Advanced Data Management Technologies

Unit 18 — MapReduce Design Patterns

J. Gamper

Free University of Bozen-Bolzano
Faculty of Computer Science
IDSE

Outline

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MapReduce Recap

- Programmers must specify:
  - **map**: $(k, v) \rightarrow (k', v')^*$
  - **reduce**: $(k', v'[]) \rightarrow (v'')^*$
    All values with the same key are reduced together
- Optionally, also:
  - **partition** $(k', \text{number of partitions}) \rightarrow \text{partition for } k'$
    - Often a simple hash of the key, e.g., $hash(k') \mod n$
    - Divides up key space for parallel reduce operations.
  - **combine**: $(k', v'[]) \rightarrow (k', v'')^*$
    - Mini-reducers that run in memory after the map phase
    - Used as an optimization to reduce network traffic
- The execution framework handles everything else
- But what should be done by these modules is not always easy

Average Income Example/1

- Task: Compute average income in each city in 2007
- Input data (sorted by SSN)

SSTable 1

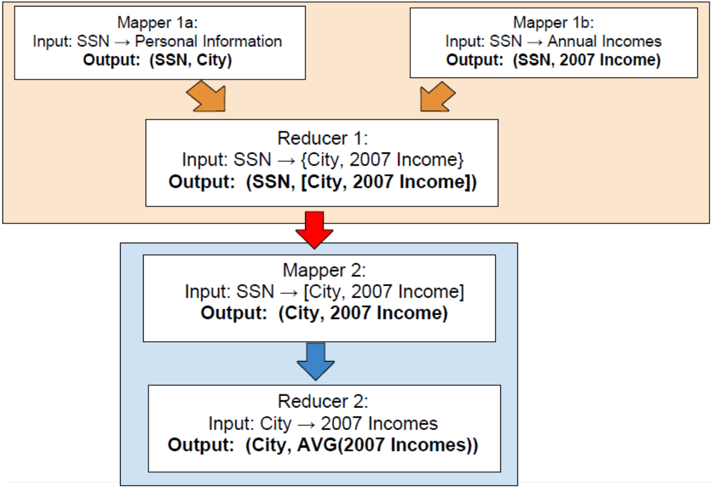
SSN	Personal Information
123456	(John Smith; Sunnyvale, CA)
123457	(Jane Brown; Mountain View, CA)
123458	(Tom Little; Mountain View, CA)

SSTable 2

SSN	year, income
123456	(2007, \$70000), (2006, \$65000), (2005, \$6000), ...
123457	(2007, \$72000), (2006, \$70000), (2005, \$6000), ...
123458	(2007, \$80000), (2006, \$85000), (2005, \$7500), ...

- The two tables need to be "joined" (mimic join in MR)

Average Income Example/2



Common Mistakes to Avoid/1

- Mapper and reducer should be **stateless**
- Don't use static variables
- After `map` and `reduce` return, they should remember nothing about the processed data!
- Reason: No guarantees about which key-value pairs will be processed by which workers!

```
HashMap h = new HashMap();
map(key, value) {
  if (h.contains(key)) {
    h.add(key,value);
    emit(key, "X");
  }
}
```

Wrong!

Common Mistakes to Avoid/2

- Don't try to do your **own I/O**!
- Don't try to read from, or write to, files in the file system
- The MapReduce framework does all the I/O for you
  - All the incoming data will be fed as arguments to map and reduce.
  - Any data your functions produce should be output via emit.

```
map(key, value) {
  File foo =
    new File("xyz.txt");
  while (true) {
    s = foo.readLine();
    ...
  }
}
```

Wrong!

