from the starting time.

Text data format is used as the input data format & output data format for the map and reduce phases for both the methods of building adjacency graph and running parallel APSP. The Text Format is used here because of its simplicity and easiness of conversions to other formats.

3.3 Diagrams

3.3.1 Class Diagram

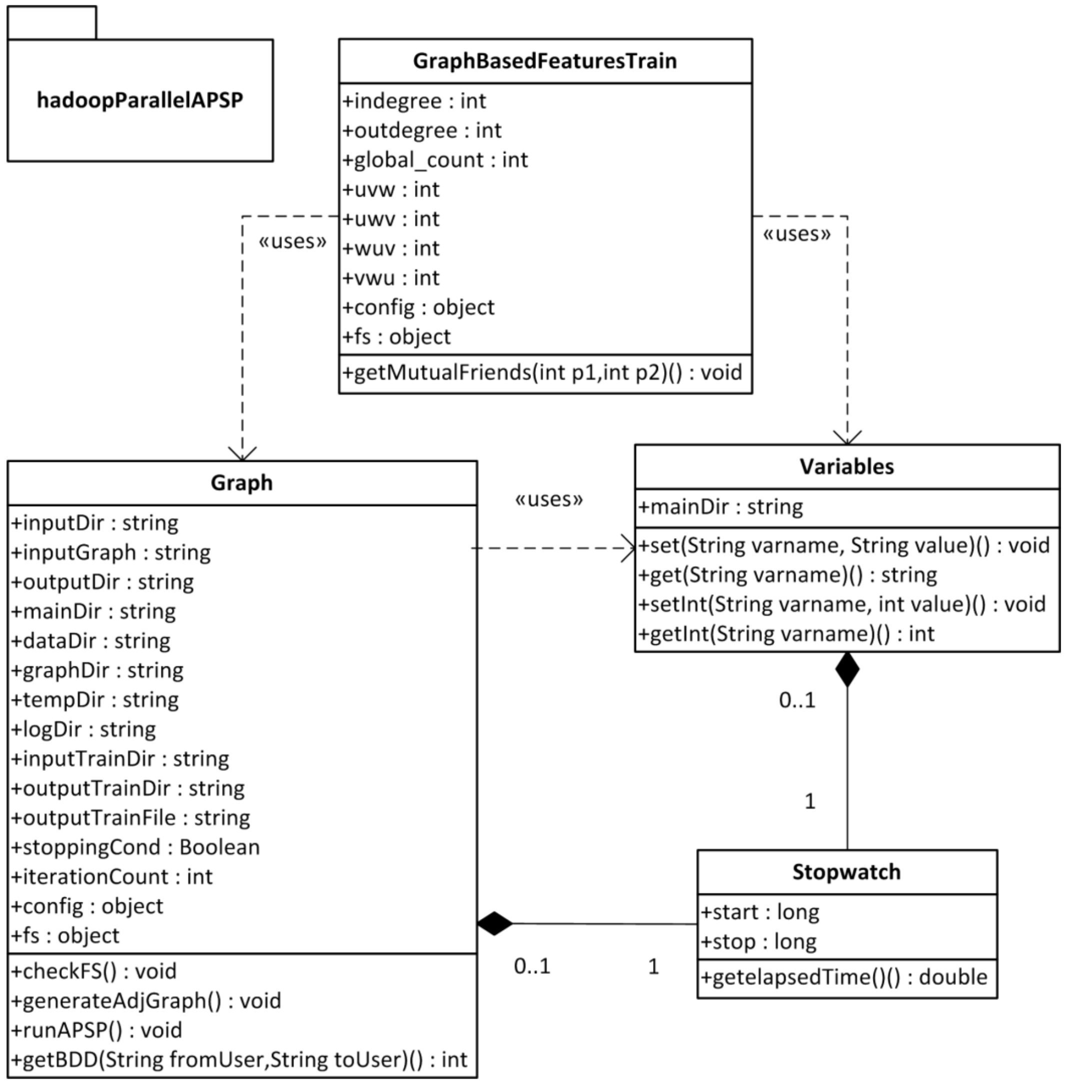


Figure 3.3.1 Class Diagram

The Figure 3.3.1 represents the class diagram for the current system. It shows how the system is organized. The diagram shows that the GraphBasedFeaturesTrain class uses the Graph and Variables classes; Graph class uses Variables class and has a Stopwatch class object. It shows that the system is organized under the package *'hadoopParallelAPSP'*.

