Map-Reduce and Spark

Introduction to Databases

CompSci 316 Spring 2019

DUKE
COMPUTER SCIENCE

Announcements (Tue., Apr. 16)

- Project demos—sign-up instructions to be emailed soon
- Homework #4 final due dates
  - Problem 3: today 04/16
  - Problems 4, 5, 6 : next Monday 04/22
  - Problem X1: next Wednesday 04/24

hadoop Map Reduce

MapReduce: motivation

- Many problems can be processed in this pattern:
  - Given a lot of unsorted data
  - Map: extract something of interest from each record
  - Shuffle: group the intermediate results in some way
  - Reduce: further process (e.g., aggregate, summarize, analyze, transform) each group and write final results

  (Customize map and reduce for problem at hand)

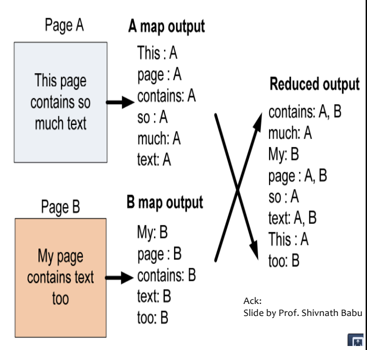
☞Make this pattern easy to program and efficient to run
  - Original Google paper in *OSDI* 2004
  - Hadoop has been the most popular open-source implementation
  - Spark still supports it

M/R programming model

- Input/output: each a collection of key/value pairs
- Programmer specifies two functions
  - $\mathrm{map}(k_1, v_1) \rightarrow \mathrm{list}(k_2, v_2)$
    - Processes each input key/value pair, and produces a list of intermediate key/value pairs
  - $\mathrm{reduce}\big(k_2, \mathrm{list}(v_2)\big) \rightarrow \mathrm{list}(v_3)$
    - Processes all intermediate values associated with the same key, and produces a list of result values (usually just one for the key)

Simple Example: Map-Reduce

- Word counting
- Inverted indexes

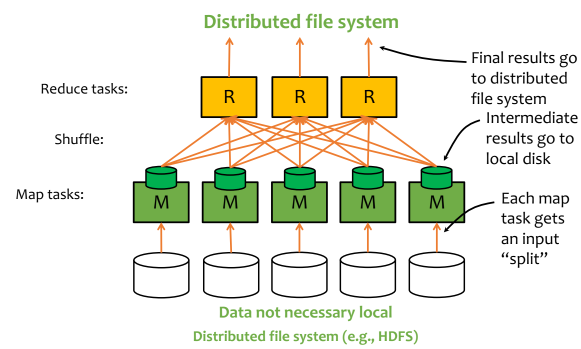


Ack:
Slide by Prof. Shivnath Babu

M/R example: word count

- Expected input: a huge file (or collection of many files) with millions of lines of English text
- Expected output: list of (word, count) pairs
- Implementation
  - $\mathrm{map}(\_, \mathrm{line}) \to \mathrm{list}(\mathrm{word}, \mathrm{count})$
    - Given a line, split it into words, and output $(w, 1)$ for each word w in the line
  - $\mathrm{reduce}(\mathrm{word}, \mathrm{list}(\mathrm{count})) \to (\mathrm{word}, \mathrm{count})$
    - Given a word w and list L of counts associated with it, compute $s = \sum_{\mathrm{count} \in L} \mathrm{count}$ and output (w, s)
  - Optimization: before shuffling, map can pre-aggregate word counts locally so there is less data to be shuffled
    - This optimization can be implemented in Hadoop as a "combiner"

M/R execution



Some implementation details

- There is one "master" node
- Input file gets divided into m "splits," each a contiguous piece of the file
- Master assigns m map tasks (one per split) to "workers" and tracks their progress
- Map output is partitioned into r "regions"
- Master assigns r reduce tasks (one per region) to workers and tracks their progress
- Reduce workers read regions from the map workers' local disks

M/R execution timeline

- When there are more tasks than workers, tasks execute in "waves"
  - Boundaries between waves are usually blurred
- Reduce tasks can't start until all map tasks are done