Common Mistakes to Avoid/3

- Mapper must not map **too much data to the same key**
- In particular, don't map everything to the same key!
- Otherwise the reduce worker will be overwhelmed.
- It's okay if some reduce workers have more work than others.
- Example: In WordCount, the reduce worker that works on the key 'and' has a lot more work than the reduce worker that works on 'syzygy'.

```
map(key, value) {
  emit("FOO", key + " " + value);
}
```

Wrong!

```
reduce(key, value[]) {
  /* do some computation on
  all the values */
}
```

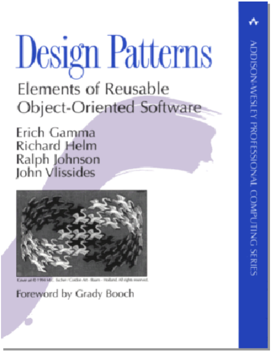
Designing MapReduce Algorithms

- Key decision: What should be done by `map` and what by `reduce`?
- `map`
  - Can do something to each individual key-value pair, but it cannot look at other key-value pairs
    - Example: Filtering out key-value pairs we don't need
  - Can emit more than one intermediate key-value pair for each incoming key-value pair
    - Example: Incoming data is text, map produces (word, 1) for each word
  - Can emit data with specific keys to all reducers, e.g., `EmitToAllReducers()`
- `reduce`
  - Can aggregate data
  - Can look at multiple values, as long as map has mapped them to the same (intermediate) key
    - Example: Count the number of words, add up the total cost, ...
- Important to get the intermediate form right!
- Design pattern help to develop algorithms.

Outline

What are Design Patterns?

- Reusable solutions to problems
- Domain independent
- Not a cookbook, but a guide
- Not a finished solution
- Makes the intent of code easier to understand
- Provides a common language for solutions
- Be able to reuse code
- Known performance profiles and limitations of solutions

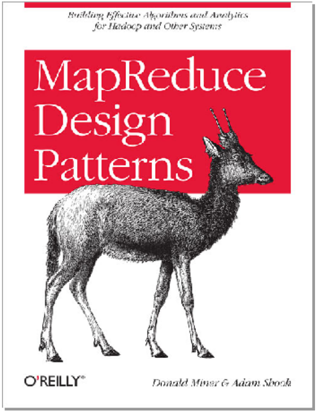


Why MapReduce Design Patterns?

- Recurring patterns in data-related problem solving
- Groups are building patterns independently
- Lots of new users every day
- MapReduce is a new way of thinking
- Foundation for higher-level tools (Pig, Hive, ...)
- Community is reaching the right level of maturity

MapReduce Design Patterns

- Book by Donald Miner & Adam Shook
- Building effective algorithms and analytics for Hadoop and other systems.
- 23 pattern grouped into six categories
  - Summarization
  - Filtering
  - Data Organization
  - Joins
  - Metapatterns
  - Input and output



Pattern Categories/1

- Filtering patterns: Extract interesting subsets of the data
    - Filtering
    - Bloom filtering
    - Top ten
    - Distinct
- Summarization patterns: Top-down summaries to get a top-level view
    - Numerical summarizations
    - Inverted index
    - Counting with counters
- Data organization patterns: Reorganize and restructure data to work with other systems or to make MapReduce analysis easier
    - Structured to hierarchical
    - Partitioning
    - Binning
    - Total order sorting
    - Shuffling

Pattern Categories/2

- Join patterns: Bringing and analyze different data sets together to discover interesting relationships.
  - Reduce-side join
  - Replicated join
  - Composite join
  - Cartesian product
- Metapatterns: Piece together several patterns to solve a complex problem or to perform several analytics in the same job.
  - Job chaining
  - Chain folding
  - Job merging
- Input and output patterns: Custom the way to use Hadoop to input and output data.
  - Generating data
  - External source output
  - External source input
  - Partition pruning

Outline

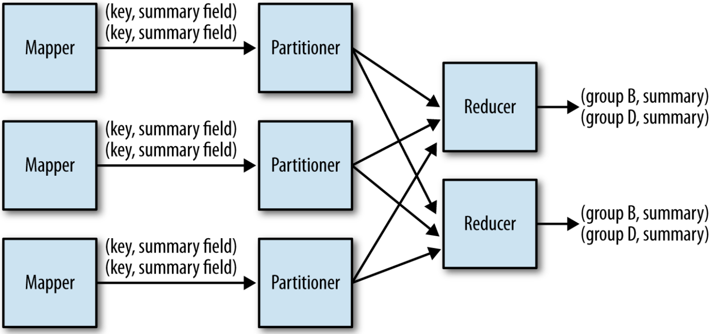
Numerical Summarizations

- Numerical Summarizations
  - A general pattern for calculating aggregate statistical values over your data, e.g., minimum, maximum, average, median, and standard deviation.
  - Group records together by a key field and calculate a numerical aggregate per group to get a top-level view of a large data set.
- Applications
  - Word count, record count
  - Min, max, count of a particular event
  - Average, median, standard deviation
- SQL resemblance

```
SELECT   MIN(numericalcol1), MAX(numericalcol1), COUNT(*)
FROM     table
GROUP BY groupcol2;
```

