Parallelism for IR

CISC689/489-010, Lecture #19

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IR in One Slide

- Document processing and indexing:
  - Each document turned into a vector of features
  - Vectors of features added to inverted list
  - Inverted lists stored on disk
- Query processing:
  - Inverted lists retrieved from disk
  - Each list decompressed and processed sequentially
  - Scores accumulated in array
- I see a lot of room for parallelization…

Parallelization

- Basic idea: we have a machine with multiple CPUs, or many machines connected together via a network
  - ir.cis has 8 nodes in a network; each node has 2 CPUs with 4 cores; 64 cores total
- We have a task that can be divided into smaller subtasks
- Parallelization involves:
  - Dividing task into smaller subtasks
  - Sending subtasks to nodes for processing
  - Aggregating results from the nodes

Simple Parallel Query Processing

- Many users submitting queries at the same time
- We don't want users to have to wait on each other
- Idea: replicate the index on each node
  - With n nodes, n users can submit queries simultaneously
  - Space usage is very high: n*size of index

Distributed Query Processing

- Instead, split index up across nodes
- Basic process
  - All queries sent to a *director machine*
  - Director then sends messages to many *index nodes*
  - Each index node does some portion of the query processing
  - Director organizes the results and returns them to the user
- Two main approaches
  - Document distribution
    - by far the most popular
  - Term distribution

Distributed Query Processing

- Document distribution
  - each index server acts as a search engine for a small fraction of the total collection
  - director sends a copy of the query to each of the index servers, each of which returns the top-*k* results
  - results are merged into a single ranked list by the director
- Collection statistics should be shared for effective ranking

Distributed Query Processing

- Parallel document-at-a-time processing:
  - For each document D
    - Locate node that indexed D
    - That node calculates a score for D
    - Each node returns a ranked list of scores for its own documents
  - Director node merges scores

Advantages of Document Partitioning

- Each node has accumulators only for its own documents
  - Lower memory usage
  - Less data transferred across network
- Each node can use document-at-a-time optimizations
  - Score just the top k documents for faster processing and better resource use

Distributed Query Processing

- Term distribution
  - Single index is built for the whole cluster of machines
  - Each inverted list in that index is then assigned to one index server
    - in most cases the data to process a query is not stored on a single machine
  - One of the index servers is chosen to process the query
    - usually the one holding the longest inverted list
  - Other index servers send information to that server
  - Final results sent to director

Distributed Query Processing

- Parallel term-at-a-time processing:
  - Locate node n1 that has longest inverted list
  - For each term t
    - Locate node that has list for t
    - Direct that node to send its list to n1
    - n1 processes list and accumulates document scores
  - n1 returns final scores to director

Disadvantages of Term Partitioning

- Term inverted lists can get very long, which means a lot of data transfer in the network
- Very common query terms will result in more load on the nodes that contain them
- Less ability to optimize

Fault Tolerance and Redundancy

- Nodes will fail
  - If failure probability is p, and there are n nodes, probability that at least one is down is $1-(1-p)^n$
- For strict partitioning, a failed node means the best result may not be found
  - Term partitioning: some inverted lists cannot be found
    - Probability that m-term query can be processed = $\left(\frac{n-1}{n}\right)^m$
  - Document partitioning: some documents cannot be scored
    - Probability that j out of top k results will be missed = $\binom{k}{j}\left(\frac{1}{n}\right)^j\left(\frac{n-1}{n}\right)^{k-j}$

Fault Probability Example

- n = 64 nodes, probability of failure is 0.01
- Probability at least one node is down = 47%
- With term partitioning:
  - If one node is down, probability that 3-term query cannot be processed is 1-(63/64)^3 = 4.6%
  - If two nodes down, probability is 9.1%
  - Probability increases with query length and failed nodes
- With document partitioning:
  - If one node is down, probability that one of the top 10 results will be lost is 10*(1/64)*(63/64)^9 = 13%
  - If two nodes down, probability is 23%
  - Probability increases with failed nodes, decreases with number of results possibly lost

Redundancy

- Replicate indexes to handle faults
- Each partition stored on two different nodes
  - Load on that partition distributed evenly between the nodes
- If one fails, all of its load is redirected to the duplicate

Parallel Indexing

- Very simple indexing pseudocode:
  - – Index(C)
    - For each document D
      - – For each term t
        - » Find inverted list for t (create it if it doesn’t exist)
        - » Append D to the end of the list
- How can we parallelize it?

Two Approaches

- Term partitioning
  - – Index(C)
    - For each document D in C
      - – For each term t in D
        - » ProcessAtNode(t, D)
  - – ProcessAtNode(t, D)
    - Find inverted list for t (create it if it doesn’t exist)
    - Append D to the end of the list
- Document partitioning or no partitioning
  - – Index(C)
    - For each document D
      - – ProcessAtNode(D)
    - Merge partial inverted lists
  - – ProcessAtNode(D)
    - For each term t in D
      - – Find inverted list for t in local space (create if it doesn’t exist)
      - – Append D to list

MapReduce

- MapReduce is a distributed programming tool for indexing and analysis tasks
- Basic idea comes from Lisp:
  - *Map* a simple function across a list of items
  - *Reduce* uses a simple function to combine a list of items into one
- Simple example of map and reduce functions:
  - map(count, (a, b, c, a, d)) → (a, 1), (b, 1), (c, 1), (a, 1), (d, 1)
  - reduce(+, (1, 2, 3, 1, 4)) → 11