3.3.2 Data Flow Diagrams

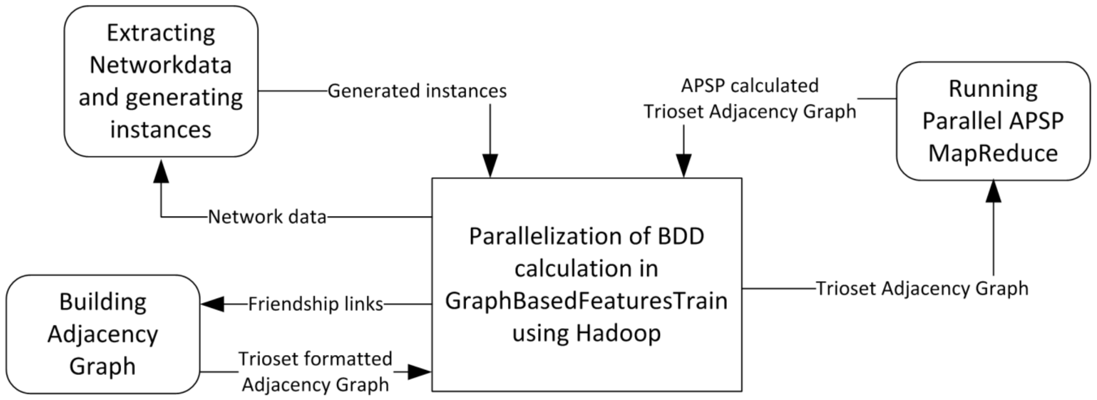

Extracting Networkdata and generating instances
Generated instances
APSP calculated Trioset Adjacency Graph
Running Parallel APSP MapReduce
Network data
Parallelization of BDD calculation in GraphBasedFeaturesTrain using Hadoop
Building Adjacency Graph
Friendship links
Trioset formatted Adjacency Graph
Trioset Adjacency Graph

Figure 3.3.2.1 Context Level Diagram

The Figure 3.3.2.1 represents the Context Level Diagram for the current system. It shows that different modules of extracting network data, building adjacency graph and running parallel APSP map-reduce.

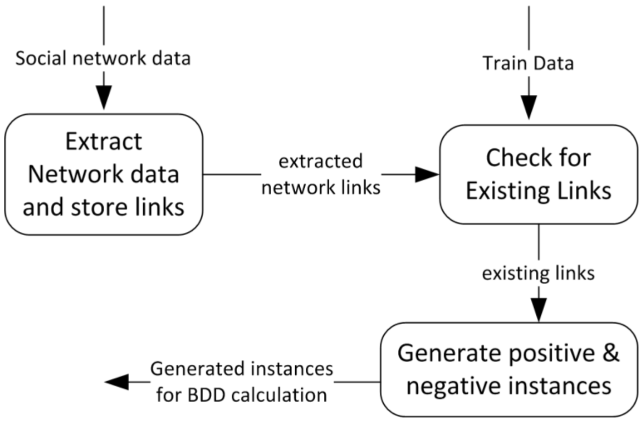

Social network data
Train Data
Extract Network data and store links
extracted network links
Check for Existing Links
existing links
Generated instances for BDD calculation
Generate positive & negative instances

Figure 3.3.2.2 Level-0-DFD - Extracting network data and generating instances

The Figure 3.3.2.2 represents Level-0-DFD for Extracting Network data and generating instances activity. It shows that the social network data is taken as input and links from network data are extracted and stored. The Train data is then compared with stored links to check whether they exist. The existing links from train data are used for generating instances.

The Figure 3.3.2.3 represents the Level-0-DFD for Building the Adjacency Graph module. It shows that the input links from the GraphBasedFeaturesTrain are formatted and sent to the Building Adjacency Graph mapper. The Building Adjacency Graph Reduce phase uses the intermediate values to build the trioset formatted Adjacency Graph.

