Incremental PageRank for Twitter Data Using Hadoop

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Abstract

Twitter is a very fast growing social networking site and has millions of users. Twitter user social relationship is based on follower concept rather that we are friend concept and following action is not mutual between Twitter user. Twitter users can be ranked using PageRank method as followers can be represented as social graph and the number of followers reflects influence propagation. In this dissertation we implemented Incremental PageRank using Hadoop MapReduce framework. We improved the existing Incremental PageRank method based on the idea that we can reduce the number of affected nodes that are descendants of changed nodes from going to recalculation stage by applying threshold restriction. We named our approach as Incremental+ method. Our experimental results show that the Incremental+ PageRank method is scalable because we successfully applied this method to calculate PageRank value for 1.47 billion Twitter following relations. Incremental+ method also produced the same ranking result as other methods even though we used approximation approach in calculating the PageRank value. The result also shows that Incremental+ method is efficient because it reduced the number of inputs per iteration and also reduced the number or iterations of power method. The difference in time per iteration is statistically signigficant if compared to naïve method but the statistical result test also shows that there is no different if compared to original Incremental PageRank method.

Acknowledgements

First of all, I would like to express my gratitudes towards my supervisor, Dr. Miles Osborne for guidance and encouragement. Thank you very much also for giving me the permission to use Hadoop Cluster and thus made this dissertation possible to work. Next, I would like to send my warmest love for my mum in Malaysia. Thank you mum, I love you so much. Last but not least, I would like to say thank you to my sponsor that has granted my wish to come true. Thank you very much.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

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Chapter 1

Introduction

One of the basic human needs is to interact and socialize with each other. We exchange knowledge and information from last millennium to the next millennium. It started from smoke signal to snail mail to telegraph and then to radio and telephone. The use of Information and Communication Technology (ICT) has rapidly changed the way we socialize among ourselves. Based on the recent report[1] by Nielsen in August 2010 on Internet consumer in United States of America, it shows that most of the time spent while online is on social networking; followed by online gaming and email. Moreover, the report result also shows that about 906 hours per month spent on social network site such as Facebook, MySpace and Twitter.

Twitter is an online microblogging service that enables registered users to post very short updates, comments or thoughts also known as "tweets" of up to 140 characters [1]. The restriction of 140 character is because Twitter was initially implemented to conform to the character limit in the Short Message System (SMS). Nowadays, users can tweet and read tweets via SMS, web and also applications in mobile devices such as iPhone and Google Android. Depending on the security and privacy settings, the tweets can be publicly be read by everyone or limited to those approved follower only. The public tweets are searchable on Twitter search or any other search engine such as Google and Bing.

Millions of tweets tweeted daily and twitter tweets are ranging from mundane daily life routines or important news events. For example, on November 26, 2008, reports about the terrorist attacks in Mumbai spiked suddenly on Twitter, drawing worldwide attention before the news media could react. The second example is when the news

[1] http://blog.nielsen.com/nielsenwire/online_mobile/what-americans-do-online-social-media-and-games-dominate-activity/

and pictures during Haiti earthquake in 2010 circulating in Twitter first and real time [3]. Furthermore, users can use retweet function to spread the news. Event detection experiments on a collection of 160 million Twitter posts show that celebrity deaths are the fastest spreading news on Twitter [16]. The trend of utilising twitter application to update what is happening around us has open opportunity for news media agency to broker current breaking news.

Some user tweets spam content, some tweets are just intended for a few friend and many are just ignored. The noisy in Twitter stream data will make it more difficult to do event detection. In addition, because of the 140 character restriction, the URLs shortener service to convey longer tweets such as bit.ly has been widely used but this also subjected to be abused by virus and spam threats. Furthermore, too many junk tweets will make the user too overwhelming to read tweets and in the the end user will give up stop using the Twitter service. Thus, it is very important to have ways to rank users so later we can deal with spam and spotting important tweets.

There are a few ways to rank Twitter user based on currently available information. First, we can rank user by statistics such as the number of tweets, retweets and frequency of updating tweets can help us to weed out spammer and non-spammer, but this method is prone to be abused by spammer. Next, we can rank user based on tweet contents but challenge in content-based analysis is to determine whether the tweet content is useful or not. Finally, we can do link analysis to help us to rank the Twitter user. In link analysis we can represent the relationship between Twitter user and followers into graph. Based on computing the graph of followers, it should yield information that is similar to PageRank link analysis algorithm.

PageRank hypothesis is that a web page is important if it is pointed to by other important pages [15]. PageRank is very popular method in the web searching community and it is usually applied to web pages and not people. So, if we apply to Twitter domain, it means if a user has a lot of followers then the chances are they are active and people are interested in reading the associated tweets. In addition, if that person follows another person, then that important person propagates authority.

The latest reported data in May 2010 (based on data crawled and collected in June 2009) shows that the total user is more than 40 million and 1.47 billion relations [11]. The huge amount of data like this will need a practical and effective method to calculate the value of PageRank. New users and users deactivation will affect the growth of users graph. In addition, as the user keeps following and unfollow will make the graph evolving. These two important factors will be taken into account in this dissertation.

PageRank calculation is based on power method which need iterative implementation. This method is very slow to reach convergence. The problem with computing PageRank for very big graph in traditional way is we need machine with high processing power and huge memory. Now we can use Hadoop MapReduce framework to calculate the PageRank in parallel computation and distribute the processing and memory usage accross cluster with cheaper machine.

In this dissertation we developed a method based on incremental PageRank method with some modification For naming convention, Desikan *et al*. original incremental method [6] will be just called Incremental method and our incremental method with threshold will be called Incremental+ (pronounce incremental plus). We will explore the hypothesis that Incremental+ PageRank is better than original PageRank on computing the ranking of Twitter user along dimension efficiency. Our second hypothesis is Incremental+ PageRank will produce same ranking result as original PageRank.

Our experimental results show that the Incremental+ PageRank method is scalable because we successfully applied this method to calculate PageRank value for 1.47 billion Twitter following relations. Incremental+ method also produced the same ranking result as other methods even though we used approximation approach in calculating the PageRank value. The result also shows that Incremental+ method is efficient because it reduced the number of inputs per iteration and also reduced the number or iterations of power method. The difference in time per iteration is statistically signigficant if compared to naïve method but the statistical result test also shows that there is no different if compared to original Incremental PageRank method.

The report will be discussed as the following chapters:

- Chapter 2: Will discuss the background theory behind Graph Theory, PageRank and MapReduce which form the base of the work in this thesis.
- Chapter 3: Will introduce to Incremental+ PageRank method.
- Chapter 4: Will discuss how we set up our solution and the implementation of the framework we used to evaluate it.
- Chapter 5: Will evaluate the performance of the features we developed with PageRank calculation methods we tried.
- Chapter 6: Will conclude the findings of the thesis and discuss future directions that our work has highlighted.

Chapter 2

Background

In this chapter the background theories and knowledge are reviewed in order to provide the necessary support for exploration of the subject area. Firstly we will be introduced to some key ideas in Graph Theory such as edges list and adjacency matrix and adjacency list. Then we will discuss the main tools for our ranking task, namely the PageRank methods. Finally we will look at Hadoop framework which will help us to calculate PageRank in efficient manner.

2.1 Social Relation Representation

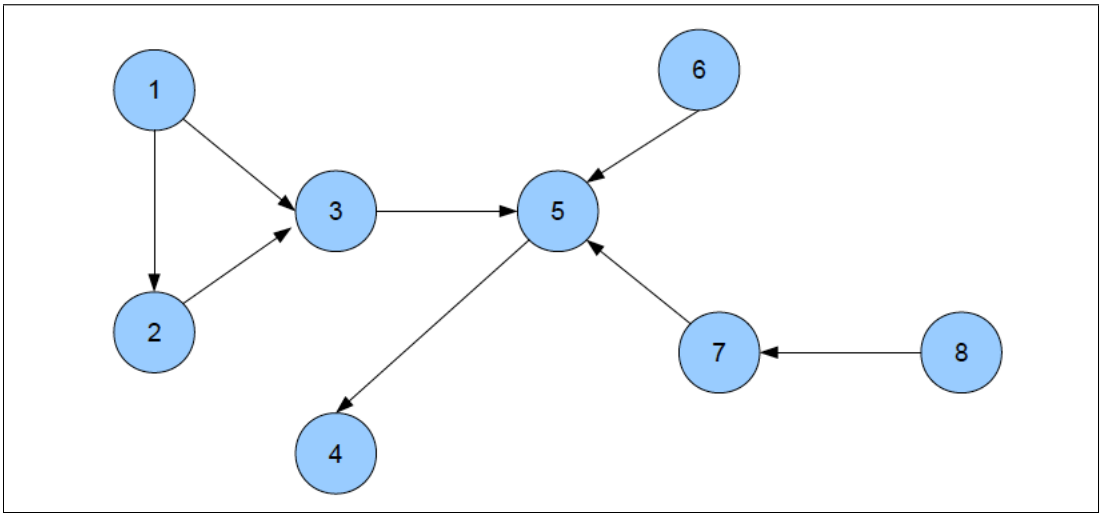


Figure 2.1: Social relation between Twitter user

We can represent the social relation among Twitter users as an edges list. As example in Figure 2.1 we can represent relation from node 1 to node 2 as $1 \longrightarrow 2$.

Twitter social relation is different from webpages in term of self link or sometimes also known as self loop. It is not possible for Twitter users to follow themselves, in constrast to web pages, sometimes the inlinks come from the webpages itself. Twitter is also very distinguish from MySpace and Facebook in reciprocality of social relation. In Facebook and MySpace, user can only add a friend upon approval by the requested user. On the other hand, the concept of follower is used in Twittersphere. Even though there is setting for follower approval but most of the Twitter just use default setting which is anyone can follow them. Overall, if user A follows user B does not mean B also follows user A and reciprocality of social relation is discussed in length by Kwak *et al.* in [11]. Thus, the collection of nodes in social relation in Twittersphere is a directed graph. This directed graph can be represent as adjacency matrix as follows:

	1	2	3	4	5	6	7	8
1	0	1	1	0	0	0	0	0
2	0	0	1	0	0	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	0	0	0	0
5	0	0	0	1	0	0	0	0
6	0	0	0	0	1	0	0	0
7	0	0	0	0	1	0	0	0
8	0	0	0	0	0	0	1	0

Rows in the first column of matrix mean source nodes and columns in the first row mean targets. Value 1 is to represent if there is a link between source and target. It shows that most of the matrix contains zero which also known as sparse matrix. Sparse matrix like this will waste storage and computing resource especially in Twitter, the total number of user is more than 40 millions, so we will end up with at least 40M x 40M matrix. Thus, it is better for us to represent the social relation in Figure 2.1 into adjacency list as follows:

1: {2,3}

2: {3}

......

4: { }

......

7: {5}

8: {7}

Each number before colon in every row is the source node and numbers inside the curley bracket represent targets. Node without any outlink like node 4 in Figure 2.1 will have empty set. The representation in adjacency list as above will greatly reduce the amount to store and will use far less computing resources compared to adjacency matrix. On the other hand, we should note that we will lose random access capability.This mean we have to sequentially to read everything before we can find what we want.

2.2 PageRank

PageRank is the link-based analysis algorithm used by Google to rank webpages was at first present as citation ranking [15]. Another popular link-based analysis is HITS by Kleinberg which is used by Teoma search engine later acquired by Ask.com search engine which is based on natural language [10]. Long before PageRank, the web graph was largely an untapped source of information[12]. Page *et al.* used the new innovative way which is not to based solely on the number of inlinks but also consider the importance of page linked to it has made PageRank a popular way to do ranking. In a nutshell, a link from a page to another is understood as a recommendation and status of recommender is also very important.

