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CLOUD COMPUTING

THE PAGE RANK ALGORITHM IN MAP REDUCE

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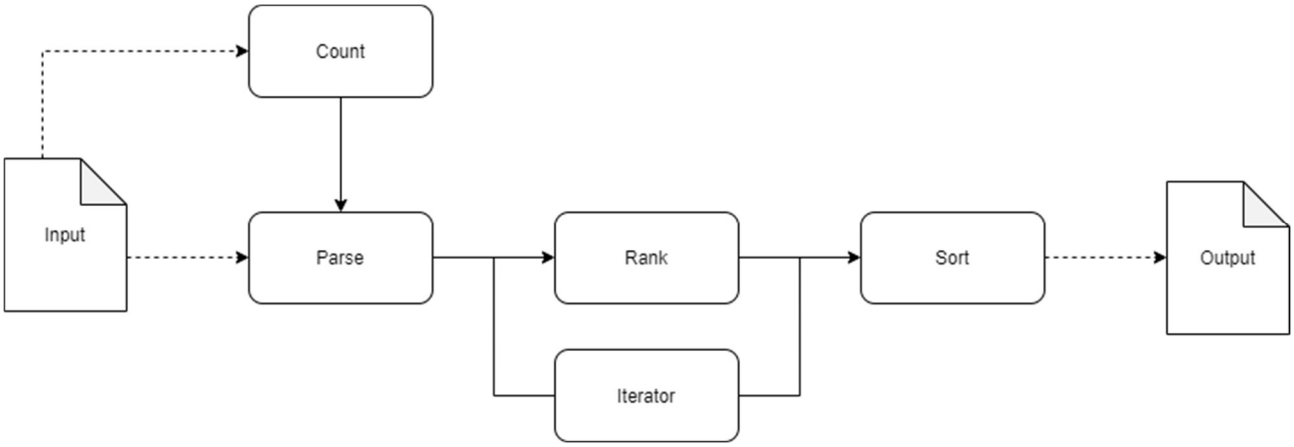
ALGORITHM DESIGN

In order to implement the PageRank algorithm we divided the computation in different stages:



In the Count stage the number of pages are counted.

In the Parse stage the nodes informations are retrieved from the xml pages, so node objects with title, adjacency list and page rank (initially set as 1 / TotalPages) are generated.

In the Rank stage the pages distribute their PageRank mass to through their out-links, and the PageRank values are updated. This stage is repeated for a number of times specified from the command line thanks to the Iterator.

In the Sort stage the Page are sorted in ascending order of PageRank.

The output directory is structured as following:

```
hadoop@namenode:~$ hadoop fs -ls output
Found 6 items
drwxr-xr-x   - hadoop supergroup          0 2021-07-17 14:19 output/count
drwxr-xr-x   - hadoop supergroup          0 2021-07-17 14:20 output/parse
drwxr-xr-x   - hadoop supergroup          0 2021-07-17 14:21 output/rank_0
drwxr-xr-x   - hadoop supergroup          0 2021-07-17 14:22 output/rank_1
drwxr-xr-x   - hadoop supergroup          0 2021-07-17 14:22 output/rank_2
drwxr-xr-x   - hadoop supergroup          0 2021-07-17 14:23 output/sort
```

Each stage reads the output of the precedent stage. The output of the Sort stage is the final result.

PSEUDOCODE

Count stage

```
class MAPPER
    method MAP(lid id, text page)
        emit("Page Count", 1)
```

```
class REDUCER
    method REDUCE(text label, counts[c0, c1, c2....])
        sum <- 0
        for each count c in counts:
            sum <- sum + c
        emit(label, sum)
```

Parse stage

```
class MAPPER
    method MAP(lid id, text page)
        title <- getTitle(page)
        outLinks <- getOutLink(page)
            if (outLinks.size() > 0)
                for each outLink in outLinks:
                    emit(title, outLink)
                    emit(outLink, null)
            else
                emit(title, null)
```

```
class REDUCER
    method Setup()
        totalPages <- readTotalPages()
    method REDUCE(title t, outLinks[outLink0, outLink1...])
    node n <- 0
        for each outLink in outLinks:
            n.adjacencyList.add(outLink)
        n.title <- t
        n.pageRank <- 1 / totalPages
        n.isNode <- true
        emit(title, n)
```