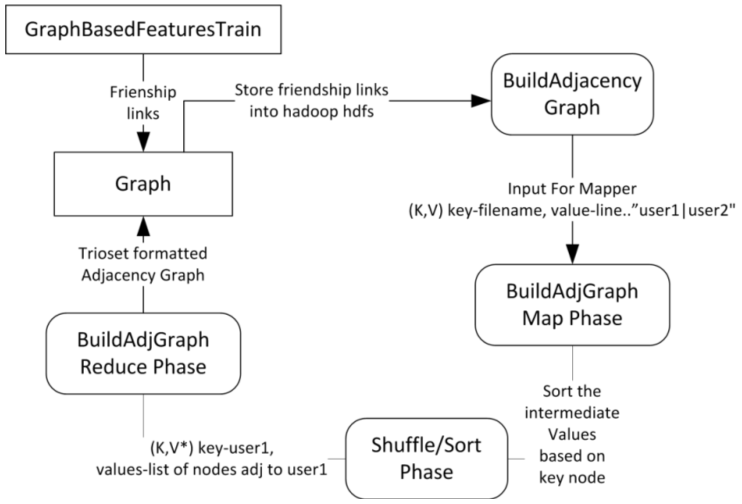

GraphBasedFeaturesTrain
Frienship links
Store friendship links into hadoop hdfs
BuildAdjacency Graph
Graph
Input For Mapper (K,V) key-filename, value-line..”user1|user2"
Trioset formatted Adjacency Graph
BuildAdjGraph Map Phase
BuildAdjGraph Reduce Phase
Sort the intermediate Values based on key node
(K,V*) key-user1, values-list of nodes adj to user1
Shuffle/Sort Phase

Figure 3.3.2.3 Level-0-DFD - Building Adjacency Graph

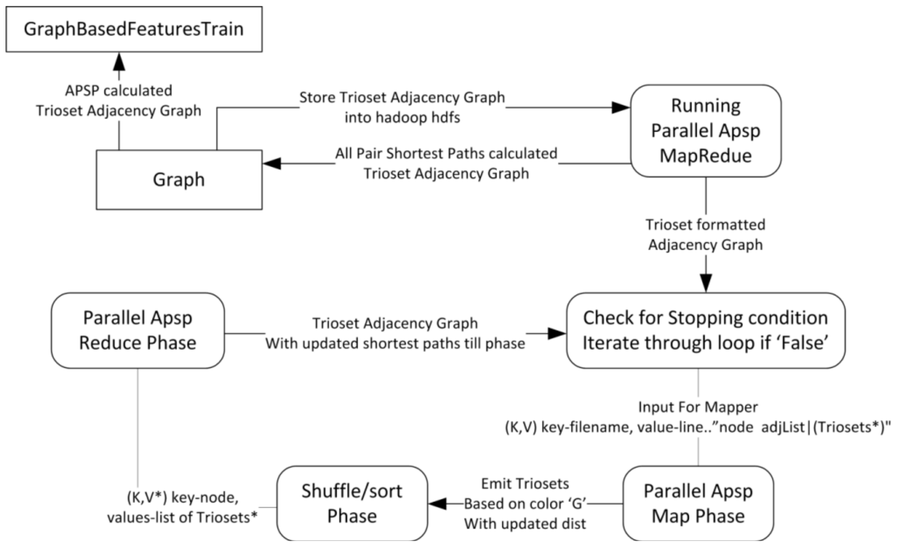

GraphBasedFeaturesTrain
APSP calculated Trioset Adjacency Graph
Store Trioset Adjacency Graph into hadoop hdfs
Running Parallel Apsp MapRedue
Graph
All Pair Shortest Paths calculated Trioset Adjacency Graph
Trioset formatted Adjacency Graph
Parallel Apsp Reduce Phase
Trioset Adjacency Graph With updated shortest paths till phase
Check for Stopping condition Iterate through loop if ‘False’
Input For Mapper (K,V) key-filename, value-line..”node adjList|(Triosets*)"
(K,V*) key-node, values-list of Triosets*
Shuffle/sort Phase
Emit Triosets Based on color ‘G’ With updated dist
Parallel Apsp Map Phase

Figure 3.3.2.4 Level-0-DFD - Running Parallel APSP Map Reduce

The Figure 3.3.2.4 represents the Level-0-DFD for Running Parallel APSP Map Reduce module. The diagram shows that trioset formatted adjacency graph is used as input. In mapping phase stopping condition is checked and triosets of adjacency list are processed according to distance and color. In the reducing phase intermediate values are merged and triosets are updated for each node. The updated adjacency list with triosets is given as input for the next iteration.