2.2.1 Simplified PageRank

Page *et al.* famous ranking formula started with a simple summation equation as in Equation 2.1. The PageRank of node u is denoted as $R(u)$, is the sum of the PageRanks of all nodes pointing into node u where B_u is the set of pages pointing into$u$ [15]. In Page *et al.* own word, they called B_u as backlinking. Finally N_v is the number of outlinks from node v. The idea behind dividing $R(v)$ with N_v can be analogy as endorsement by Donald Trump is far better than recommendation letter by a normal high school teacher. This is because it is hard and very rate to get endorsement by Donald Trump compared to a high school teacher recommendation letter [12].

$$R(u) = \sum_{v \in B_u} \frac{R(v)}{N_v} \tag{2.1}$$

2.2.2 Iterative Procedure

The problem with Equation 2.1 is that the ranking value $R(v)$ is not known. Page *et al*. use iterative procedure to overcome this problem. All node is assign with initial equal PageRank like 1. Then rule in Equation 2.1 is successively applied, subtituting the values of the previous iterate into $R(u)$. This process will be repeated until the PageRank scores will eventually converge to some final stable values. The formula representing the iterative procedure is as in Equation 2.2. Each iteration is denoted by value of k. $k+1$ means next iteration and k is previous iteration This method also known as power method.

$$R_{k+1}(u) = \sum_{v \in B_u} \frac{R_k(v)}{N_v} \tag{2.2}$$

2.2.3 Random Surfer Model

Page *et al*. made further adjustment to the basic model of PageRank by introducing Random Surfer Model which is based on description of the behavior of an average web user. According to Random Surfer Model, we can analogy that a web surfer who bounces along randomnly following the hyperlink structure of the web. Random surfer will arrive at a page with several outlinks and has to choose randomnly of one them that leads to new page and this random decision process will continue indefinitely. In the long run, the proportion of time spent on a given page is measure of the relative importance of that page. Random surfer will repeatedly found that some page is randomly revisited repeatedly. Pages that random surfer revisits often must be important because they must be appointed to by other important pages.

Random surfer will encounter two problems while doing the random surfing. First, random surfer will find out it keep revisits the same cycle of node and get stuck in a loop. Random surfer will never get a chance to visit node 5 as in Figure 2.2.

Next problem that random surfer will encounter when arriving at a dangling node. Dangling node is a node without outlinks and this will get random surfer to stuck. This situation can be illustrate as in Figure where random surfer will get stuck after arriving at node 5 because node 5 does not have any outlinks. Usually, in real world, it's not that node 5 always does not have outlinks, but rather it still need to be crawled and download yet.

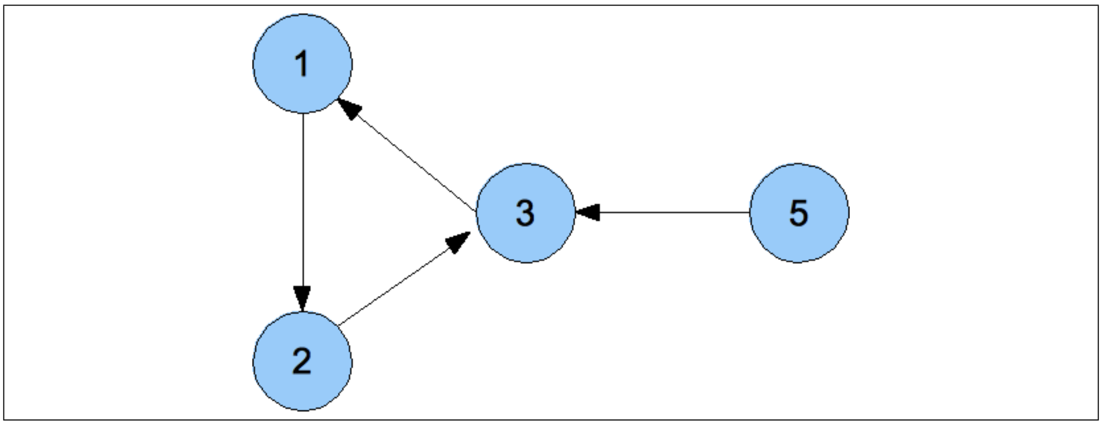


Figure 2.2: Simple loop which act as cycle

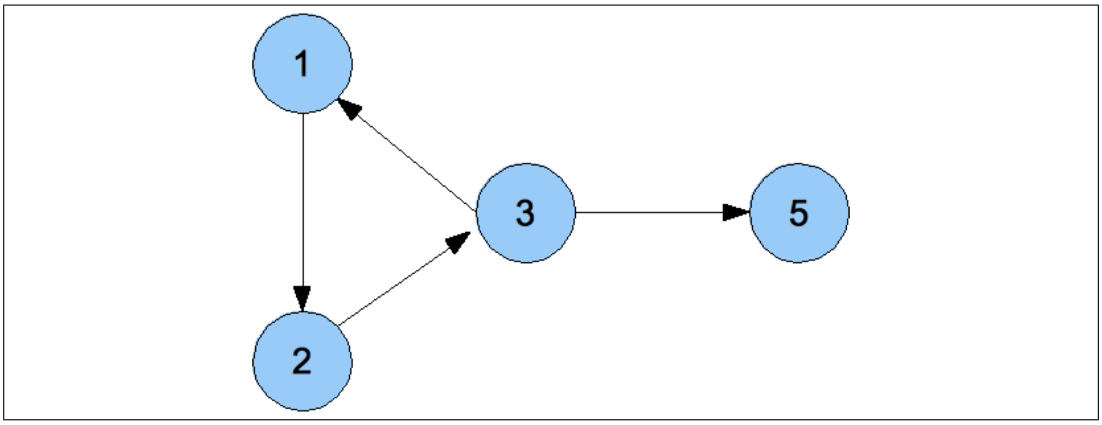


Figure 2.3: Dangling node

2.2.4 Damping Factor

$$R_{k+1}(u) = \frac{1-d}{N} + d \sum_{v \in B_u} \frac{R_k(v)}{N_v} \tag{2.3}$$

In order to solve cyclic and dangling node problem, a new concept of damping factor, constant d as in Figure 2.3 was introduced by Page *et al*. Damping factor is the probability that will help random surfer at any step to continue to any another node not in the path. It also known as teleportation factor. The damping factor is subtracted from 1 and divided by number of nodes, N for normalisation. Different value of damping factor have been studied by various studies [2, 4, 19], but normally the damping factor will be set to 0.85. Suppose $d = 0.85$, then 85% of the time the random surfer follows the hyperlink structure and the remaining 15% of the time the random surfer will teleport to a new page. The convergence of PageRank calculation

also sensitive to the setting of damping factor parameter. Generally if damping factor is set too big, it will take longer time to reach convergence but result in the site's total PageRank growing higher. Since there is little damping (1 - d), PageRank received from external pages will be passed around in the system. If d value is too small it will converge earlier but the relative PageRank will be determined by PageRank received from external pages rather than the internal link structure [12]. We can see the effect of d on expected number of power iteration in Table 2.1 as follows.

d	Number of Iterations
.5	34
.75	81
.8	104
.85	142
.9	219
.95	449
.99	2,292
.999	23,015

Table 2.1: Effect of d on expected number of power iterations. Source:[12]

2.2.5 Relation to Twitter

How are we going to relate Random Surfer Model and damping factor in Twitter domain? We need to change from analogy of random walking to randomnly add new user to be followed. First method to add new user to be followed is to browse through other user from the list either follower list or followee list The second method is to search for specific user or we can search by trends. The third method is through Twitter wall. Every Twitter user has a Twitter wall displaying tweets stream from the people they followed. It really look like a river stream of tweets and sometimes can be analogy as people writing graffiti on public toilet wall. On this wall, user can see tweets have been retweeted and this might trigger the interest user to follow the followee who tweets is being retweeted interestingly enough to be followed. It is like a word of mouth concept. If our tweets is being circulated and spread, there is a high probability that our follower will grow too.

2.2.6 Convergence criterion

The criteria for convergence or iteration termination is when the value of PageRank is stable, but how are we going to determine it is stable? Ideally, it is stable when sum value of difference in PageRank value reach zero, $\sum \|R_{k+1} - R_k\| == 0$. We should note the absolute value of the difference between R_{k+1} and R_k. In real world implementation, social graph is full of cyclic and dangling problem, thus, it will quite difficult to reach zero. That is why the termination criteria of iteration is setup to some tolerance, t value $\sum \|R_{k+1} - R_k\| < t$. For Google, 3 significant digit accuracy or t = 0.001 is used for calculating PageRank. This degree of accuracy is apparently adequate for Google's ranking needs. Haliwala conducted experiment to verify Google decision for t value setting and the the result shows that the exact value of PageRank are not important as as the correct rank ordering [8]. Rank ordering between two rankers can be compared using a measure such as Kendall's Tau [7].

2.3 Hadoop MapReduce

Google came out with Google File System (GFS) in order to deal massive web data and implement MapReduce paradigm based on C++ to calculate PageRank in parallel and distributed manner but this software is a proprietary system [5]. However, Hadoop is a free distribution opensource framework based on Java by Apache Group and funded by Yahoo! for running applications in reliable, scalable and distributed computing [9]. The Hadoop framework transparently provides applications both reliability and data motion. It implements a computational paradigm named MapReduce, where the application is divided into many small fragments of work, each of which may be executed or re-executed on any node in the cluster. In addition, it provides a distributed file system (HDFS) that stores data on the compute nodes, providing very high aggregate bandwidth across the cluster. Both MapReduce and the distributed file system are designed so that node failures are automatically handled by the framework.

2.3.1 HDFS

HDFS stands for Hadoop Data File System and it is a cloud storage platform provides high throughput access to application data. HDFS can handle large data, usually more than 1 TeraBytes and even can handle PetaBytes. The most efficient data processing pattern is write once and read many times pattern; which HDFS is built around this idea

and this made HDFS could handle streaming data access very well. Usually, a dataset is generated or copied from source and then many analyses are performed on them over time. Each analysis will involve a large portion, so the time to read the whole dataset is more important than the latency in reading the first record. Hadoop also does not require expensive and highly reliable hardware in order to run. It's design to run on clusters of commodity hardware and vendor independent. The chance of node failure across the cluster is high at least for large clusters. Thus, HDFS is design to carry on working without a noticeable interruption to the user in the face of such failure [18].

On the other hand, it is also worth to mention that HDFS is not good in the following situation. First, applications that require low-latency access to data, in the ten of miliseconds range, will not work well with HDFS because HDFS is optimized for delivering high throughput of data. This may be at the expense of latency. Second, HDFS is not suitable for lots of small files. Namenode is the master machine that serve data file to processing machines (workers) can holds file system metadata in memory but the limit to the number of file system is controlled by the amount of memory on the namenode. A block takes out about 150 bytes, so if we have one million small files, each taking one block, we will need at least 300MB of memory. Storing millions small files is feasible but billions is not supported by current hardware [17].