More implementation details

- Numbers of map and reduce tasks
  - Larger is better for load balancing
  - But more tasks add overhead and communication
- Worker failure
  - Master pings workers periodically
  - If one is down, reassign its split/region to another worker
- "Straggler": a machine that is exceptionally slow
  - Pre-emptively run the last few remaining tasks redundantly as backup

M/R example: Hadoop TeraSort

- Expected input: a collection of (key, payload) pairs
- Expected output: sorted (key, payload) pairs
- Implementation
  - Using a small sample of input, find $r - 1$ key values that divides the key range into r subranges where # pairs is roughly equal across them
  - $\mathrm{map}(k, \mathrm{payload}) \to (j, \langle k, \mathrm{payload} \rangle)$
    - If k falls within the j-th subrange
  - $\mathrm{reduce}(j, \mathrm{list}(\langle k, \mathrm{payload} \rangle)) \to \mathrm{list}(k, \mathrm{payload})$
    - Sort the list of $(k, \mathrm{payload})$ pairs by k and output

APACHE pySpark

We will focus on the Python dialect,
although Spark supports multiple languages

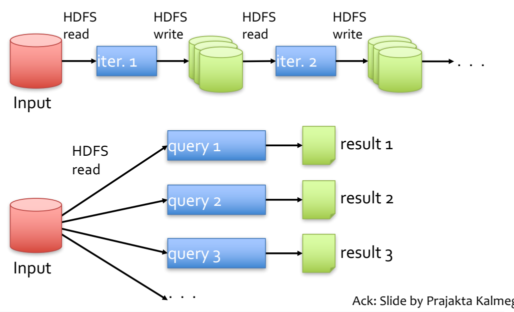
Why a New Programming Model?

- MapReduce greatly simplified big data analysis
- But as soon as it got popular, users wanted more:
  - More complex, multi-stage iterative applications (graph algorithms, machine learning)
  - More interactive ad-hoc queries
  - More real-time online processing
- All three of these apps require fast data sharing across parallel jobs

Ack: Slide by Prajakta Kalmegh

Borrowed slide

Data Sharing in MapReduce

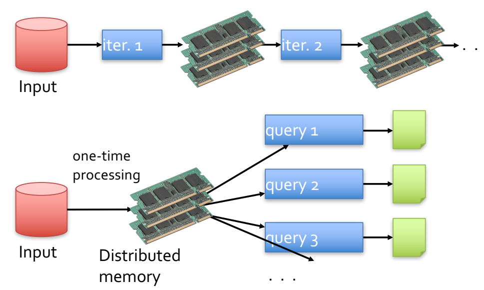


Ack: Slide by Prajakta Kalmegh

Slow due to replication, serialization, and disk IO

Borrowed slide

Data Sharing in Spark



10-100× faster than network and disk

Ack: Slide by Prajakta Kalmegh

Borrowed slide

Addressing inefficiencies in Hadoop

- Hadoop: no automatic optimization

☞Spark
  - Allow program to be a DAG of DB-like operators, with less reliance on black-box code
  - Delay evaluation as much as possible
  - Fuse operators into stages and compile each stage
- Hadoop: too many I/Os
  - E.g., output of each M/R job is always written to disk
  - But such checkpointing simplifies failure recovery

☞Spark
  - Keep intermediate results in memory
  - Instead of checkpointing, use "lineage" for recovery

RDDs

- Spark stores all intermediate results as Resilient Distributed Datasets (RDDs)
  - Immutable, memory-resident, and distributed across multiple nodes
- Spark also tracks the "lineage" of RDDs, i.e., what expressions computed them
  - Can be done at the partition level

What happens to a RDD if a node crashes?

