Parallel Nested Loops

- For each tuple s_i in S
  - For each tuple t_j in T
    - If $s_i = t_j$, then add (s_i, t_j) to output
- Create partitions S_1, S_2, T_1, and T_2
- Have processors work on (S_1,T_1), (S_1,T_2), (S_2,T_1), and (S_2,T_2)
  - Can build appropriate local index on chunk if desired
- Nice and easy, but…
  - How to choose chunk sizes for given S, T, and #processors?
  - There is data duplication, possibly a lot of it
    - Especially undesirable for highly selective joins with small result

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Parallel Partition-Based

- Create n partitions of S by hashing each S-tuple s, e.g., to bucket number (s mod n)
- Create n partitions of T in the same way
- Run join algorithm on each pair of corresponding partitions

- Can create partitions of S and T in parallel
- Choose n = number of processors
- Each processor locally can choose favorite join algorithm
- No data replication, but…
  - Does not work well for skewed data
  - Limited parallelism if range of values is small

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More Join Thoughts

- What about non-equi join?
  - Find pairs (s_i,t_j) that satisfy a predicate like inequality, band, or similarity (e.g., when s and t are documents)
- Hash-partitioning will not work any more
- Now things are becoming really tricky…
- We will discuss these issues in a future lecture.

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Median

- Find the median of a set of integers
- Holistic aggregate function
  - Chunk assigned to a processor might contain mostly smaller or mostly larger values, and the processor does not know this without communicating extensively with the others
- Parallel implementation might not do much better than sequential one
- Efficient approximation algorithms exist

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Parallel Office Tools

- Parallelize Word, Excel, email client?
- Impossible without rewriting them as multi-threaded applications
  - Seem to naturally have low degree of parallelism
- Leverage economies of scale: *n* processors (or cores) support *n* desktop users by hosting the service in the Cloud
  - E.g., Google docs

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Before exploring parallel algorithms in more depth, how do we know if our parallel algorithm or implementation actually does well or not?

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Measures Of Success

- If sequential version takes time t, then parallel version on n processors should take time t/n
  - Speedup = sequentialTime / parallelTime
  - Note: job, i.e., work to be done, is fixed
- Response time should stay constant if number of processors increases at same rate as "amount of work"
  - Scaleup = workDoneParallel / workDoneSequential
  - Note: time to work on job is fixed

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Things to Consider: Amdahl's Law

- Consider job taking sequential time 1 and consisting of two sequential tasks taking time t_1 and $1-t_1$, respectively
- Assume we can perfectly parallelize the first task on n processors
  - Parallel time: $t_1/n + (1 – t_1)$
- Speedup = $1 / (1 – t_1(n-1)/n)$
  - $t_1=0.9$, n=2: speedup = 1.81
  - $t_1=0.9$, n=10: speedup = 5.3
  - $t_1=0.9$, n=100: speedup = 9.2
  - Max. possible speedup for $t_1=0.9$ is 1/(1-0.9) = 10

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Implications of Amdahl's Law

- Parallelize the tasks that take the longest
- Sequential steps limit maximum possible speedup
  - Communication between tasks, e.g., to transmit intermediate results, can inherently limit speedup, no matter how well the tasks themselves can be parallelized
- If fraction x of the job is inherently sequential, speedup can never exceed 1/x
  - No point running this on an excessive number of processors

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Performance Metrics

- Total execution time
  - Part of both speedup and scaleup
- Total resources (maybe only of type X) consumed
- Total amount of money paid
- Total energy consumed
- Optimize some combination of the above
  - E.g., minimize total execution time, subject to a money budget constraint

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Popular Strategies

- Load balancing
  - Avoid overloading one processor while other is idle
  - Careful: if better balancing increases total load, it might not be worth it
  - Careful: optimizes for response time, but not necessarily other metrics like $ paid
- Static load balancing
  - Need cost analyzer like in DBMS
- Dynamic load balancing
  - Easy: Web search
  - Hard: join

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Let's see how MapReduce works.

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MapReduce

- Proposed by Google in research paper
  - Jeffrey Dean and Sanjay Ghemawat. MapReduce: Simplified Data Processing on Large Clusters. OSDI'04: Sixth Symposium on Operating System Design and Implementation, San Francisco, CA, December, 2004
- MapReduce implementations like Hadoop differ in details, but main principles are the same

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Overview

- MapReduce = programming model and associated implementation for processing large data sets
- Programmer essentially just specifies two (sequential) functions: map and reduce
- Program execution is automatically parallelized on large clusters of commodity PCs
  - MapReduce could be implemented on different architectures, but Google proposed it for clusters

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Overview

- Clever abstraction that is a good fit for many real-world problems
- Programmer focuses on algorithm itself
- Runtime system takes care of all messy details
  - Partitioning of input data
  - Scheduling program execution
  - Handling machine failures
  - Managing inter-machine communication

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Programming Model

- Transforms set of input key-value pairs to set of output values (notice small modification compared to paper)
- Map: (k1, v1) → list (k2, v2)
- MapReduce library groups all intermediate pairs with same key together
- Reduce: (k2, list (v2)) → list (k3, v3)
  - Usually zero or one output value per group
  - Intermediate values supplied via iterator (to handle lists that do not fit in memory)