2.3.2 MapReduce

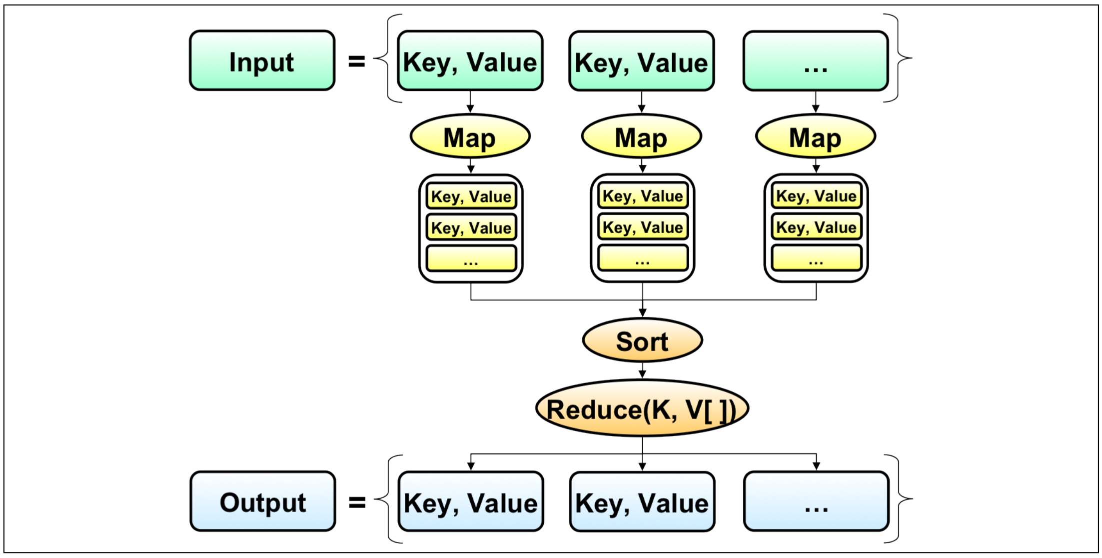


Figure 2.4: MapReduce flow. Source: [9]

MapReduce is a software framework for distributed processing of large data sets

on computer clusters. As we can see in Figure 2.4, MapReduce consists of two parts: map and reduce phase, hence the name MapReduce. Each phase has key-value pairs as input and output. The input will be split into key-value pairs before go to map function. In map phase it will produce new set of key-value pairs. For each distinct key, it will be processed by reduce function. In reduce function it will produce one key-value pair for each distinction key. Finally, the final output will be a set of key-value pairs. Basic idea behind MapReduce is we will process in parallel manner on each lines in input file.

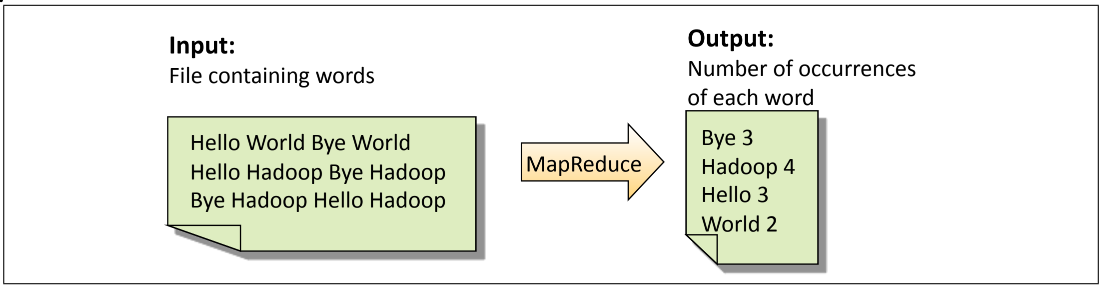


Figure 2.5: MapReduce word count example application

It will be easier to understand MapReduce if we introduce MapReduce with a simple application. A classic example of MapReduce application is word count application. Let say we have input file containing a text like in Figure 2.5. In map phase, we will read the input file, line by line and tokenize the sentences to words. For each every word we met we will output it to next phase as <word,1>. The output from map phase will be shuffle and sort by key before going to reduce phase. In reduce phase, for example word "Bye", the output from map phase is <Bye,1>,<Bye,1> and <Bye,1>. So, in reduce phase we can sum the word occurence and output as <Bye,3>.

In order to use MapReduce, we have to make sure the calculation that we need to run is one that can be composed. That is, we can run the calculation on a subset of the data, and merge it with the result of another subset. Most aggregation or statistical functions allow this, in one form or another. The final result should be smaller than the initial data set. MapReduce is suitable for calculation that has no dependencies external input except the dataset being processed. Our dataset size should be big enough that splitting it up for independent computations will not hurt overall performance.

It also worth to note when it is not suitable to use MapReduce, particularly in following situations. MapReduce is not suitable for online processing. It is more suitable for batch processing. If we need fresh results and quick, MapReduce is not applicable. Trying to invoke MapReduce operation for a user request is going to be

very expensive, and not something that we really want to do. Another set of problems that we cannot really apply MapReduce to are recursive problems. Fibonacci being the most well known among them. We cannot apply MapReduce to Fibonacci for the simple reason that we need the previous values before we can compute the current one. That means that we cannot break it apart to sub computations that can be run independently.

2.4 Related Works

In this section we will review two matters that are related to this dissertation. First, we will look into researches that have attempted to improve efficiency in PageRank calculation. Then, we will discuss on related work that have been done on Twitter data specifically about evolving graphs.

There are two issues need to be addressed in calculating PageRank; accelerating PageRank computation and updating the calculation when the social graph changing because of addition and deletion of social relation. PageRank calculation is based on classical power method which is already known for slow convergence. However, power method is still a favoured method due to limitation of the huge size and sparsity of the web matrix that will constrain the way we can implement it. The next issue is how are we going to efficiently update PageRank vector. The naïve way to update the PageRank vector is to reinitialize and recalculate the whole graph which will be time consuming and wasting computing resources. Many attempts have been done to accelerate PageRank calculation but basically it will break down to two ways. We can either reduce the works per iteration or reduce the total number of iterations. Normally if we reduce the number of iterations, there will be slightly increase in the works per iteration, and vice versa [12].

Algorithm 2.1 Incremental PageRank algorithm by Desikan *et al.*. Source[6]

IPR(G,V_u,V_c) :-
Step 1 – Initialize the list V_Q
Step 2 – Pop a Vertex N from V_c
 2.1 For all the children of N
  if children of N$\in$ list V_u
   remove them from V_u
   push them in V_c
 2.2. Push N in V_Q and repeat step 2 till
   queue V_c is empty
Step 3 – For each element in list V_u
 3.1 Take the element and scale the
  previous pagerank value to get new
  pagerank value.
 3.2 Look up whether any of the children, of the
 element of V_u belong to V_Q, if so remove this
 element of V_u, copy it in V_b.
Step 4 – Scale Border Nodes in V_b for stochastic
  property
  Perform Original PageRank($V_Q \cup V_b$)

v_b = Vertex on the border of the left partition from which there are only outgoing edges to the right partition.
v_{ul} = vertex on the left partition which remains unchanged
The set of unchanged vertices can be represented as, $V_u = \{v_u, \forall v_u \in V\}$where v_u is a vertex which has not changed.
v_{ur} = Vertex on the right partition which remains unchanged, but whose PageRank is affected by vertices in the changed component.
v_{cr} = Vertex on the right partition which has changed, or has been a new addition.
$V_{ur} = \{v_{ur}, \forall v_{ur} \in V\}$
$vV_b = \{v_b, \forall v_b \in V\}$
$V_{Q=}V_c \cup V_{ur} \cup V_b$

In attempt to reduce the number of iterations, Desikan *et al.* [6] introduced incremental method to compute Pagerank over evolving graphs. The hypothesis behind this work is the changes in web graphs is slow, with large parts of it remaining unchanged, so we can develop algorithm to calculate PageRank incrementally. In the initial stage, the PageRank must be calculated in normal way; using power method. Later when there are new links, the old graph will be compared with the new graph. The key idea behind Incremental PageRank is to partition the new graph into two main parts. The first part consists of unchanged nodes from previous graph and the second part is contained with changed nodes together with affected nodes. The PageRank value for the first part will be rescaled while PageRank value for second part will be recalculated in iterative method. The number of iterations to calculated the updated graph is reduced by eliminating unchanged nodes from going to recalculation with

power method.

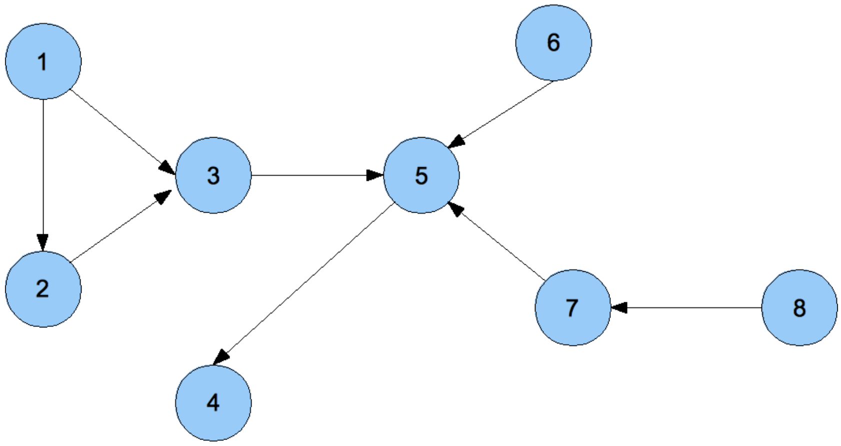


Figure 2.6: Before graph

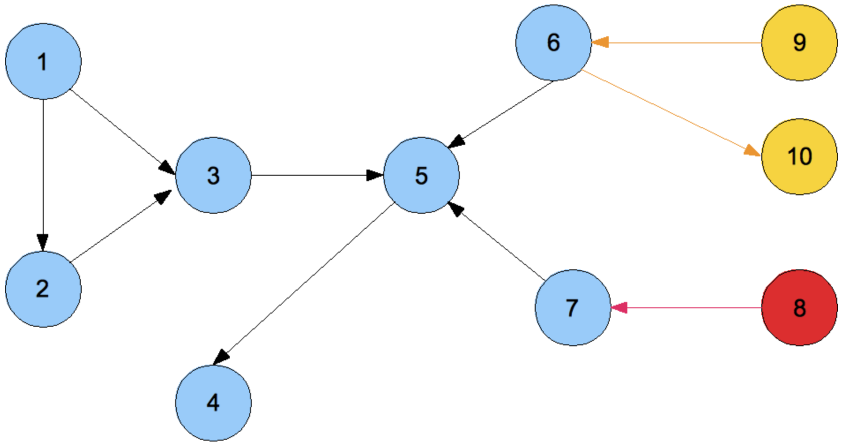


Figure 2.7: After graph

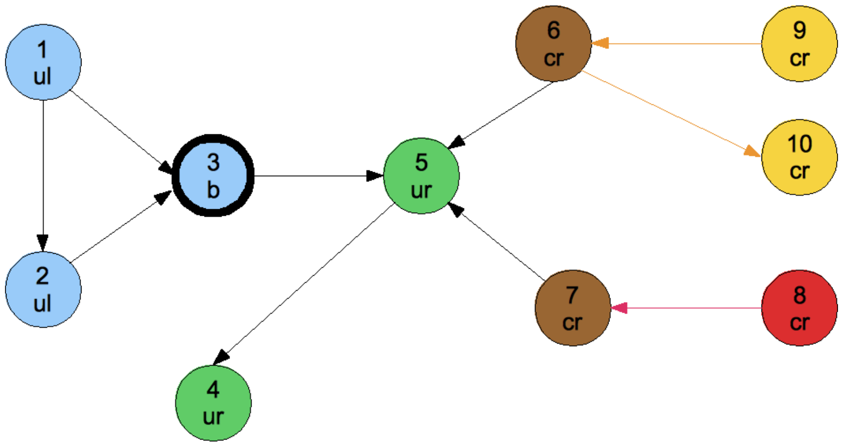


Figure 2.8: Tagging the graph

As a working example we will start from Figure2.6 where we have 8 nodes. Then after some times, the graph changed as in Figure 2.7 where we added node 9 and 10 and delete node 8. In Incremental PageRank we will tag the node as in Figure 2.8 before we partition it. We will start from new and deleted node and find all descendant of it using Breadth-First Search algorithm. Node 6 and 7 are categorised as changed node because node 6 added new inlink while node 7 lost an inlink. We also will find all descendant for these two nodes. Node 5 and 4 are unchanged node but it will be recalculated because their PageRank value is contributed by changed nodes, node 6 and 7. Node 3 will go to recalculation stage but will not be recalculated. Node 3 needed in recalculation stage because node 3 contributed to PageRank value for node 5. Node 1 and 2 wil just be scaled and will not go to iterative recalculation stage because they are unchanged and not descendant of changed node.