Numerical Summarizations Structure

- Mapper: outputs keys that consist of each field to group by, and values consisting of any pertinent numerical items.
- Reducer: receives a set of numerical values $(v_1, v_2, v_3, \ldots, v_n)$ associated with a group-by key and performs the (aggregate) function $\theta(v_1, \ldots, v_n)$.



Performance Analysis

- Aggregations typically perform well when the combiner is properly used.
  - These types of operations are what MR was built for
- Data skew of reduce groups is problematic
  - many more intermediate key/value pairs with a specific key than other keys;
  - one reducer is going to have a lot more work to do than others.

Map Output / Combiner Input

Combiner executes over Group 1 and 2. Does not execute over last two rows.

	Input Key	Input Value		
	User	Minimum	Maximum	Count
Group 1	12345	10	10	1
Group 1	12345	8	8	1
Group 1	12345	21	21	1
Group 2	54321	1	1	1
Group 2	54321	47	47	1
	99999	7	7	1
	99999	12	12	1

Combiner Output / Reducer Input

Output Key	Output Value		
	Minimum	Maximum	Count
12345	8	21	3
54321	1	47	2
99999	7	7	1
99999	12	12	1

Numerical Summarizations Example/1

- Given a list of user comments in a mailing list, determine the first and last time a user commented and the total number of comments from that user.
- User comment
  - `<row Id="8189677" PostId="6881722" Text="Have you looked at Hadoop?" CreationDate="2011-07-30T07:29:33.343" UserId="831878" />`
- After a grouping operation, the reducer has to iterate over all values associated with a group and to compute the aggregate functions.

Numerical Summarizations Example/2

- Create Writable object MinMaxCountTuple to store the mapper output (instead of using a Text object)

```
public class MinMaxCountTuple implements Writable {
    private Date min = new Date(), max = new Date();
    private long count = 0;
    public Date getMin() { return min; }
    public void setMin(Date min) { this.min = min; }
    public Date getMax() { return max; }
    public void setMax(Date max) { this.max = max; }
    public long getCount() { return count; }
    public void setCount(long count) { this.count = count; }
    public void readFields(DataInput in) throws IOException {
        // Read the data out in the order it is written
        min = new Date(in.readLong());
        max = new Date(in.readLong());
        count = in.readLong();
    }
    public void write(DataOutput out) throws IOException {
        // Write the data out in the order it is read
        out.writeLong(min.getTime());
        out.writeLong(max.getTime());
        out.writeLong(count);
    }
}
```

Numerical Summarizations Example/3

```
public static class MinMaxCountMapper extends Mapper<Object,Text,Text,MinMaxCountTuple>...{
    // Our output key and value Writables
    private Text outUserId = new Text();
    private MinMaxCountTuple outTuple = new MinMaxCountTuple();

    public void map(Object key, Text value, Context context)
        throws IOException, InterruptedException {
        Map<String, String> parsed = transformXmlToMap(value.toString());

        // Grab the "CreationDate" and UserID field, and parse the string into a Date object
        String strDate = parsed.get("CreationDate");
        String userId = parsed.get("UserId");
        Date creationDate = frmt.parse(strDate);

        // Set the minimum and maximum date values and the count
        outTuple.setMin(creationDate);
        outTuple.setMax(creationDate);
        outTuple.setCount(1);

        // Set our user ID as the output key
        outUserId.set(userId);

        // Write out the userID and the values
        context.write(outUserId, outTuple);
    }
}
```