Chapter 4 - Evaluation

4.1 Testing

Once the application is developed, it needs to be tested to make sure the application meets all the functional requirements for which it was designed for. Testing is classified mainly into two types. They are Black Box Testing and White Box Testing. Black Box Testing involves testing the system for different types of external inputs and its behavior. In this testing the internal structure of the system is not known to the tester. It includes different types of testing like Load Testing, Performance Testing, System Testing and Acceptance Testing. For the current project Performance Testing and System Testing are used. White Box Testing involves testing the internal structure and implementation of the system. In this testing the internal units of the system are rigorously tested for all kinds of valid and invalid inputs, all logical paths, conditional statements and loops. It determines how well the system behaves and also gives an overview of integrity of the system. It includes different types of testing like Unit Testing and Integration Testing. Unit testing is used for the current project.

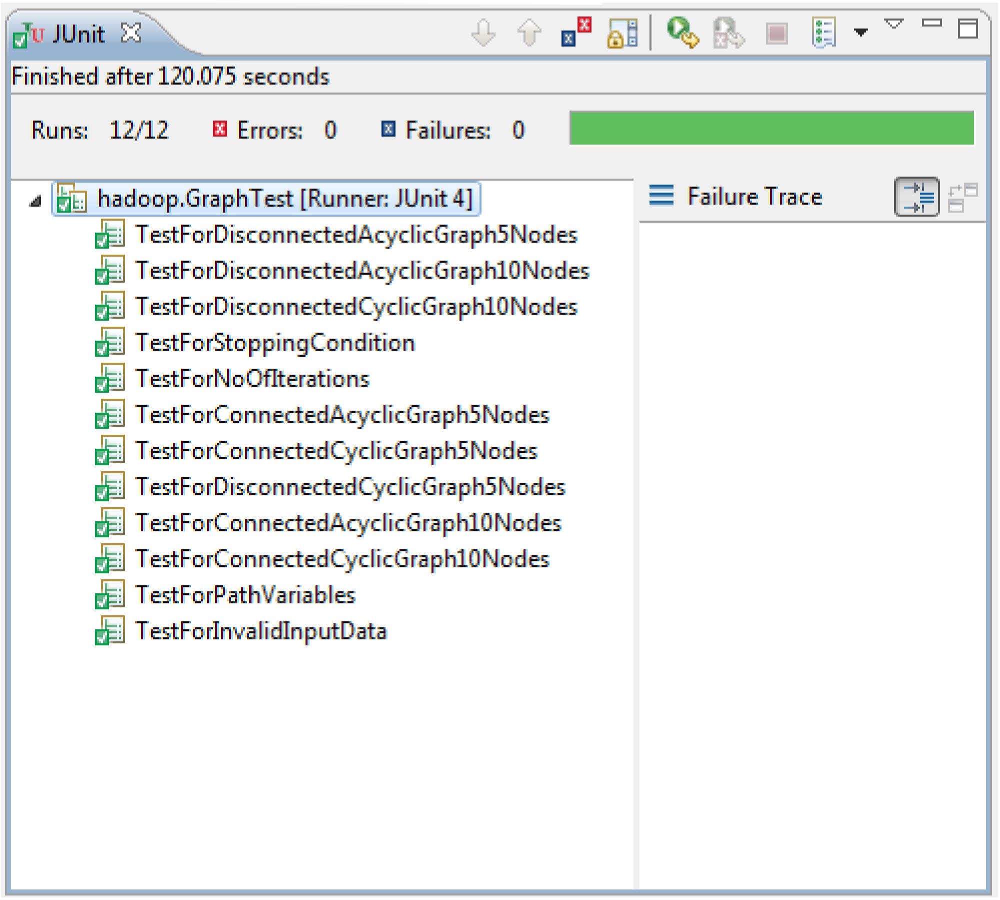
4.2 Test Methods & Test plan

4.2.1 Unit Testing

As the current system is developed in java we have used JUnit for unit testing the system. JUnit is a testing framework for writing test cases and unit testing java applications. It has a Text Fixture java object for setting the test environment and Test Case java object for writing and testing different test cases. We try to check for the correctness of the system by unit testing it for various test cases. We test the system to check if it is returning the correct output for different types of graphs, if the paths and variables are preserved correctly at each phase, if it tries to check for the invalid data format. We also check if it is preserving the stopping condition correctly at each and every phase. The directed graphs with graph size 5 and 10 nodes are used in this testing. The unit testing considering testing the system for both the types of graphs of cyclic graphs and acyclic graphs. The below Table 4.2.1 shows different test cases used for unit testing the system.