Rank stage

```
class REDUCER
    method Setup()
        alpha <- readAlpha()
        totalPages <- readTotalPages()
    method REDUCE(nid id, nodes[node1, node2....])
        node m <- 0
        rank <- 0
        for each n in nodes:
            if n.isNode():
                m <- n
            else:
                rank <- rank + n.pageRank
        m.pageRank <- (alpha / totalPages) + (1 - alpha) * rank
        emit(id, m)
```

```
class MAPPER
    method MAP(nid id, node n)
        emit(id, n)
        node m <- 0
        m.pageRank <- n.pageRank / |n.adjacencyList|
        m.isNode <- false
        for each nodeId in n.adjacencyList:
            m.setTitle <- nodeId
            emit(nodeId, m)
```

Sort stage

```
class MAPPER
    method MAP(nid n, node N)
        nodeKey.title <- N.title
        nodeKey.pageRank <- N.pageRank
        emit(nodeKey, null)
```

```
class REDUCER
    method REDUCE(node N, [null, null...])
        emit(N.title, N.pageRank)
```

EFFICIENCY ISSUES

On the Hadoop implementation, we used customized object Node: a WritableComparable implementation which stores all the information of a node (title, adjacency list and page rank) used as value by Parse Reducer, Rank Mapper and Rank Reducer, and as key by the SortMapper and SortReducer. This object is used to pass nodes informations along the stage pipeline, to distribute the page rank mass along the graph and, through the implementation of the compareTo method, to sort results directly exploiting the Shuffle & Sort phase of the framework.

To reduce the quantity of intermediate data produced, we implemented some Combiners and tested them on the wiki-micro dataset:

- An In-Mapper Combining in the Count stage(from 2427 to 1 intermediate pair)
- A Combiner in the Rank stage(from 80592 to 68966 intermediate pair)

They allow us to reduce the amount of data moved across the network.

We exploited the setup method to read configuration files in order to get parameters and to read the output of the Count stage. The cleanup method is used by the CountMapper in order to emit the total page count.

We made some test with our application using more than 1 Reducer, that is passed from command line to *Parse* and *Rank* class. We set 3 iteration in the Rank and alpha 0.8 in all the tests.

In order to analyze the performance varying with the number of reducers, we test our application with 1, 2, 3, 5 Reducer. The performance will be analyzed using this 4 values:

- Map Task Failed
- Total time spent by all map tasks (ms)
- Total time spent by all reduce tasks (ms)

NUMBER REDUCER : 1

	Map Task Failed	*Maps Time (ms)*	*Reduce Time (ms)*
Parse	0	2595	4570
Rank1	1	8107	3934
Rank2	1	9388	4085
Rank3	3	20073	6053
Sort	1	7595	2420

NUMBER REDUCERS: 2

	Map Task Failed	*Maps Time (ms)*	*Reduce Time (ms)*
Parse	1	7053	8364
Rank1	1	153446	14511
Rank2	1	8908	8188
Rank3	1	7324	7016
Sort	0	6561	3798