Numerical Summarizations Example/4

```
public static class MinMaxCountReducer extends
    Reducer<Text, MinMaxCountTuple, Text, MinMaxCountTuple> {
    // Our output value Writable
    private MinMaxCountTuple result = new MinMaxCountTuple();

    public void reduce(Text key, Iterable<MinMaxCountTuple> values, Context context)...{
        // Initialize result
        result.setMin(null);
        result.setMax(null);
        result.setCount(0);
        int sum = 0;

        // Iterate through all input values for this key
        for (MinMaxCountTuple val :  values) {
            if (result.getMin() == null || val.getMin().compareTo(result.getMin()) < 0) {
                result.setMin(val.getMin());
            }
            if (result.getMax() == null || val.getMax().compareTo(result.getMax()) > 0) {
                result.setMax(val.getMax());
            }
            sum += val.getCount();
        }
        result.setCount(sum);

        context.write(key, result);
    }
}
```

Outline

1. Motivation
2. Overview of MR Design Patterns
3. Summarization Patterns
4. **Filtering Patterns**
   - Filtering
   - Bloom Filtering
   - Top Ten
   - Distinct
5. Join Patterns
   - Reduce Side Join
   - Replicated Join
   - Composite Join
   - Cartesian Product

Filtering Patterns

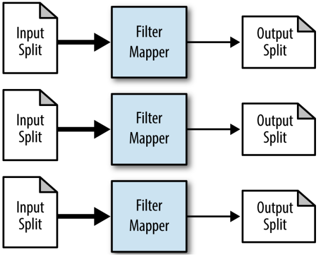
- To understand a smaller piece/subset of data
  - e.g., a top-ten listing, the results of a de-duplication
- Sampling as a special form of filtering
  - Get a small representative sample of a data set.
- Filtering does not change the actual records
- Filtering Patterns:
  - Filtering
  - Bloom Filtering
  - Top Ten
  - Distinct

Filtering

- Filtering is the most basic pattern and evaluates each record separately based on some condition.
- Intent
  - Filter out records that are not of interest.
  - You want to focus your analysis on a subset of a large data set.
- Applications
  - Closer view of data
  - Tracking a thread of events
  - Distributed grep
  - Data cleansing
  - Removing low scoring data (if you can score your data)
- SQL resemblance
  - `SELECT * FROM table WHERE value < x`

Filtering Structure

- No reducer needed, i.e., no further processing/aggregation of the data
- ```
  map(key, record) {
      if we want to keep record then
          emit key, value
  }
  ```


  ```

Performance Analysis

- No reducers
  - Both the sort phase and the reduce phase are cut out
  - Data never has to be transmitted between the map and reduce phase.
- With one single reducer, all data would be collected into a single file.
- Most of the map tasks pull data off of their locally attached disks and then write back out to that node.

Random Sampling Example

- Task: Grab a random subset of a dataset
- Random number generator produces a number: if the value is below a threshold, keep the record, otherwise skip it
- Hadoop provides a setup method that is called once for each mapper prior to the many calls to `map`.

```
public static class SRSMapper extends Mapper<Object, Text, NullWritable, Text> {
    private Random rands = new Random();
    private Double percentage;

    protected void setup(Context context) throws ... {
        // Retrieve the percentage that is passed in via the configuration
        // like this: conf.set("filter_percentage", .5) for .5%
        String strPercentage = context.getConfiguration().get("filter_percentage");
        percentage = Double.parseDouble(strPercentage) / 100.0;
    }