Test No.	**Initial State**	**Test Case**	**Expected Result**
1	Connected cyclic graph with size 5	Compare output shortest paths of parallel Map Reduce APSP with pre-calculated shortest paths.	Success: Output Results match the pre-calculated shortest paths.
2	Connected cyclic graph with size 10	,,	,,
3	Disconnected cyclic graph with size 5	,,	,,
4	Disconnected cyclic graph with size 10	,,	,,
5	Connected Acyclic graph with size 5	,,	,,
6	Connected Acyclic graph with size 10	,,	,,
7	Disconnected Acyclic graph with size 5	,,	,,
8	Disconnected Acyclic graph with size 10	,,	,,
9	Connected cyclic graph with size 10	Check if the system preserves the input and output directory path variables	Success: Yes it preserves the input and output path variables
10	Connected cyclic graph with size 10	Check if the stopping condition is set correctly	Success: Yes the stopping condition set.
11	Connected cyclic graph with size 10 (invalid data format)	Check if the input data format is valid or invalid.	Exception: Input has invalid data format

Table 4.2.1 Test Cases for Unit Testing



Finished after 120.075 seconds

Runs: 12/12 Errors: 0 Failures: 0

```
hadoop.GraphTest [Runner: JUnit 4]
    TestForDisconnectedAcyclicGraph5Nodes
    TestForDisconnectedAcyclicGraph10Nodes
    TestForDisconnectedCyclicGraph10Nodes
    TestForStoppingCondition
    TestForNoOfIterations
    TestForConnectedAcyclicGraph5Nodes
    TestForConnectedCyclicGraph5Nodes
    TestForDisconnectedCyclicGraph5Nodes
    TestForConnectedAcyclicGraph10Nodes
    TestForConnectedCyclicGraph10Nodes
    TestForPathVariables
    TestForInvalidInputData
```

Figure 4.2.1 Test Results for Unit Testing

The above diagram Figure 4.2.1 shows the results for the Unit Testing. It tells us that the system has passed the entire unit testing test cases successfully.

4.2.2 Performance Testing

The System is tested for performance testing to analyze different factors like scalability, efficiency and speedups. It gives us an idea of responsiveness of the system under a given work load. In order to judge the true parallel computing capability of the system, we try to test for its performance using inputs of different data sizes. The graphs with sizes from 50 nodes to 1,000,000 nodes are taken as input for measuring the performance of the system with number of cores ranging from 2 to 16 cores. The Table 4.2.2 gives us the performance testing results.

	General Floyd Warshall APSP	Parallel Map Reduce APSP				
Graph Size		Building Adjacency Graph	Running Parallel Map Reduce APSP	Total Time	Longest Shortest Path	# Cores / RAM
50	0.278	3.65	24.968	28.618	8	2 Cores 4GB RAM
500	0.775	16.193	146.944	163.137	23	2 Cores 4GB RAM
1000	4.829	26.598	147.063	173.661	17	4 Cores 8GB RAM
5000	236.443	80.87	343.943	424.813	9	4 Cores 8GB RAM
10000	1370.771	172.516	1169.063	1341.579	19	4 Cores 8GB RAM
20000	2656.631	146.794	1955.428	2102.222	12	4 Cores 8GB RAM
30000	11621.479	214.312	1563.712	1778.024	8	4 Cores 8GB RAM
50000	40735.363	396.489	1672.237	2068.726	8	4 Cores 8GB RAM
100000		238.056	1029.256	1267.312	8	4 Cores 8GB RAM
200000		135.498	623.317	758.815	8	8 Cores 16GB RAM
500000		332.677	1244.931	1577.608	8	8 Cores 16GB RAM
1000000		201.361	890.544	1091.905	8	16 Cores 32GB RAM
200000		469.399	1774.103	2243.502	8	4 Cores 8GB RAM
500000		592.262	2149.402	2741.664	8	4 Cores 16GB RAM
1000000		670.386	3314.856	3985.242	8	4 Cores 32GB RAM
1000000		330.402	1882.528	2212.93	8	8 Cores 32GB RAM