MapReduce Setup

- n map nodes, m reduces nodes
- Engine developer defines a map operator that takes a value and outputs a set of values
- Developer defines a reduce operator that takes a set of values and reduces them to a single value
- Details of distributing jobs across nodes handled inside the MapReduce internals

Map

- Define map in terms of a key and value
  - E.g. key = document name/number, value = contents
- For each value, apply some function
  - E.g. document parser
- The function can then be applied to each value over n nodes
  - Parse the contents of n documents in parallel

Map Pseudocode

```
Map(String key, String value)
    // key = document name
    // value = document contents
    T = parse(value)
    For each term t in T
        output(t, 1)
```

Reduce

- Define reduce in terms of a key and set of values
  - E.g. a term and m 1s
- Apply some function to the set of values
  - E.g. sum of m 1s = m
- Return the key and the reduced value
- Many reduce jobs can run in parallel, since they only require access to a key, value pair

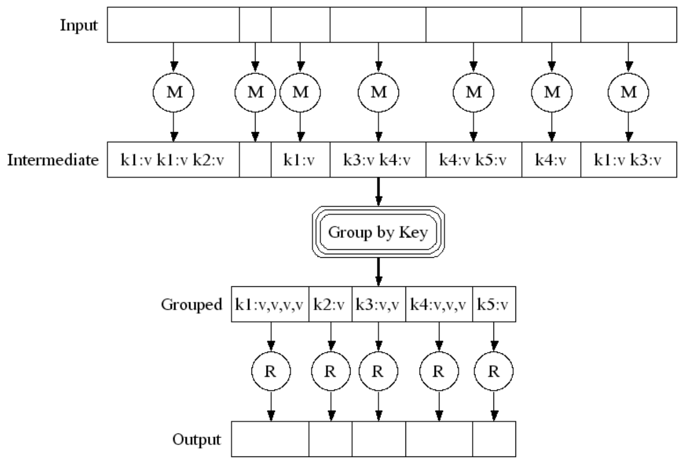
Reduce Pseudocode

```
Reduce(String key, Array values)
    // key = a term
    // values = a list of integers
    m = 0
    For each value v
        m += v
    output(key, m)
```

Shuffling

- The reducer requires that all pairs with the same key are together
  - E.g. (t1, (1, 1, 1)), (t2, (1, 1)), …
- The mapper just outputs the key with a 1
- Before applying the reducer, we apply a shuffler to aggregate the map outputs
  - (t1, 1), (t2, 1), (t1, 1), (t1, 1), (t2, 1) …
    - → (t1, (1, 1, 1)), (t2, (1, 1)), …

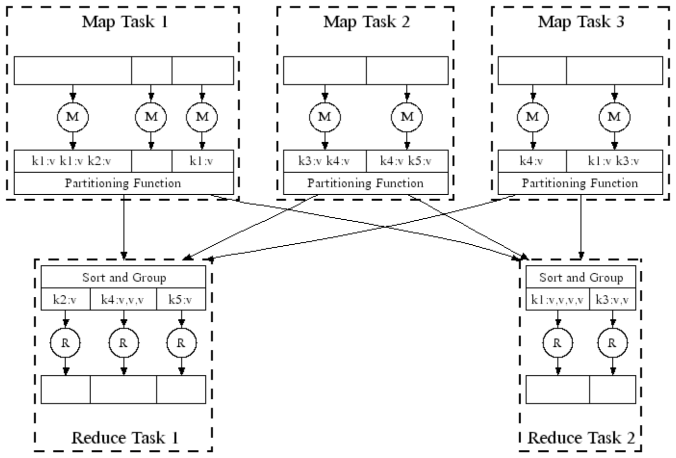
Workflow



Partitioning

- Before the shuffler can be applied, it needs to collect all of the map outputs
  – Possibly requiring sending them over the network
- To reduce bandwidth requirements, we could make sure all map outputs end up on the same node that will be reducing them
- Use a hash function to determine which node the map output will go to
  – hash(word) mod n

Parallelized Workflow



Using MapReduce

- How many map jobs?
- How big should each job be?
- How many reduce jobs?

Number and Size of Jobs

- Many more jobs than processors
  - This makes load balancing easier: whenever one node can take more jobs, there will be one available
  - Original paper: 200,000 jobs for 5,000 machines
- Size of jobs
  - As small as possible
  - Original paper: no more than 64Mb of data
  - Smaller jobs are easier to restart if they fail
- Number of reduce nodes
  - Original paper: 5,000 for 200,000 map jobs

Advantages of MapReduce

- Not just for parallelization
  - Also used for processing very large files that could not be kept in memory
- Fault tolerance
  - If a worker node fails, the job on it can simply be redistributed to another node
- Redundant execution
  - As map jobs are finishing, if one worker is particularly slow, redistribute its jobs to finished workers
  - Whoever finishes first "wins"

Indexing Example

```
procedure MapDocumentsToPostings(input)
    while not input.done() do
        document ← input.next()
        number ← document.number
        position ← 0
        tokens ← Parse(document)
        for each word w in tokens do
            Emit(w, document:position)
            position = position + 1
        end for
    end while
end procedure

procedure ReducePostingsToLists(key, values)
    word ← key
    WriteWord(word)
    while not input.done() do
        EncodePosting(values.next())
    end while
end procedure
```

Other Applications

- Link extraction and counting
  - Mapper outputs set of (URL, 1) tuples; reducer adds up 1s for each URL
- PageRank (more on Wednesday)
- Clustering
  - Mapper outputs (cluster, docid) tuples; reducer adds up document representations to make centroid
- And many, many more