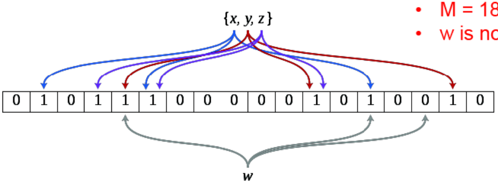
    public void map(Object key, Text value, Context context) throws ... {
        if (rands.nextDouble() < percentage) {
            context.write(NullWritable.get(), value);
        }
    }
}
```

Bloom Filtering/1

- Intent
  - Keep records that are member of a predefined set of hot values
  - Some false positives are acceptable, i.e., some records will get through the filter although they are not in the hot values
- Applications
  - Removing most of the non-watched values
  - Prefiltering a data set for an expensive set membership check

Bloom Filtering/2

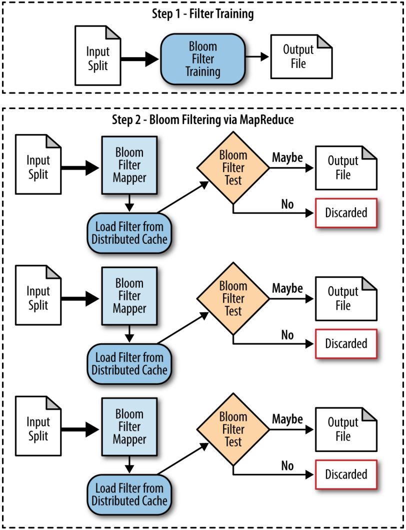
- A Bloom filter (B.H. Bloom, 1970) is a space-efficient probabilistic data structure that is used to test set membership.
- Filter returns either possibly in set or definitely not in set
  - i.e., false positive matches are possible, but not false negatives
- The filter is represented by a bit vector of size m and k different hash functions that map each element (hot value) of the set to one of the m bits.
- Training phase: for all elements in the set, the k hash functions are computed and the corresponding bits are set to 1.
- Check membership: compute the k hash functions for the element
  - if all hash functions map to 1 $\rightarrow$ possibly in the set
  - if at least one hash functions maps to 0 $\rightarrow$ not in the set



- M = 18, k = 3
- w is not in the set {x, y, z}

Bloom Filtering Structure

- Structure
  - The Bloom filter is first trained and stored in the HDFS.
  - The mapper then calls the `setup` method to load the Bloom filter before processing the input data.
  - The `DistributedCache` is a Hadoop utility that ensures that a file in the HDFS is present on the local file system of each task that requires it.



Performance Analysis

- Loading up the Bloom filter is not that expensive since the file is relatively small.
- Checking a value against the Bloom filter is also a relatively cheap operation by $O(1)$ hashing

Bloom Filtering Example

- Task: Given a list of user comments, filter out a majority of the comments that do not contain any of a set of predefined keywords

```
public static class BloomFilteringMapper extends Mapper<Object, Text, Text, NullWritable> {
    private BloomFilter filter = new BloomFilter();

    protected void setup(Context context) throws ...  {
        // Get Bloom filter from the DistributedCache
        URI[] files = DistributedCache.getCacheFiles(context.getConfiguration());
        DataInputStream strm = new DataInputStream(new FileInputStream( files[0].getPath()));
        filter.readFields(strm);
        strm.close();
    }

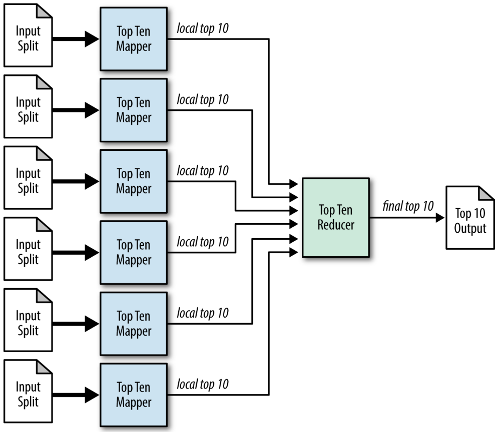
    public void map(Object key, Text value, Context context) throws ...  {
        Map<String, String> parsed = transformXmlToMap(value.toString());
        // Get the value for the comment
        String comment = parsed.get("Text");
        StringTokenizer tokenizer = new StringTokenizer(comment);
        // For each word:  if the word is in the filter, output the record and break
        while (tokenizer.hasMoreTokens()) {
            String word = tokenizer.nextToken();
            if (filter.membershipTest(new Key(word.getBytes()))) {
                context.write(value, NullWritable.get());
                break;
            }
        } } }
```

Top Ten

- Intent
  - Retrieve a small number of top K records, according to some ranking/criterion
- The number of output records should be significantly lower than the number of input records.
- It must be possible to determine an ranking.
- Applications
  - Outlier analysis
  - Select interesting data (most valuable data)
- SQL Resemblance
  - SQL: `SELECT * FROM table WHERE col4 DESC LIMIT 10`

Top Ten Structure

- Mapper: find local top K
- (only one) Reducer: $K \cdot M$ records $\rightarrow$ the final top K



Performance Analysis with one Reducer

- Reducer gets $K * M$ records
- The sort can become expensive if the reducer gets too many records and sorting needs to be done on local disk instead of in memory
- The reducer host will receive a lot of data over the network
  $\Rightarrow$ might create a network resource hot spot
- Scanning through all the data in the reduce will take a long time if there are many records to look through.
- Writes to the output file are not parallelized

Top Ten Example

- Hadoop provides a cleanup method that is called once after all key/value pairs have been through map (just like setup which is called before)