Table 4.2.2 Test Results of Performance Testing

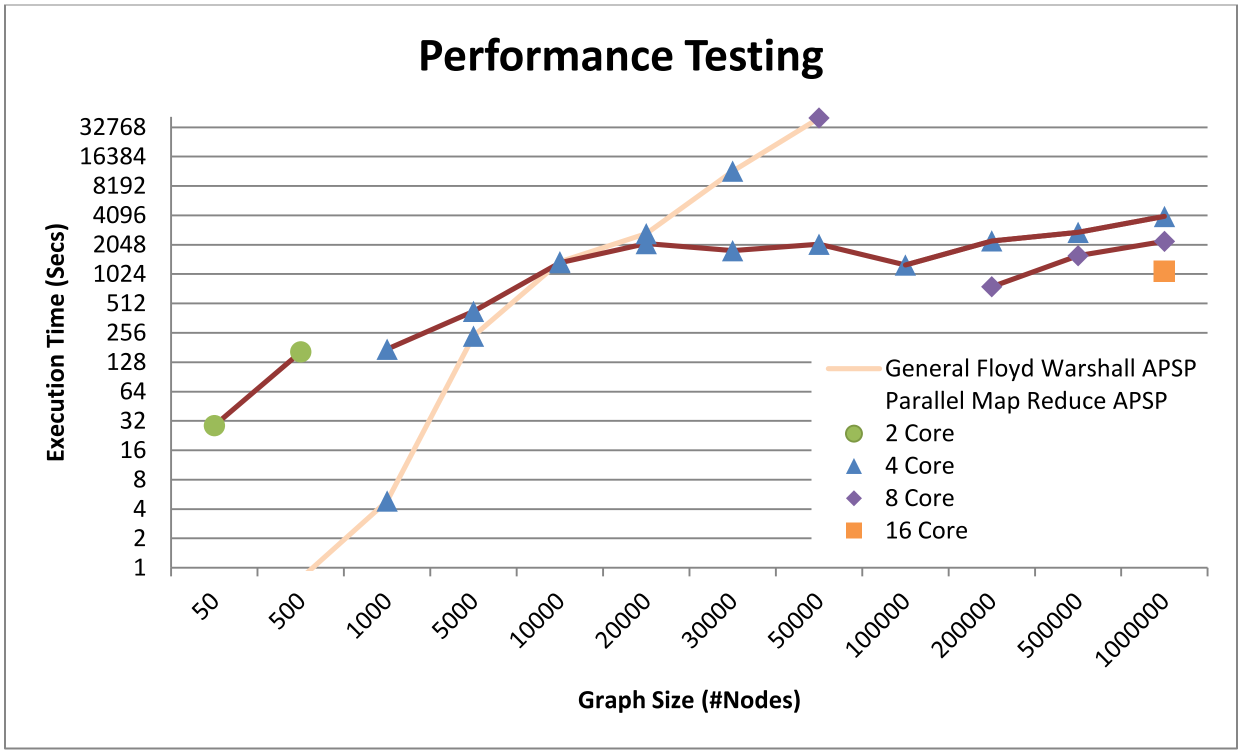


Figure 4.2.2 Line Graph representing Performance Testing Results

The Table 4.2.2 and Figure 4.2.2 represents the results for performance testing with General Floyd Warshall APSP execution vs. Parallel Map Reduce APSP approach. It shows that system was not able to perform at full throttle for small graphs with graph size less than and around 5000 nodes, though it considerably reduces the execution time when compared to the general Floyd-Warshall execution. By analyzing the graphs we can say that the algorithm may not perform its best for small size graphs, but as the graph size increases it begins to show its performance. This is because the overhead of File-IO read/write time and initialization of map-reduce tasks is relatively more for small graphs when compared to the execution time of a single task. It shows its performance for graphs with sizes more than 5000 nodes.