NUMBER REDUCERS : 3

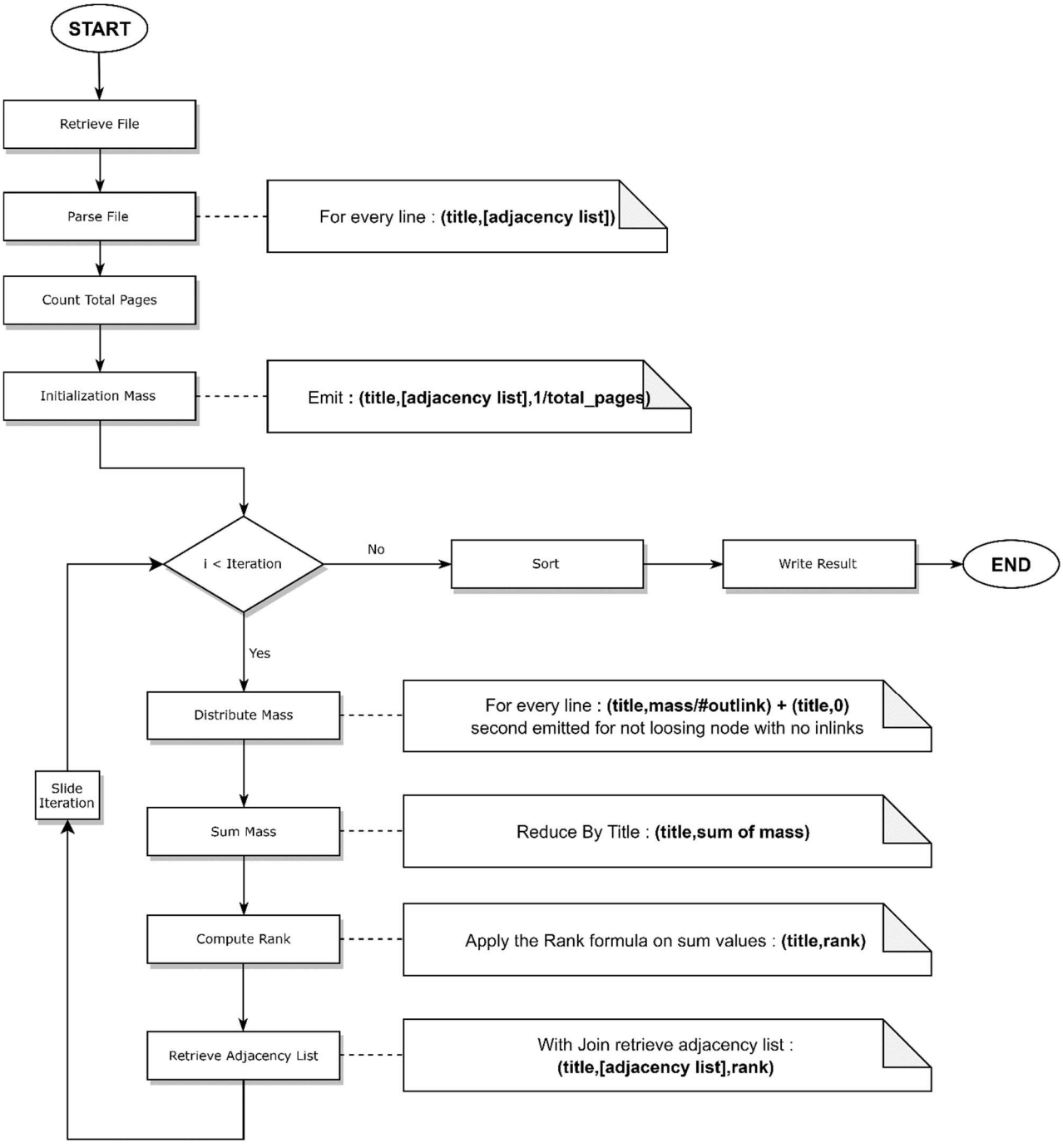
	Map Task Failed	*Maps Time (ms)*	*Reduce Time (ms)*
Parse	0	2807	9847
Rank1	1	16024	11622
Rank2	6	76442	79245
Rank3	1	25494	11973
Sort	3	34603	3785

NUMBER REDUCERS : 5

	Map Task Failed	*Maps Time (ms)*	*Reduce Time (ms)*
Parse	0	2739	19299
Rank1	8	117792	114711
Rank2	8	116096	136699
Rank3	4	89197	71278
Sort	2	78695	12004

As we can see from these tables of data, increasing the number of reducers make increase the ranking and sorting operation time. The meaning of this result is that our dataset is very tiny and when we increase the number of reducer, we introduce more I/O operation because the data need to be slit across the reducers, that will require network transfer time. So instead of creating 1 file for the reducer, it will creates a lot of files.

SPARK IMPLEMENTATION



RDD PERSISTENCE

We have decided to store in main memory **node RDD** using cache() function because is the most used RDD and it not changes during the execution. This RDD is used to count the pages, to initiate the mass and at every iteration to restore the tuple with the adjacency list.