```
class mapper:
   setup():
      initialize top ten sorted list

   map(key, record):
      insert record into top ten sorted list
      if length of array > 10 then
         truncate list to a length of 10

   cleanup():
      for record in top sorted ten list:
         emit null, record

class reducer:
   setup():
      initialize top ten sorted list

   reduce(key, records):
      sort records
      truncate records to top 10
      for record in records:
         emit record
```

Distinct

- Intent
  - Find a unique set of values from similar records with potential duplicates
- Applications
  - Deduplicate data
  - Getting distinct values
  - Protecting from an inner join explosion
- SQL Resemblance
  - SQL: `SELECT DISTINCT * FROM table;`

Distinct Structure

- Exploits MapReduce's ability to group keys together to remove duplicates
- The mapper outputs the input value as intermediate key
- Reducer groups all duplicates together and simply outputs the key
- Duplicate records are often located close to each other in a data set, so a combiner will deduplicate most of them in the map phase

```
map(key, record):
    emit (record, null)

reduce(key, records):
    emit (key)
```

Performance Analysis

- Finding the right number of reducers is crucial
- If duplicates are very rare within an input split, almost all of the data is sent to the reduce phase, hence use many reducers
- If there are many duplicates, many reducers might produce very small output files, and therefore unecessary overhead

Outline

Join Patterns

An SQL query walks into a bar, sees two tables and asks them "May I join you?"

- Joins are very important in RDBMS, but among the most complex operations in MapReduce
  - MR is good in processing datasets by looking at each record in isolation
  - Joining/combining datasets does not fit gracefully into the MR paradigm
- Refresh of RDMS equality joins
  - Inner Join
  - Outer Join
  - Cartesian Product
  - Anti Join = full outer join − inner join
- Join patterns in MR
  - Reduce Side Join
  - Replicated Join
  - Composite Join
  - Cartesian Product

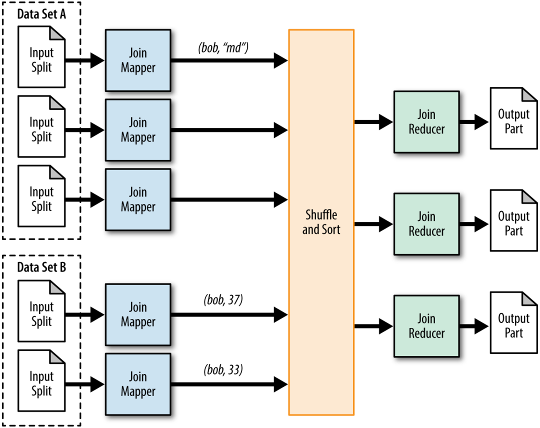
Reduce Side Join

- Reduce Side Join: Reducer executes the actual join
  - Join large multiple data sets by a foreign key
  - Simple to implement in Reducers
  - Supports all different join operations
  - No limitation on the size of the data sets
- SQL resemblance