- The partition of this RDD on this node will be lost
- But with lineage, the master simply recomputes the a lost partition when needed
  - Requires recursive recomputation if input RDD partitions are also missing

Example: votes & explanations

- Raw data reside in lots of JSON files obtained from ProPublica API
- Each vote: URI (id), question, description, date, time, result
- Each explanation: member id, name, state, party, vote URI, date, text, category
  - E.g., "P000523", "David E. Price", "NC", "D", "https://api.propublica.org/congress/v1/115/house/sessions/2/votes/269.json", "2018-06-20", "Mr. Speaker, due to adverse weather and numerous flight delays and cancellations in North Carolina, I was unable to vote yesterday during Roll Call 269, the motion…", "Travel difficulties"

Basic M/R with Spark RDD

```
explain_fields = ('member_id', 'name', 'state', 'party', 'vote_api_uri',
        'date', 'text', 'category')
```

Map function: $\text{map}(k_1, v_1) \to \text{list}(k_2, v_2)$

```
def rdd_count_by_category_map(record):
  if len(record) == len(explain_fields):
    return [(record[explain_fields.index('category')], 1)]
  else:
    return []
```

Reduce function: $\text{reduce}(k_2, \text{list}(v_2)) \to \text{list}(v_3)$

```
def rdd_count_by_category_reduce(record):
  key, vals = record
  return [(key, len(vals))]
```


Basic M/R with Spark RDD

```
# setting up one RDD that contains all the input:
rdd = sc. ...
# count number of explanations by category; order by
# number (descending) and then category (ascending):
result = rdd\
  .flatMap(rdd_count_by_category_map)\
  .groupByKey()\
  .flatMap(rdd_count_by_category_reduce)\
  .sortBy(lambda x: (-x[1], x[0]))
for row in result.collect():
  print('|'.join(str(field) for field in row))
```

Be lazy: build up a DAG of "transformations," but no evaluation yet!

Optimize & evaluate the whole DAG only when needed, e.g., triggered by "actions" like collect()

Be careful: Spark RDDs support map() and reduce() too, but they are not the same as those in MapReduce

Moving "BD" to "DB"

Each element in a RDD is an opaque object—hard to program

- Why don't we make each element a "row" with named columns—easier to refer to in processing
  - RDD becomes a *DataFrame* (name from the R language)
  - Still immutable, memory-resident, and distributed
- Then why don't we have database-like operators instead of just MapReduce?
  - Knowing their semantics allows more optimization
- Spark in fact pushed the idea further
  - Spark *Dataset* = DataFrame with type-checking
  - And just run SQL over Datasets using *SparkSQL*!

Spark DataFrame

```
from pyspark.sql import functions as F
explain_fields = ('member_id', 'name', 'state', 'party', 'vote_api_uri',
        'date', 'text', 'category')

# setting up a DataFrame of explanations:
df_explain = sc. ...

# count number of explanations by category; order by
# number (descending) and then category (ascending):
df_explain.groupBy('category')\
    .agg(F.count('name'))\
    .withColumnRenamed('count(name)', 'count')\
    .sort(['count', 'category'], ascending=[0, 1])\
    .show(10000, truncate=False)
```

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Another Spark DataFrame Example

Check yourself

```
from pyspark.sql import functions as F
vote_fields = ('vote_uri','question','description','date','time','result')
explain_fields = ('member_id', 'name', 'state', 'party', 'vote_api_uri',
        'date', 'text', 'category')
# setting up DataFrames for each type of data:
df_votes = sc. ...
df_explain = sc. ...
# what does the following do?
df_votes.join(df_explain.select('vote_api_uri', 'name'),
        df_votes.vote_uri == df_explain.vote_api_uri, 'left_outer')\
    .groupBy('vote_uri', 'date', 'time', 'question', 'description', 'result')\
    .agg(F.count('name'), F.collect_list('name'))\
    .withColumnRenamed('count(name)', 'count')\
    .withColumnRenamed('collect_list(name)', 'names')\
    .sort(['count', 'date', 'time'], ascending=[0, 0, 0])\
    .select('vote_uri', 'date', 'time', 'question', 'description', 'result',
        'count', 'names')\
    .show(20, truncate=False)
```

For each vote, find out which legislators provided explanations; order by the number of such legislators (descending), then date and time (descending)