4.2.2.1 Speedup

Speedup is a factor which determines the parallel computing capability of a system. It is ratio of the execution time in sequential process to the execution time in distributed process. If *‘p’* is the number of processors and T_1 is the time for serial execution and T_2 is the time taken for distributed execution then the speed up for the system is

$$\text{Speedup } (S_p) = T_1 / T_2$$

A system is said to be ideal if the speedup is equal to *‘p’*. For our system, when can compare the execution times of 2core with that of more than 2cores. From the performance testing results table we can clearly see that system has Speedup values more than *‘1’*. For 1million node graph, when executed on 4core has execution time 3985.242 and when executed on 16core has a value 1091.905 which is nearly equal to (3985.242 / 4 =) 996.25, which tells us that our system is capable of fully parallelizing the calculations. It means that we increase the number of cores by 4 times the execution time gets reduced by 4 times. The system was able to achieve high speedup with values ranging from *0.87p* to *0.92p*, where *‘p’* is the number of processors. It tells us that the system was able to achieve *Linear Speedup* and shows the properties of ideal system with optimal performance and very good scalability.

4.2.3 System Testing

The System testing phase requires the system to pass all the above testing modules. In this testing the system is tested to see if it meets all the functional requirements specifications and system requirements specifications. We test the overall integrity of the system and ensure if it is working correctly. The above results show that the system has passed all the above tested cases. The system meets all the functional specifications and behavioral specifications. The system is manually testing by checking each and every unit for any undiscovered error or bugs. The project has been successfully tested to check for its integrity. The system has passed all the test cases and meets all the specifications and is said to be deployable.

4.3 Results

From the above testing procedures we can see that the project has passed all the test cases successfully and has the optimum performance. The application meets all the user specific requirements and satisfies the objectives of the system. The test results were found to be satisfactory. Though the system is implemented successfully, we have encountered some bottlenecks during the execution due to the system environment variables in which it was executed. The following presents the bottlenecks encountered and how they are resolved.

4.3.1 Bottlenecks

Some of the bottlenecks encountered in this project are as follows. During the intermediate phase, if the buffer size is not enough to handle the values emitted by the mapper, it will spill the intermediate values to disk i.e., it will write the values to the disk instead of holding it in the memory. This will cause additional FileIO operations reducing the performance. In our implementation we observed that the default buffer size *'io.file.buffer.size'* is '4k'. We resolved it by increasing the buffer size to 128MB to accommodate to more intermediate values. Another bottleneck observed is that the default dfs block size is 64MB. Because of this each mapper was only able to read 64MB size of the data at a time and it makes the hadoop to read more number of chunks degrading the performance. This is resolved by increasing the dfs block size to 128MB. In our algorithm the output of the running map-reduce apsp yields large number of small files which is the input to the next iteration. Hadoop will invoke each map task to each small input file and there will be large number of map tasks needed which degrades the performance. We resolved this by merging all the small files into one single file and feeding it as input for the next iteration.

Chapter 5 - Conclusion

There have been number of approaches for solving the social network analysis in a better way. None of them could show a better implementation for large social network graph algorithms. The current project tries to solve one of the social network analysis problems of friendship prediction for large network graphs by solving for APSP problem using a parallel APSP map reduce approach. The system designed is able to handle the problem efficiently. As the overhead of initializing the map reduce task is relatively high, it is inefficient for small graphs which have less than 5000 nodes. The system shows its performance for graphs with size of 7000 and over. It over performs all the existing systems with optimal time complexity. The system is tested for performance and correctness using various testing methods and the results were found to be fantastic. In overall the project was implemented successfully and presents a new approach for solving the APSP problem associated with the social network analysis of large network graphs.

5.1 Limitations

Though the project is implemented successfully it has some limitations. The limitations encountered in this project are as follows:

- Initialization of map reduce tasks consumes a fraction of execution time from 2% to 5% depending on graph size.
- HDFS file system cannot be mounted by an operating system directly.
- Though hadoop preserves file permissions, it does not provide any security model for the data.

5.2 Future Work

The project was started as a small approach and it could be extended to increase the efficiency and reduce the computation time further. It could be extended as follows

- As the project requires creating simple ad hoc jobs we can use Python instead of Java.
- Reducing number of computations further by using a flag for a node, which tells us that if a node has all the shortest paths covered in it and no need to process it further.
- Adding a data structure which maintains the trace of shortest path covered along with shortest distance.

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