Incremental PageRank was experimented by Desikan *et al.* with small dataset which is just a departmental university website that only need at most 12 iterations if the PageRank vector is calculated in naïve way. The result of experiment shows that if the changes between old graph and new graph is less than 5% the number of iterations needed to recalculate is about 30% - 50% less than naïve way. However, if the changes is more than 50%, it only can save 2 iterations out of 12 iterations. The good thing about this method is the PageRank value is exactly the same compared to naïve update. On the other hand, the problem with this method is if there is a new node pointing to a node that large number of descendants. It will create a ripple effect and will bring all descendants to iterative stage. Let say the nodes have a million connected to it and later on it just add one new node. The addition will not affect that much on current PageRank but the effort taken to recalculate the PageRank is so big.

Lin and Schatz managed to reduce works per iteration by 69% using Hadoop framework and implemented design pattern called "Schimmy" for calculating PageRank on Carnegie Mellon University ClueWeb09 collection of web graph with 1.4 billion edges in [13]. The size of collection is coincidentally similar to Twitter data by Kwak *et al.* in [11]. Schimmy is a combination of the authors' name, Schatz and Jimmy. The idea behind this Schimmy design pattern is message passing. The message passing design pattern is claimed to address issue in existing best practices for MapReduce graph algorithms that have significant shortcomings which limit performance, especially with respect to partitioning, serializing, and distributing the graph. Typically, such algorithms iterate some number of times, using graph state from the previous iteration as input to the next iteration, until some stopping criterion is met.

Lin and Schatz explained that in the basic PageRank algorithm implementation in Hadoop MapReduce framework, there are two separate dataflows from mappers to reducers. First, messages passed from source to destination vertices and then the graph structure itself. By emitting each vertex's structure in the mapper, the appropriate reducer receives messages destined for that vertex along with its structure. This allows the reducer to perform a computation and to update the graph structure, which is written to disk for the next iteration. Since the algorithms such as graph partitioning and breadth first search are iterative and require multiple MapReduce jobs, it is highly inefficient to shuffle the graph structure between the map and reduce phases. Frequently, the output in reducers much larger than in mappers because it includes graph structure with metadata and other state information.

The main idea behind the schimmy design pattern is the parallel merge join. Suppose the input key-value pairs representing the graph structure were partitioned into n files (i.e., parts), such that $G = G_1 \cup G_2 \cup ... \cup G_n$, and within each file, vertices are sorted by vertex id. The same partition function will be used as the partitioner in MapReduce graph algorithm, and the number of reducers is equal to the number of input files (i.e., parts). This guarantees that the intermediate keys (vertex ids) processed by reducer R_1 are exactly the same as the vertex ids in G_1; the same for R_2 and G_2, R_3 and G_3, and so on up to R_n and G_n. Since the MapReduce execution framework guarantees that intermediate keys are processed in sorted order, the corresponding R_n and G_n parts are also sorted in exactly the same manner. The intermediate keys in R_n represent messages passed to each vertex, and the G_n key-value pairs comprise the graph structure. Therefore, a parallel merge join between R and G suffices to unite the result of computations based on messages passed to a vertex and the vertex's structure, thus enabling the algorithm to update the vertex's internal state. They managed to eliminate the need to shuffle$G$ across the network. With the MapReduce implementation of PageRank using the schimmy design pattern, there is no need to emit the graph structure in the map phase of processing. Thus, we can reduce work by per iteration for calculating PageRank.

Previously, studies involving evolving graphs rely heavily on small dataset and sometimes synthetic dataset due to lack of access to big public dataset. Now, researchers especially social media analysts can crawl Twitter data via Twitter API and do research on evolving graphs. Kwak *et al.* managed to crawl the entire Twitter user profiles as until June 31st, 2009 and did the first quantitative study on the entire Twittersphere and information diffusion on it [11]. Kwak *et al.* compared three ranking

methods to rank Twitter users. First they rank by number of follower, then PageRank and followed by retweet.

The results shows that there is big difference in ranking of Twitter user when ranking results are compared. In other words, if the user has many followers, it will be reflected in PageRank value, but if the user has high number of follower and PageRank value it will not be reflected in their tweets will be retweeted by those who subscribed to their tweets. They also found out that following is not so mutual among Twitter users as the result shows only 29% of Twitter user followed each other. This is because Twitter used “I follow you” concept rather than “We are friend” like in Facebook and MySpace. In its follower-following topology analysis they have found a non-power-law follower distribution, a short effective diameter, and low reciprocity, which all mark a deviation from known characteristics of human social networks [14].

In [11], other than ranking, the authors also analyzed the tweets of top trending topics and reported on the temporal behavior of trending topics and user participation. They classify the trending topics based on the active period and the tweets and show that the majority (over 85%) of topics are headline or persistent news in nature. A closer look at retweets reveals that any retweeted tweet is to reach an average of $1,000$ users no matter what the number of followers is of the original tweet. Once retweeted, a tweet gets retweeted almost instantly on the 2nd, 3rd, and 4th hops away from the source, signifying fast diffusion of information after the 1st retweet.

Kwak *et al.* did not mention how they processed the 1.47 billion following relations in [11] nor how they did the PageRank calculation. Information like how many iterations until the PageRank vector converged and the epsilon threshold are also not available for us to compare. We decided to compare the top 10 Twitter users in their report with our result as a cross-checking to evaluate our method since we are going to use the data made available by them. The result might be different because of the choice of epsilon threshold parameter to terminate the iteration in power method. In addition, the result will be different if the method to calculate PageRank is either approximation or exact value method.

Chapter 3

Incremental+ PageRank

3.1 Approach Proposal

Desikan *et al*. incremental method [6] can be implemented with Hadoop environment with a challenge. The challenge is to find all the nodes affected if addition or deletion of nodes occured. Again we will use iterative approach such breadth-first search to find all the descendants of changed nodes. This is the overhead of the method in exchange of less iteration in power method.

We proposed a solution that can maximised the benefit of incremental method. All Twitter users with a large number of follower will not be recalculated in iterative stage even though there is new follower following them except if the changes is more than the threshold that we have set.

For example, we will set the threshold to 1% and if user A has 10,000 and in later stage user A has 10,050 or 9,550 followers, we wil not recalculate PageRank for this particular Twitter user. We will only recalculate if and only if the changes is at least to 11,000 or 9,000. We also will not bring all the descendants to the recalculation stage. This additional step will help us to reduce the number of iterations.

For naming convention, Desikan *et al*. original incremental method [6] will be just called Incremental method and our incremental method with threshold will be called Incremental+ (pronounce incremental plus).

3.2 Hypotheses

3.2.1 First Hypothesis

H_0^1 : Mean time per iteration to calculate PageRank is same for every method.
H_a^1 : At least there is one method is different in mean time per iteration to calculate PageRank based on methods.

3.2.2 Second Hypothesis

H_0^2 : At least one of the methods will not produce the same ranking result for Twitter user.
H_a^2 : All the methods to calculate PageRank will produce the same ranking result for Twitter user.

Chapter 4

Experimental Framework

This chapter outlines various experimental settings. The conceptual designs of the experiments come from a number of decisions which are also discussed. We firstly introduce the main dataset and explain experiment procedure in a calculating PageRank with naïve, Desikan *et al*. Incremental PageRank and our version of incrementally PageRank with treshold methods. Finally we discussed evaluation methods.

4.1 Hadoop Cluster

We are so lucky to to process 1.47 billion following relation data and run our experiments on a Hadoop Cluster . This Hadoop Cluster is belong to Statistical Machine Translation Group of University of Edinburgh. This cluster has 8 working datanodes and 48TB of storage with 50GB RAM per node. This cluster is installed with Hadoop version 0.19.2-dev. The number of Mapper is 250 while the number of Reducer is 72. We will run and test our code on local machine before run it on Hadoop Cluster.

4.2 Dataset

Twitter offers an Application Programming Interface (API) that is easy to crawl and collect data. Again, we are so lucky to have Twitter user profiles already available for processing. This data was crawled by social media analyst research group from Korean Advanced Institute of Technology KAIST). They published a paper on Twitter tweets stream analysis and Twitter user topological relation graph and ranking in [11]. This data is available for public download at http://an.kaist.ac.kr/traces/WWW2010.html.

The file is in the following format: USER \t FOLLOWER \n. (\t is tab and \n is newline). USER and FOLLOWER are represented by numeric ID (integer) and same as numeric IDs Twitter managed. So we can access a profile of user 123 via http://api.twitter.com/1/users/show.xml?user_id=123.

Example of data:

```
1   2
1   3
2   4
```

Based on example above, 1 is following 2 and 3 while 4 is followed by 2. In order to collect user profiles, Kwak *et al*. began with Perez Hilton who has over one million followers and crawled breadth-first along the direction of followers and followings. Twitter rate limits id 20,000 requests per hour per whitelisted IP. Using 20 machines with different IPs and self-regulating collection rate at 10,000 requests per hour, they collected user profiles from July 6th to July 31st, 2009. Overall there are 147 compressed files with cumulated size of 8GB.

4.3 Data Preprocessing

There are 1.47 billion of following relations and sorted in ascending or by follower id. In order to emulate incremental environment we have to partition the data into three parts. The data does not consists of history of when the relation is created. If we have we can easily divided the data according to date that we will set date as threshold. Unfortunately we do not have that information, therefore, we will randomly shuffle the position of sorted data before we group into parts. First part is unchanged relations, then the second part will consists of additional relations followed by third part which contains deleted relations. Randomness is very important to make sure it emulates real world application where Twitter user will follow based on other follower or followee list and will unfollow whomever they feel to unfollow.

There is no official report about the user retention and how fast is Twitter user growing. There is an unofficial online report[1] stating that the user retention is around 40% but this is just approximation and not very reliable to be ground foundation for our decision. We decided to use classical Pareto Distribution[2] or also known as 80-20 rule. The data will be divided to 80% unchanged and 20% changed. The 20% part is consists

[1] http://blog.nielsen.com/nielsenwire/online_mobile/twitter-quitters-post-roadblock-to-long-term-growth/

[2] http://en.wikipedia.org/wiki/Pareto_distribution

of 15% of new following relations while the remaining 5% is for deleted relation. We will have two different final experiment datasets for the purpose of repetition and avoid bias and skewed result. It is also important to avoid overfitting.

4.4 PageRank variable setting

$$R_{k+1}(u) = \frac{1-d}{N} + d \sum_{v \in B_u} \frac{R_k(v)}{N_v} \tag{4.1}$$

$$R_o(v) = \begin{cases} 1 & , v \in B_u \neq 0 \\ \frac{1-d}{N} & , v \in B_u = 0 \end{cases} \tag{4.2}$$

We will use PageRank formula based on Random Surfer Model with power method as in Figure4.1. We will set damping factor, $d = 0.85$ and iteration termination threshold ε = 0.0001. This setting is based on normal setting by other experiments like in [15, 8][15, 8]. At initial stage or iteration $k = 0$, we will set initial PageRank value, $R_0(v) = 1$ and $R_0(v) = \frac{1}{N}$ if the node does not have any inlinks as in Equation 4.2. The reason for setting $R_0(v) = 1$ for any other nodes with inlinks is on assumption that the Twitter user has at least one follower. We do not set nodes with inlinks with $\frac{1}{N}$ as suggested in [12] because our N is so big as in million and the value will too small. The main reason for setting $R_0(v) = \frac{1-d}{N}$ for node without any inlinks is to help our PageRank calculation to meet the convergence quicker because the value will not change after first iteration.