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Example: Word Count

- Insight: can count each document in parallel, then aggregate counts
- Final aggregation has to happen in Reduce
  - Need count per word, hence use word itself as intermediate key (k2)
  - Intermediate counts are the intermediate values (v2)
- Parallel counting can happen in Map
  - For each document, output set of pairs, each being a word in the document and its frequency of occurrence in the document
  - Alternative: output (word, “1”) for each word encountered

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Word Count in MapReduce

Count number of occurrences of each word in a document collection:

```
map(String key, String value):
  // key: document name
  // value: document contents
  for each word w in value:
    EmitIntermediate(w, "1");
```

```
reduce(String key, Iterator values):
  // key: a word
  // values: a list of counts
  int result = 0;
  for each v in values:
    result += ParseInt(v);
  Emit(AsString(result));
```

Almost all the coding needed
(need also MapReduce specification object with names of input and output files, and optional tuning parameters)

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Execution Overview

- Data is stored in files
  - Files are partitioned into smaller splits, typically 64MB
  - Splits are stored (usually also replicated) on different cluster machines
- Master node controls program execution and keeps track of progress
  - Does not participate in data processing
- Some workers will execute the Map function, let's call them mappers
- Some workers will execute the Reduce function, let's call them reducers

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Execution Overview

- Master assigns map and reduce tasks to workers, taking data location into account
- Mapper reads an assigned file split and writes intermediate key-value pairs to local disk
- Mapper informs master about result locations, who in turn informs the reducers
- Reducers pull data from appropriate mapper disk location
- After map phase is completed, reducers sort their data by key
- For each key, Reduce function is executed and output is appended to final output file
- When all reduce tasks are completed, master wakes up user program

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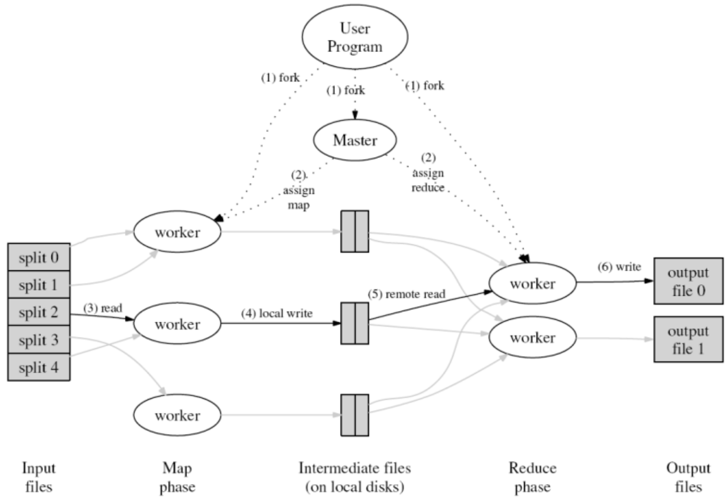
Execution Overview



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Master Data Structures

- Master keeps track of status of each map and reduce task and who is working on it
  - Idle, in-progress, or completed
- Master stores location and size of output of each completed map task
  - Pushes information incrementally to workers with in-progress reduce tasks

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Example: Equi-Join

- Given two data sets $S=(s_1,s_2,\ldots)$ and $T=(t_1,t_2,\ldots)$ of integers, find all pairs (s_i,t_j) where $s_i.A=t_j.A$
- Can only combine the s_i and t_j in Reduce
  - To ensure that the right tuples end up in the same Reduce invocation, use join attribute A as intermediate key (k2)
  - Intermediate value is actual tuple to be joined
- Map needs to output (s.A, s) for each S-tuple s (similar for T-tuples)

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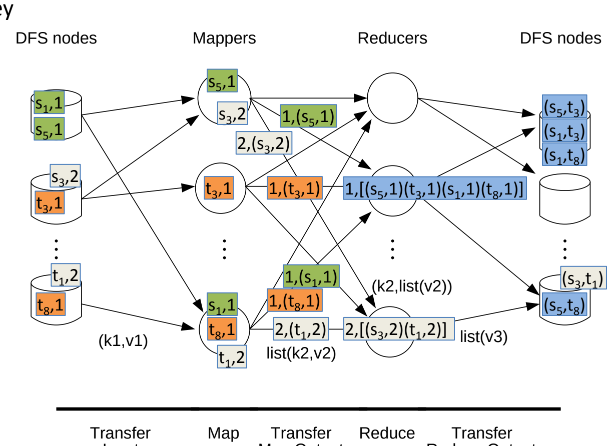
Equi-Join in MapReduce

- Join condition: S.A=T.A
- Map(s) = (s.A, s); Map(t) = (t.A, t)
- Reduce computes Cartesian product of set of S-tuples and set of T-tuples with same key



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Comments

- Programming model might appear very limited
- But, map and reduce can do anything with their input
  - Could implement a Turing machine inside…
  - …which could compute anything, but…
  - …would not result in a good parallel implementation.
- Challenge: find best MapReduce implementation for a given problem

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Basic MapReduce Program Design

- Tasks that can be performed independently on a data object, large number of them: Map
- Tasks that require combining of multiple data objects: Reduce
- Sometimes it is easier to start program design with Map, sometimes with Reduce
- Select keys and values such that the right objects end up together in the same Reduce invocation
- Might have to partition a complex task into multiple MapReduce sub-tasks

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