```
SELECT users.ID, users.Location, comments.upVotes
FROM   users [INNER|LEFT|RIGHT] JOIN comments
       ON users.ID = comments.UserID
```

Reduce Side Join Structure

- Mapper prepares `(key, record)`
  - `key` is the join attribute, the (data) record is flagged with ID of data set
- Reducer performs join operation on identical keys
  - Creates for each key a list for each data set and joins them



Performance Analysis

- Cluster's network bandwidth is bottleneck!!!
  - Pretty much all of the data is sent to the shuffle and sort step
- Utilize relatively more reducers than for other analytic tasks

Reduce Side Join Example/1

- Task: Enrich comments with user information
  - Table A contains user information, table B contains user comments
  - Connected by user ID
- Mapper
  - The UserJoinMapper adds “A” in front of each value/record
    - Thus, the reducer knows from which relation the value comes
  - Similar, the CommentJoinMapper prepends “B”

```
public static class UserJoinMapper extends Mapper<Object, Text, Text, Text> {
   private Text outkey = new Text();
   private Text outvalue = new Text();

   public void map(Object key, Text value, Context context) throws ...{
      // Parse the input string and extract the user ID
      String userId = value.toString().get("Id");
      // The foreign join key is the user ID
      outkey.set(userId);
      // Flag this record for the reducer and then output
      outvalue.set("A" + value.toString());
      context.write(outkey, outvalue);
   }
}
```

Reduce Side Join Example/2

- Reducer iterates through all values of each group and separates the values
- Join logic is applied then on these lists (and differs depending on the join)

```
public static class UserJoinReducer extends Reducer<Text, Text, Text, Text> {
   private ArrayList<Text> listA = new ArrayList<Text>();
   private ArrayList<Text> listB = new ArrayList<Text>();
   private String joinType = null;

   public void setup(Context context) {
      joinType = context.getConfiguration().get("join.type");
   }

   public void reduce(Text key, Iterable<Text> values, Context context) throws ...{
      listA.clear(); listB.clear();

      // Iterate through all values and separate them into an A-list and B-list
      while (values.hasNext()) {
         tmp = values.next();
         if (tmp.charAt(0) == 'A') {
            listA.add(new Text(tmp.toString().substring(1)));
         } else if (tmp.charAt('0') == 'B') {
            listB.add(new Text(tmp.toString().substring(1)));
         }
      }

      // Execute our join logic now that the lists are filled
      executeJoinLogic(context);
   }
   ...
```

Reduce Side Join Example/3

- executeJoinLogic computes the actual join as part of the reducer task
- Inner join: if both lists are not empty, simply perform two nested loops and join each of the values.

```
private void exectueJoinLogic(Context context) throws ...  {
   ...
   if (joinType.equalsIgnoreCase("inner")) {
      // If both lists are not empty, join A with B
      if (!listA.isEmpty() && !listB.isEmpty()) {
         for (Text A : listA) {
            for (Text B : listB) {
               context.write(A, B);
            }
         }
      }
   }
   ...
```

Reduce Side Join Example/4

- Left outer join:
  - if the right list is not empty, join A with B;
  - otherwise, output each record of A with an empty string.
- Right outer join is similar.

```
...
else if (joinType.equalsIgnoreCase("leftouter")) {
   // For each entry in A
   for (Text A : listA) {
      if (!listB.isEmpty()) {
         // Join A and B
         for (Text B : listB) {
            context.write(A, B);
         }
      } else {
         // Output A with empty string
         context.write(A, "");
      }
   }
}
...
```

Reduce Side Join Example/5

- Full outer join: all records need to be kept
  - if list A is not empty, for every element in A:
    - join with B if B is not empty;
    - otherwise, output A;
  - if A is empty, just output B.