4.5 Experiment Procedures

4.5.1 The Before Graph

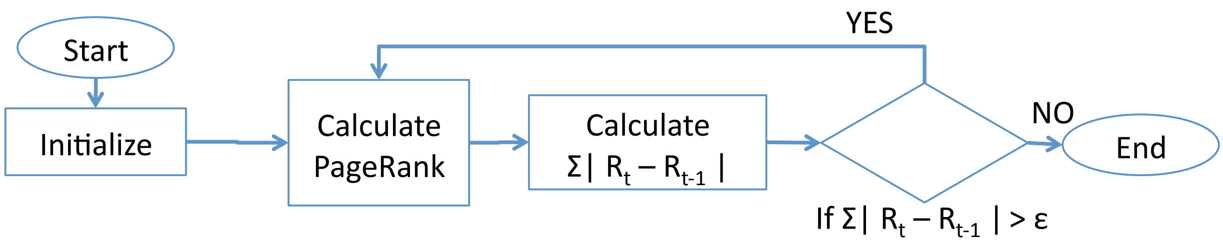


Figure 4.1: PageRank calculation workflow using naïve method.

Algorithm 4.1 MapReduce algorithm for naïve method.

```
1.  Initialize
1.1 Map
1.1.1 Input :   k:  follower  \t  v:  followee
1.1.2 Output:
 k:  follower    v:  followee
 k:  followee    v:  follower
1.2 Reduce
1.2.1 Output: k:  follower  \t  v:  old PageRank | new PageRank | outlinks
2.  Calculate PageRank
2.1 Map
2.1.1 Input: k:  follower  \t  v:  old PageRank | new PageRank | outlinks
2.1.2 Output:
 k:  follower    v:  old PageRank | outlinks
For every outlinks:
 k:  followee    v:  new PageRank=(0.15/N) + (0.85*old PageRank)
2.2 Reduce
2.2.1 Output: k:  follower  \t  v:  old PageRank | new PageRank | outlinks
3.  Calculate Total Residual
3.1 Map
3.1.1 Input: k:  follower  \t  v:  old PageRank | new PageRank | outlinks
3.1.2 Output: k:  difference    v:  new PageRank - old PageRank
3.2 Reduce
3.2.1 Output: k:  total residual  \t  v:  sum of difference
Repeat 2 and 3 until total residual < ε
Note :  k is key, v is value
```

First, we will calculate PageRank value for the graph at time before any changes happen, we call it at time,G_t. We will use Hadoop Map Reduce to compute the PageRank Value. There will be three MapReduce jobs as illustrated in Figure 4.1. In the first job we will read the input in edge list format or also known as following list into adjacency list that will list follower and outlinks or also known as followee list. We also initialise the PageRank value as in Equation 4.2. The output from reducers in initialisation stage will be input in the next job to calculate PageRank value. It is also worth to note that we should use BigDecimal type when we calculate PageRank value instead of float or double value type, because there is accuracy issue in Java float and double type especially in division operation. We just use BigDecimal as for calculation

but we still output it as Text to next job. In the next job we calculate the absolute value of difference between previous PageRank and current PageRank in the map phase and in the reduce phase we will sum the value. In the next step we use unix shell command to check whether the sum is greater or smaller than ε value. If the sum value is less than ε, then we will stop the iteration otherwise we keep calculate the PageRank value until it reach termination criterion. It is a good practice to delete output from previous iteration so that our server will not get full by temporary results. Another good practice is to use Hadoop MapReduce -mv (move) shell command instead of -cp (copy) before take one ouput from previous job as input in another job.

4.5.2 The After Graph

4.5.2.1 Baseline

In the next step we calculate the PageRank value for the graph at after changes happen, we call it at G_{t+1}. As a baseline for comparison with other methods, we will calculate the PageRank value same way we calculate the PageRank value for the graph at G_t. We will record the number of iterations and time to complete.

4.5.2.2 Incremental PageRank

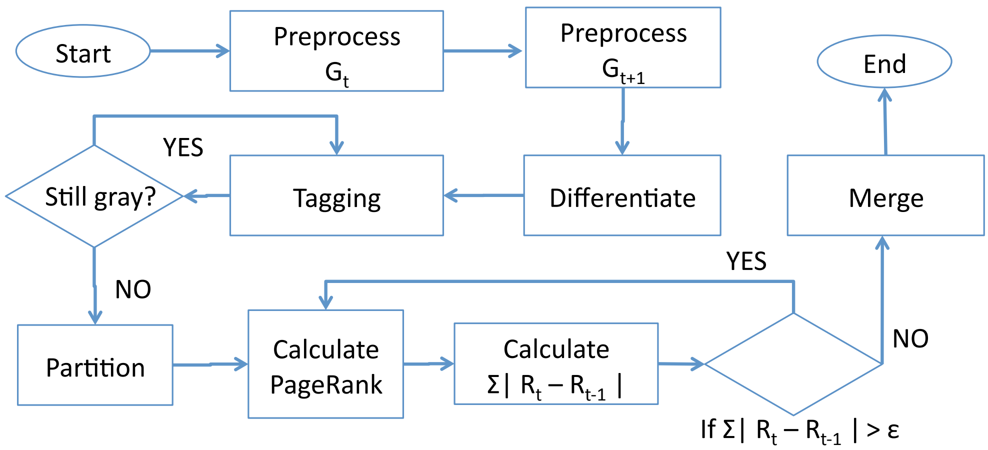


Figure 4.2: PageRank calculation workflow using incremental method

Algorithm 4.2 MapReduce algorithm for Incremental method : Part A

```
1.  Preprocess before graph
1.1 Map
1.1.1 Input: k:  follower  \t  v:  old PageRank | new PageRank | outlinks
1.1.2 Output:
 k:  follower  \t  v:  old PageRank | new PageRank | outlinks
 k:  follower    v:  followee
 k:  followee    v:  follower
1.2 Reduce
1.2.1 Output:
 k:  follower  \t  v:  old PageRank | new PageRank | outlinks | inlinks
note :outlinks and inlinks must be sorted
2.  Preprocess new graph
2.1 Map
2.1.1 Input :   k:  follower  \t  v:  followee
2.1.2 Output:
 k:  follower    v:  followee
 k:  followee    v:  follower
2.2 Reduce
2.2.1 Output:
 k:  follower  \t  v:  old PageRank | new PageRank | outlinks | inlinks
note :outlinks and inlinks must be sorted
3.  Differentiate graphs
3.1 Map
3.1.1 Input :  output from 1.2.1 and 2.2.1
3.1.2 Output:
if new node:
 k:  follower  \t  v:  gray | old PageRank | new PageRank | outlinks | inlinks
else if no changes in both dataset:
 k:  follower  \t  v:  white | old PageRank | new PageRank | outlinks | inlinks
else if has changes in either dataset:
 k:  follower  \t  v:  gray | old PageRank | new PageRank | outlinks | inlinks
continue with Algorithm 4.3
```

Algorithm 4.3 MapReduce algorithm for Incremental method: Part B

```
4.  Tagging
4.1 Map
4.1.1 Input:
 k:  follower  \t  v:  color | old PageRank | new PageRank | outlinks | inlinks
4.1.2 Output:
if gray:
for every outlinks:
change color to gray
for every inlinks:
change color to red
 k:  follower  \t  v:  black | old PageRank | new PageRank | outlinks | inlinks
else:
 k:  follower  \t  v:  color | old PageRank | new PageRank | outlinks | inlinks
4.2 Reduce
4.2.1 Output
 k:  follower  \t  v:  color | old PageRank | new PageRank | outlinks | inlinks
repeat 4 until no more gray
5.  Partition
5.1 Map
5.1.1 Input:
 k:  follower  \t  v:  color | old PageRank | new PageRank | outlinks | inlinks
5.1.1 Output:
if white and red:
save in partition A
else if black and red:
save in partition B
6.  Recalculate black node but maintain red node using Algorithm 4.1
until total residual < ε
7.  merge partition A and output from step 6
```

We will continue our experiment with calculation PageRank for G_{t+1} using incremental method suggest by Desikan *et al.* in [6]. We illustrated the process for incremental method as in Figure 4.2. The difference between naïve and incremental method is the extra overhead work need to be done before enter the calculation stage. We will start with preprocess graph G_t and G_{t+1}. In preprocessing stage, graph G_{t+1} will be converted from edge list to adjacency list with outlinks and inlinks. Output from

converged PageRank vector for G_t also will be converted to adjacency list of outlinks and inlinks. It is worth to note that in Hadoop MapReduce, only the key will be sorted but the values are not. Sometimes output from MapReduce job will be 1\t2,3,4 and sometimes it will output as 1\t3,4,2 (\t stands for tab). Therefore if we are going to do comparison the system will say that this two list are not the same but in fact they are the same list. So we have to make sure the order of outlinks and inlinks are the same.

Next, we will differentiate this two graphs. In Hadoop MapReduce we can compare two different datasets by setting the input parameter for MapReduce job as CompositeInputFormat class and set join expression to outer join. The reason we use outer join is to detect any missing or new record compared to the graph G_t. In differentiating stage, we will check if the record is not exist in before graph, we will tag it as new record and set the initial PageRank value as in Equation 4.2. If the record is appear in both graph and the number of outlinks and inlinks are same, we will output as it is, but if there is different in the number of outlinks or inlinks we will output to next stage with previous PageRank value and latest outlinks and inlinks list. By doing this, the calculation we be faster to converge as we use previous PageRank value to calculate. All the previous PageRank value will be rescaled (previous PageRank value multiply the number of nodes in previous G_t and then divide by the number of nodes in G_{t+1}). All nodes will be tag with either gray color or white. Color gray is for new nodes and changed nodes while white is for unchanged nodes.

After that we will continue to the tagging stage. In tagging stage we will start with all nodes tagged with gray color will be processed and changed to black color and subsequently changed the color of nodes in its outlinks to gray color too and the nodes in its inlinks will be changed to red color to remark as border nodes. In the next iteration it will do the same until there is no more gray color left. In Hadoop MapReduce we keep track the number of gray nodes with Custom Counter class. All white nodes will be remained as it is.

We will continue to partition all the white and red nodes as one output and we do not have to do recalculate this partition as we already rescaled the PageRank value in preprocessing stage. All the black nodes and red nodes will go to recalculation stage. The reason we bring the red nodes is because this nodes are contributing to black nodes PageRank value, but we do not recalculate the value of red nodes themselves. After convergence, we will merge the output from the partitioned output and the output from this stage as final PageRank vector output.

4.5.2.3 Incremental+ PageRank

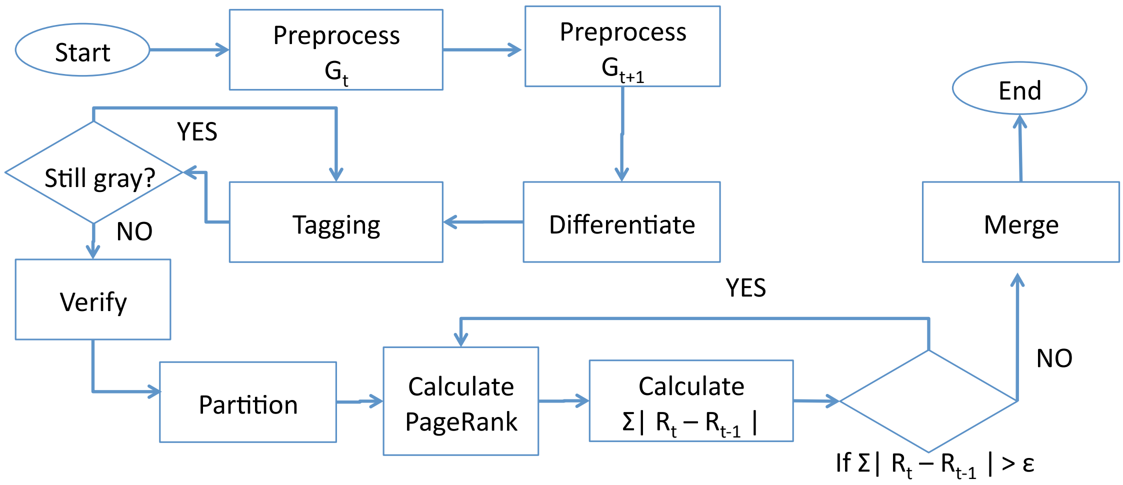


Figure 4.3: PageRank calculation workflow using incrementa+l method

Algorithm 4.4 MapReduce algorithm for Incremental+ method

```
1.  Follow all step in Algorithm 4.2 and continue with step 4 in
Algorithm 4.3
2.  Verify
2.1 Map
2.1.1 Input :  output from 1.2.1 from Algorithm 4.2 and 4.2.1 from
Algorithm 4.3
2.1.2 Output:
if descendant of changed node && black && no new outlink && number of new
inlinks less than threshold:
change to white and save to partition A
else:
remain color and partition accordingly
3.  Recalculate black node but maintain red node using Algorithm 4.1
until total residual < ε
4.  merge partition A and output from step 3
```

The next step is to run experiment using our version of incremental PageRank update with threshold method also known as Incremental+ method. All the step is same with Desikan *et al*. method but we add extra stage. After tagging stage, we will find

all nodes tagged as black color and the number of outlinks is the same with previous graph. The reason it must be nodes with same number of outlinks from previous state is it will not point to any new node that need it as border node for recalculation purpose. Then we check if the number of inlinks is changed either less or more compared to previous graph. If the new addition is bigger than threshold percentage, let say 10% of the number of inlinks in previous graph, we will remained the color tag as black and recalculate the PageRank value for the node. Otherwise, we change change the color to white and do not need to recalculate the PageRank for the particular node. The reason we do not incorporate this in tagging stage is because tagging stage is an iterative mode. By separating the process we will just run it once, thus we can save the computation time. As we just approximate the verified node with previous and scaled PageRank value, we will calculate the mean squared error compared to the actual value of PageRank calculated using naïve method.

4.6 Evaluation Methods

We will discuss about the methods we used to evaluate our method for calculating PageRank. We will look into two perspectives. First, how efficient is our method based on time cost and workload. Then we will look into how effective is our method. We will use Root Mean Square Error (RMSE) and Kendall's Tau coefficient to measure the effectiveness of our method.

4.6.1 Efficiency

We need to measure how our method can save time and reduce workload when calculate PageRank value compared to other methods.

4.6.1.1 Time cost

We have three methods to compare so we used ANalysis Of VAriance between groups (ANOVA) for significant test instead of student-T Test to compare the means of time taken to calculate PageRank per iteration. We will combine the time to finished the job in calculating PageRank and job to calculate the sum of residual at each of every iteration. Sum of residual is the difference between previous rank and current rank. Our first hypothesis null, $H1_0$: all the method took the same amount of time to calculate PageRank per iteration. We will used 5% significance level, so at 5%

significant level if F-ratio > 3.68, we can reject H_0^1 and can say that the time taken to calculate PageRank per iteration is not the same. Then, we will do post-hoc analysis to find which method is the best.

We also used descriptive statistics to compare the three methods. The information that we compared are the time taken to finished the whole process, the number of iterations and used Faster metrics as used by Desikan *et al.* in [6]. The method with the least time taken to finish the whole process of calculating PageRank is considered the best. On the other hand, the method with largest value of metrics Faster is considered the best. Desikan *et al.* defined the metrics Faster to compare how fast if compared to base method as follows.

Number of Times Faster = Number of Iterations for Based Method / (1 + (fraction of changed portion) * (Number of Iterations for Improved Method))

4.6.1.2 Workload

Next, we used information such as how many input going for recalculation and from this information we can derive how many input we can save from recalculation when compared with another method. This is as suggested by Langville and Meyer in [12], in order to measure how many works we reduce per iteration. The best method will have the highest percentage of input prevented to go to recalculation stage. We also will pair with extra overhead cost in order to get the savings, as a penalty measure.

4.6.2 Effectiveness

We also need to measure how accurate our method compared to other methods. The most common measurement for accuracy is Root Mean Square Error while Kendal's Tau coefficient is best for measuring which ranker is the best when compared.

4.6.2.1 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a common statistical tool to measure the differences between values predicted by a model or an estimator and the values actually observed from the thing being modeled or estimated. In our case we will compare the PageRank value computed by Incremental+ with PageRank value computed with naïve method which is the exact or true value. We have to calculate Root Mean Square Error (RMSE) for our version of incremental PageRank because we approximated the PageRank value for the nodes that has no changes in the number of outlinks but

has changes in the number of inlinks, either addition or deletion that is less than the threshold that we set. In our experiments we set our threshold as 10%. If the value is RMSE small or near zero it means we can conclude that our model is a good approximator and effective ranker. The formula for root mean square error is as follows.

$$RMSE(\theta_1, \theta_2) = \sqrt{\frac{\sum_{i=1}^{n} (x_{1,i} - x_{2,i})^2}{n}} \tag{4.3}$$

4.6.2.2 Kendall's Tau coefficient

Kendall rank correlation coefficient, commonly referred to as Kendall's tau (τ) coefficient, is a statistic used to measure the association between two measured quantities. There are few variations of Kendall's Tau formula. We used the simplest formula of Kendall's tau coefficient as follows.

$$K(\tau) = \frac{P - Q}{P + Q} \tag{4.4}$$

P = Number of correctly-ordered pairs

Q = Number of incorrectly ordered pairs

Our second null hypothesis regarding efficiency in ranking are:

H_0^2 :The ranking order of whole Twitter user of our version of incremental PageRank is not the same as ranking order by Desikan *et al*. Incremental PagRank method.

If our Kendall's tau value is equal to 1 for comparison among rankers, then we can reject second null hypothesis and claim that our method produce the same ranking as other methods.

Chapter 5

Experimental Evaluations

In this chapter we present and discuss experimental results based on experimental framework we discussed in previous chapter. Descriptive analysis along two dimensions; efficiency and effectiveness is discussed in the first part. On the second part we present the hypotheses testing results as the ground judgment to evaluate our Incremental+ PageRank method. For naming convention, Desikan *et al*. original incremental method [6] will be just called Incremental method and our incremental method with threshold will be called Incremental+ (pronounce incremental plus).

5.1 Efficiency

5.1.1 Time cost

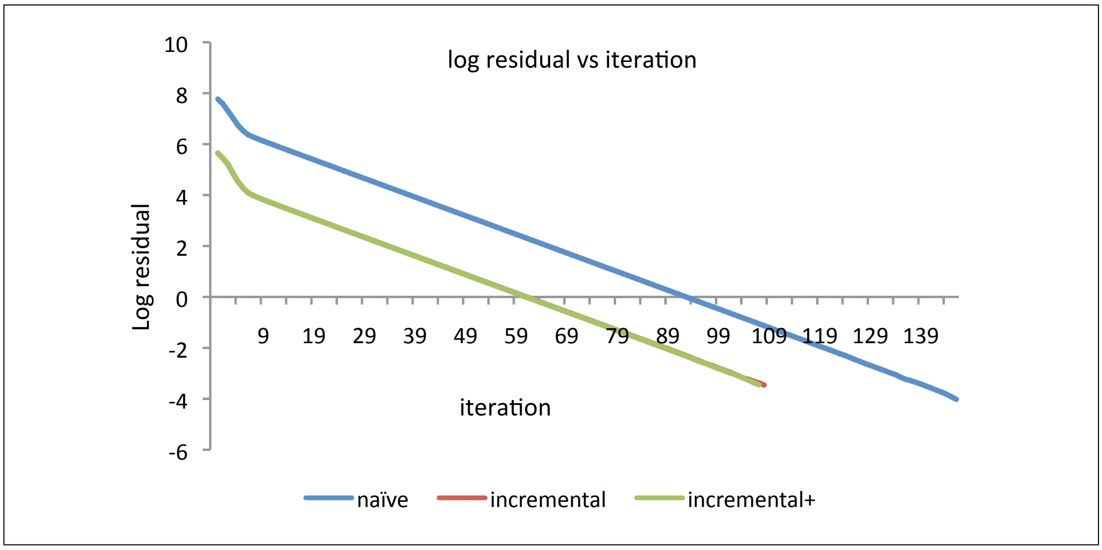


Figure 5.1: Rates of convergence

In dimension of efficiency, we focused our evaluation on the performance of our method based on time cost and task workload. For time cost evaluation, method that took less time to finish the process to produce output is considered as a better method. In addition, the less workload we put on desired task also will produce faster result.

For every method we used to calculate PageRank vector, we plotted the log value of residual for each iteration and present it in Table 5.1. Residual is the total difference of current PageRank from previous iteration. We use log instead of the real value of residual for better visual representation and data analysis. It help us to see how each method reach convergence and the rate of convergence. All methods have faster rate of convergence in first eight iterations and after that it become slower in gradual manner. We can see that naïve method took longer time to converge compared to Incremental and Incremental+ method. Another observation can be made is, if we look closely, Increment+ log residual value is on top incremental method. It shows that the values is very close and we can see only a little red line visible representing Incremental method log residual value. This is because Incremental+ has only less one iteration compared to Incremental method.

Method	Number of iteration	Iteration Saved	Faster
naïve	147	-	-
incremental	109	25.85%	6.45
incremental+	108	26.53%	6.50

Table 5.1: Percentage of iteration saved

We continued our evaluation on how efficient is our method compared to others by looking on how many iteration saved for calculating the PageRank vector as in Table 5.1. We save 26.53% by ommiting the new inlinks that is just too small to contribute to PageRank value for Twitter user that has large number of follower. However, the difference is just 0.68% compared to Incremental method or in other words, we only have one less iteration. The faster column in Table 5.1 is based on Desikan *et al.* metrics to evaluate how fast is the method compared to naïve method. The formula is discussed as in Equation in previous chapter. This formula is not just comparing number of iteration but also incorporated the percentage of changes portion in the graph. This extra effort is to approximate measure to compare the computational cost versus the naïve method.

Method	Time to complete (seconds)	Overhead cost (seconds)
naïve	162,846	1,142
incremental	114,040	8,626
incremental+	116,904	10,562

Table 5.2: Overhead cost for time to complete

Even though there is visible difference in term of reduced number of iteration in power method, we also have to measure how much is overhead cost to get less iteration and less time to complete the task. We present the overhead cost as in Table 5.2. Overhead for naïve method is just to convert from edge list to adjacency list and intialize the PageRank value and it took about 45 hours to calculate PageRank vector. For Incremental method it took 32 hours to complete the task and need to 2.4 hours to differentiate the graphs and partition it before into recalculation stage. Incremental+ need extra 30 minutes compared to Incremental method for verifying and preventing some affected nodes from being into recalculation stage.

Number of iterations for tagging	Time taken for tagging (seconds)	Changed nodes	Affected nodes
10	5,583	221,543	41,567,014

Table 5.3: Ripple effect in incremental method

Next, we look into which component in both incremental and incremental+ method that cost a lot of time based on the overhead cost. Based on result in Table 5.3, more than 50% of overhead cost is contributed by tagging operation, where we find all affected nodes which are the descendants of changed nodes. The tagging stage is based on breadth-first seach algorithm and this algorithm requires iterative implementation. Tagging stage will cause ripple effect or viral effect as we can see that only 22 thousand changed nodes but they are affecting 42 million descendants nodes and it took 10 iterations to tag all affected descendants. The most important observation is for iteration number 7 to 10, it only affecting one node for each iteration. It is such a waste of time and computing resources just to find and tag a single affected node. This is the main danger of incremental method that we should aware of. Maybe we can use the same idea with incremental+ method which is using threshold to improve this

matter in future by stopping the tagging stage when it reach less than certain number of nodes and these nodes also has less than certain number of descendants.

		naïve	incremental	incremental+
Sampel size		147	109	108
Mean		778.67	680.57	683.10
Std. Deviation		78.060	113.970	25.528
Std. Error		6.438	10.916	2.456
Confidence Interval for Mean	Lower Bound	765.95	658.93	678.23
	Upper Bound	791.40	702.21	687.97
Minimum		615	537	640
Maximum		947	1080	770

Table 5.4: Descriptive statistics of time per iteration to calculate PageRank

We further our investigation on performance evaluation by looking into time per iteration to calculate PageRank. PageRank calculation is based on power method and involve many iterations. We would like to know which method will require less time to calculate PageRank vector. The early analysis is by doing descriptive statistics on time per iteration as shown in Table 5.4. Sample size is limited to number of iterations for each method. In this stage, we can judge the performance the performance by looking at the average value or also known as mean value, but we have to do ANOVA if we want to compare the means in more meaningful and statistically significant.

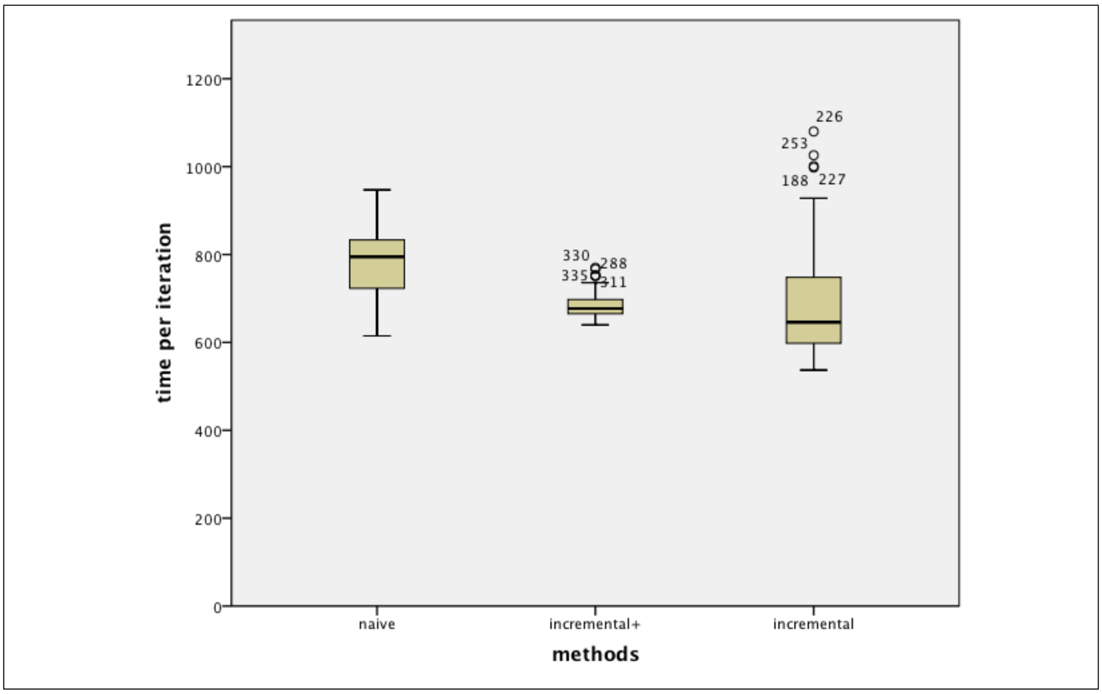


Figure 5.2: Box plot for time per iteration to calculate PageRank

We compared dataset side by side using box plot as in Figure5.2. Box plot is very useful for us to look for early indication about the data symmetry and skewness. This information is very important regarding using ANOVA as method to compare means. We also can spot outliers in the Incremental and Incremental+ time per iteration dataset. Incremental+ has the smallest variance, followed by naïve and Incremental method.

5.1.2 Workload

Method	Number of inputs into recalculation stage	Workload Saved
naïve	41,589,858	-
incremental	41,567,014	0.05%
incremental+	41,500,793	0.21%

Table 5.5: Dataset 1 : Number of input into recalculation stage

In this sub section, we explored the result that contribute to main idea of Incremental+ method. The main idea behind Incremental+ method is to reduce the number of

input into recalculation stage. This is because recalculation stage is an iterative implementation. If we manage to reduce the workload, we will get faster result and this will contribute to efficiency score to our Incremental+ method. Even though the workload saved is less than 1% compared to whole graph, but compared to Incremental method, there is 4 folds increased due to Incremental+ method. The number of input saved is dependent on the ripple effect as we discussed previously.

5.2 Effectiveness

Along dimension of effectiveness, our main objective is to measure how close is our approximation of PageRank value when we use Incremental+ method compared to the actual value of the PageRank calculated using naïve method. In the following table in Table 5.6, we presented some sample node that are approximated using Incremental+ method.

Twitter UserID	PageRank value	
	naïve	incremental+
17850012	7.4785665E-5	7.4577755E-5
12687952	1.19557885E-4	1.18717405E-4
16409683	1.9018753E-4	1.89662145E-4
14224719	2.6821515E-4	2.66313615E-4
813286	3.35394135E-4	3.34627945E-4

Table 5.6: Comparison of sample PageRank value for naïve and Incremental+ method

In this stage, we can say that the difference of PageRank value between Incremental+ and naïve in the sample above is very small. In order to find more about how far the deviation between result from these two methods, we calculated the Root Mean Square Error as shown in Table 5.7.

Number of Nodes	Number of nodes PR approximated	Percentage	Root Mean Square Error
41,589,858	66,221	0.16%	1.23693E-9

Table 5.7: Root Mean Square Error

As we can see in Table 5.7, the Root Mean Square Error is indeed very small, near to zero. Therefore, we can conclude that our Incremental+ method is very effective to calculate PageRank because the approximation is really close to the result from naïve method and deviation as shown in Root Mean Square Error is very small.

5.3 Hypotheses Testing

5.3.1 First Hypothesis Testing

Based on Table 5.4 and Figure 5.2 we can say that there is visible difference in time per iteration but we have to test whether the difference is statistically significant. Our first hypothesis is regarding efficiency in calculating PageRank based on methods we tested in the experiments. The null hypothesis and alternative hypothesis is as follows.

H_0^1 : Mean time per iteration to calculate PageRank is same for every method.

H_a^1 : At least there is one method is different in mean time per iteration to calculate PageRank based on methods.

We used one-way ANOVA to compare the means because we have more than two groups to compare, rather than using multiple pair-wise t-test in order to minimize Type-I Error. In order to use ANOVA, these following conditions must be met first, so that our result and conclusion are valid. The first condition is that the data for each group of method we tested must come from a normal distribution. We used The Kolmogorov-Smirnov test to see whether our data come from normal distribution and the result is as following.

Methods	Statistics	Degree of freedom	Significance Level
naive	0.102	147	0.01
incremental	0.144	109	0.00
incremental+	0.141	108	0.00

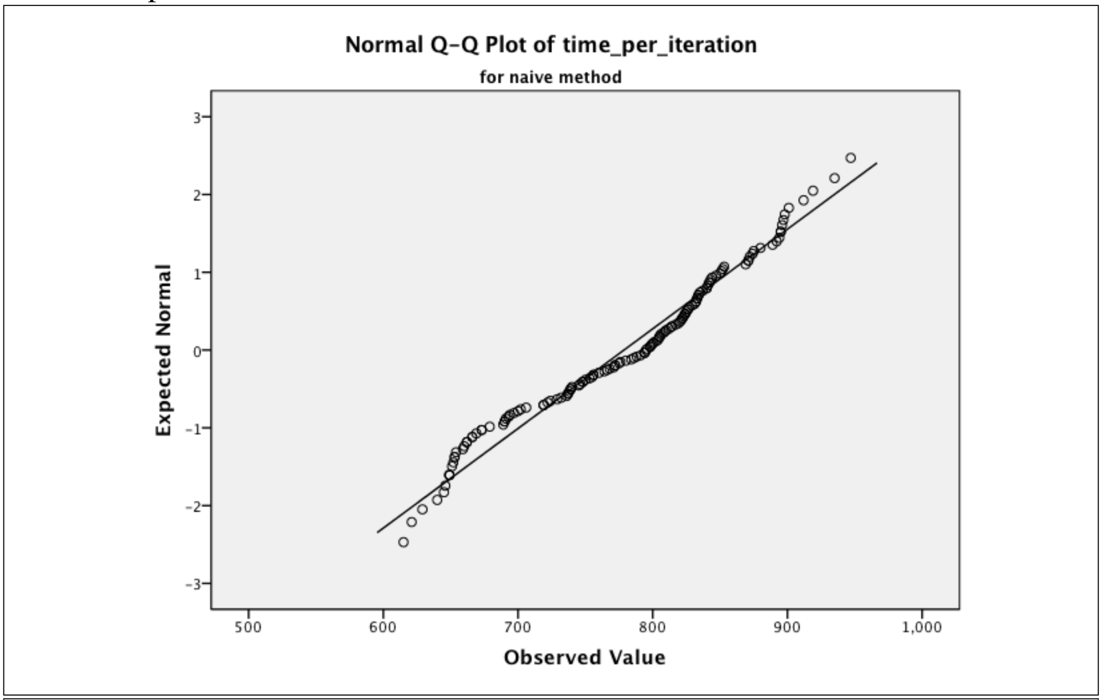
Table 5.8: The Kolmogorov-Smirnov Test for normality test

The Kolmogorov-Smirnov test is defined by:

H_0: The data follow a specified distribution

H_a: The data do not follow the specified distribution

According to Kolmogorov-Smirnov test, at 95% confidence level, we can reject null hypothesis because the statistics value is greater than the critical value. Therefore the data is does not come from normal distribution. Sometimes, statistic test can be misleading, so we decided to do more test and use graphical method like Normal Q-Q plot to look at the normality issue. We plotted Normal Q-Q plot for all methods we tested in the experiments as follows.



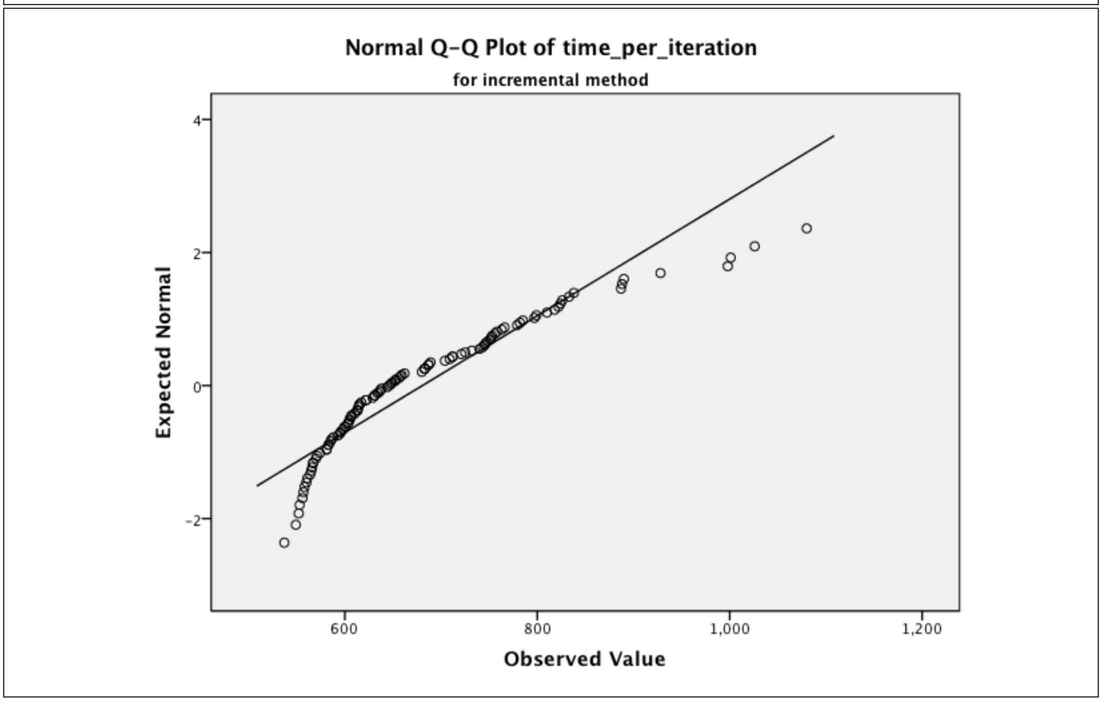
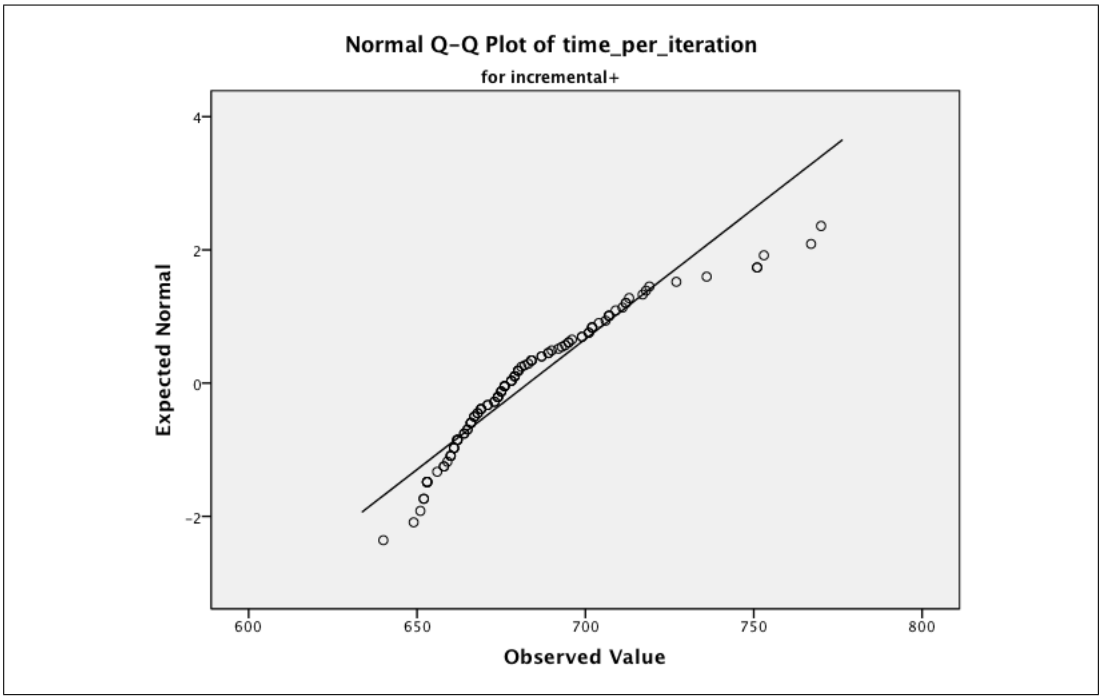


Figure 5.3: Normal Q-Q Plot for normality testing



As a rule of thumb, we can say that the data come from normal distribution if all the data are on the straight line. In our case, we can even though it is not perfectly lie on the line, but most of our collected data are on the line. We also can observe that there are some outliers in our data. Usually outliers will affect on statistical test results. In our case, the outliers comes from the processing machine that are also use for other applications and sometimes there are other Hadoop job that also running at the same time in our experiment. This is normal in real world because the Hadoop cluster will be used for other job too rather than exclusively for running PageRank calculation. In the end we decided to conclude that our time per iteration data for all methods come from normal distribution.

Levene Statistics	Degree of freedom 1	Degree of freedom 2	significance Level
63.495	2	361	0.000

Table 5.9: Levene Test for equal variance testing

Next, in order to use ANOVA we will have to test whether the variances in the experiments are equal. We use Levene test to check that there is homogeneity of variances. In Levene test, the null hypothesis that the population variances are equal which also known as homogeneity of variance. If the resulting p-value of Levene's

test is less than critical value, 0.000, the obtained differences in sample variances are unlikely to have occurred based on random sampling. Thus, the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances in the population. In our case, at 95% confidence level, the p-value is greater than 0.000, so we failed to reject null hypothesis so the variances in our experiment are equal.

	Sum of Squares	df	Mean Square	F value	Sig.
Between Groups	822,251.730	2	411,125.865	62.830	0.000
Within Groups	2.362E6	361	6,543.465		
Total	3.184E6	363			

Table 5.10: ANOVA Test result

First Hypothesis:
H_0^1 : Mean time per iteration to calculate PageRank is same for every method.
H_a^1 : At least there is one method is different in mean time per iteration to calculate PageRank based on methods.

After all the conditions of ANOVA have been met, we proceed with ANOVA for significance test and we present the ANOVA result as in Table 5.10. At 95% confidence level, we can reject our first null hypothesis because the F-value is greater than critical value. Therefore, we can conclude that there is at least one method is different in mean time per iteration to calculate PageRank based on methods we experimented. Based on ANOVA result we only can tell that there is different in performance of various methods but result from ANOVA do not tell us which one performed better. In order to find out which method perform better we did a post-hoc analysis. We chose to use Tukey's Honestly Significance Difference (HSD) test as we assume equal variance based on Levene test we did before. The result of Tukey's HSD is as follows.

I (method)	J (method)	Mean Difference (I-J) p-value	Std. Error	Sig.
naive	incremental	98.105*	10.225	0.000
	incremental+	95.572*	10.252	0.000
incremental	naive	-98.105*	10.225	0.000
	incremental+	-2.533	10.983	0.971
incremental+	naive	-95.572*	10.252	0.000
	incremental	2.533	10.983	0.971

Table 5.11: Tukey's HSD test result

Based on the result on Table 5.11, at 95% confidence level, we can say that incremental and incremental+ performed better than naive method in calculating PageRank because the p-values for these case are greater than critical value. However, incremental and incremental+ method performance have no significance different because there is not enough evidence to reject null hypothesis that claim incremental and incremental+ has the same mean time to calculate PageRank per iteration. Even though, incremental+ has visible difference as shown in Table 5.5 in saving the inputs from going to recalculation stage, but apparently the benefit of incremental+ method is not statistically good enough. Perhaps, in the future we can set the threshold parameter bigger than 10% so that we can save more inputs from going to recalculation stage.

5.3.2 Second Hypothesis Testing

The main output of PageRank calculation in this dissertation is to rank Twitter user based on propagation of influential follower. Even though the main formula is same but the method for calculation may produce different result especially for incremental+ method because we used approximation in calculating PageRank value for certain affected nodes instead of exact calculation. Our second hypothesis is about the effectiveness of the ranker based on the ranking result. We stated our second hypothesis is as follows.

H_0^2 : At least one of the methods will not produce the same ranking result for Twitter user.

H_a^2 : All the methods to calculate PageRank will produce the same ranking result for Twitter user.

Rank	Naive	Incremental	Incremental+	Remark
1	BarackObama	BarackObama	BarackObama	Barack Obama
2	Number10gov	Number10gov	Number10gov	UK Prime Minister
3	WholeFoods	WholeFoods	WholeFoods	Whole Foods Market
4	britneyspears	britneyspears	britneyspears	Britney Spears
5	omnomnome	omnomnome	omnomnome	Nominius N. Nomerson
6	zappos	zappos	zappos	Zappos.com CEO -Tony
7	TheOnion	TheOnion	TheOnion	The Onion
8	BJMendelson	BJMendelson	BJMendelson	Brandon Mendelson
9	threadless	threadless	threadless	Threadless
10	Radioblogger	Radioblogger	Radioblogger	Duane Patterson

Table 5.12: Top 10 Twitter User Ranking

Based on the ranking result of Twitter data in Table 5.12, we can visibly see that all ranker has the same result but we need to prove it has statistically same result by applying Kendall's Tau Test. Kendall's Tau Test is a non-parametric test to check if the output from the rankers produce the same ranking result. Kendall's Tau test is based on Kendall's Tau coefficient and can be calculated by using the following formula. $K(\tau) = \frac{P-Q}{P+Q}$ where P is the number of concordant pairs and Q is the number of discordant pairs. If $K(\tau) = 1$, it means the rankers has the same result, while if $K(\tau) = -1$ the rankers have opposite ordering of ranking. On the other hand if $K(\tau) = 0$ it means the rankers have no output with the same ranking at all.

First Ranker	Second Ranker	P	Q	$K(\tau)$
naive	incremental	10	0	1
naive	incremental+	10	0	1
incremental	incremental+	10	0	1

Table 5.13: Kendall's Tau Test result.

We can reject our second hypothesis null, H_0^2 , if at least one of the $K(\tau)$ value in Table 5.13 produce other than $K(\tau) = 1$. Since $K(\tau) = 1$ for every comparison case

among rankers, we can conclude that all of the methods will produce same ranking result, thus it show that our method, incremental+ is effective to rank Twitter user even though we approximate some of the PageRank value for Twitter user.

Chapter 6

Discussion

6.1 Conclusion

Our aim in this dissertation is to calculate PageRank value for Twitter user. We used Hadoop MapReduce framework to process 1.47 billion following relations in 32 hours and came out with improved version of Incremental PageRank method which called Incremental+ method. Incremental+ method managed to reduce the number of inputs going to recalculation stage by applying threshold to restrict affected nodes which is descendant of changed nodes from being into power method stage. Incremental+ also manage to reduce the number of iteration in power method. Even though the result shows there is improvement in time taken to calculate per iteration, unfortunately the result is not statistically significant enough if compared to original Incremental method but it is statistically significant if compared with naive method. On the other hand, the result shows that even though we approximate the value of PageRank for some nodes that suppose to be recalculated, the result shows that the Root Mean Square Error is very small and negligible. We also successfully proved that Incremental+ can produce same ranking result as other methods.

6.2 Future Works

There are a few things can be improved in this project. First we can try to minimize the time to tag all affected descendant of changed nodes. Currently we are using iterative method based on Breadth-First Search and based on observation we found that it is not very optimal way to do this task. This is because sometimes before tagging stage stop, it will have a few iteration that only tag a single node per iteration. This is not

very efficient and wasting computing resources. Maybe we can use the same idea that we implemented on Incremental+ method, which we can stop the processs of tagging when it reach certain final nodes such as 100 nodes.

We also can try to set the threshold value to higher value, perhaps until 40% and find out whether it will produce same result and the Root Mean Square error is still small.

Since we use the same number of mapper and reducer throughout the whole experiment, maybe in the future we can tweak the mapper and reducer number parameter. It is worth to note that when we reduced the input into recalculation stage, we should also reduce the number of mapper and reducer. On preliminary post experimental test, we tested on PageRank calculation on small dataset but we set the number of mapper and reduce too high and it cause the computing is too slow compared to when we change the parameter of mapper and reducer to small number. We also can try to use compression to see if there is significant difference. Also, we can upgrade Hadoop cluster to the latest version and test whethere there is significant difference.

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