```
else if (joinType.equalsIgnoreCase("fullouter")) {
   if (!listA.isEmpty()) {
      for (Text A : listA) {
         if (!listB.isEmpty()) {
            // Join A with B
            for (Text B : listB) {
               context.write(A, B);
            }
         } else {
            // Output A with empty string
            context.write(A, "");
         }
      }
   } else {
      // list A is empty:  just output B
      for (Text B : listB) {
         context.write("", B);
      }
   }
}
```

Reduce Side Join Example/6

- Anti join: if exactly one of the lists is empty, output the records from the non-empty list with an empty text.
  - Recall that the anti-join contains only those tuples from both relations that do not have a match in the other relation.

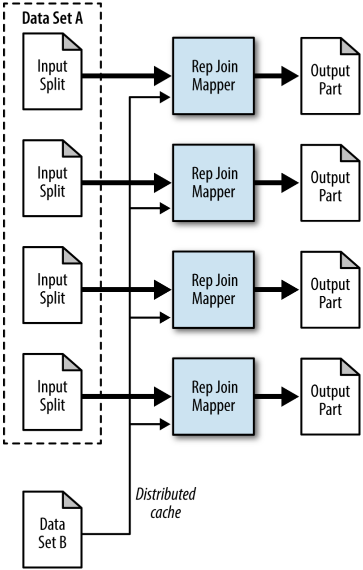
```
...
else if (joinType.equalsIgnoreCase("anti")) {
   // If list A is empty and B is not empty or vice versa
   if (listA.isEmpty() XOR listB.isEmpty()) {
      // Iterate over both A and B
      // The previous XOR check will make sure exactly one of
      // these lists is empty and therefore the list will be skipped
      for (Text A : listA) {
         context.write(A, EMPTY_TEXT);
      }
      for (Text B : listB) {
         context.write(EMPTY_TEXT, B);
      }
   }
}
...
```

Replicated Join

- Replicated Join: Mapper implements the actual join, no reducer is used
- All data sets, except a large one, are read into memory during the setup phase of each map task
- The large data set is the “left” part of the join.

Replicated Join Structure

- Map-only pattern, i.e., no combiner, partitioner or reducer is used
- Read all files from the distributed cache during the setup of the mapper method and store them into in-memory lookup tables.
- Mapper processes each record and joins it with all the data stored in memory.



Performance Analysis

- Eliminates the need to shuffle any data to the reduce phase.
- A replicated join can be the fastest type of join because no reducer is required
- Limited by the amount of data that can be stored safely inside JVM.

Replicated Join Example/1

- Task: Enrich comments (large relation) with user information (small relation)

```
public static class ReplicatedJoinMapper extends Mapper<Object, Text, Text, Text> {
    private HashMap<String, String> userIdToInfo = new HashMap<String, String>();
    private Text outvalue = new Text();
    private String joinType = null;

    public void setup(Context context) throws ...  {
        Path[] files = DistributedCache.getLocalCacheFiles(context.getConfiguration());
        // Read all files in the DistributedCache
        for (Path p :  files) {
            BufferedReader rdr = new BufferedReader(...  new File(p.toString())...);
            String line = null;
            while ((line = rdr.readLine()) != null) {
                // Get the user ID for this record
                String userId = line.get("Id");
                // Map the user ID to the record
                userIdToInfo.put(userId, line);
            }
        }
        // Get the join type from the configuration
        joinType = context.getConfiguration().get("join.type");
    }
    ...
```

Replicated Join Example/2

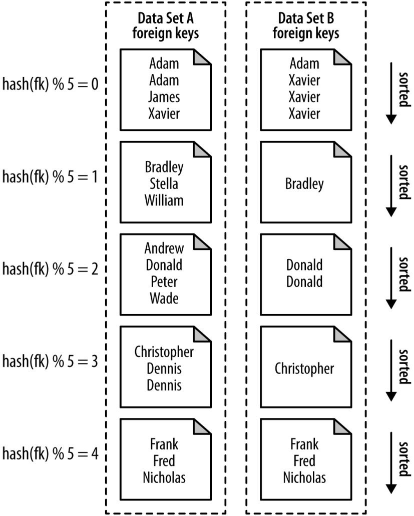
```
    ...
    public void map(Object key, Text value, Context context) throws ...  {
        String userId = value.toString().get("UserId");
        String userInformation = userIdToInfo.get(userId);
        if (userInformation != null) {
            // If the user information is not null, then output
            outvalue.set(userInformation);
            context.write(value, outvalue);
        } else if (joinType.equalsIgnoreCase("leftouter")) {
            // For a left outer join output the record with an empty value
            context.write(value, "");
        }
    }
}
```

Composite Join

- Composite join is performed on the map-side with many very large inputs.
- Completely eliminates the need to shuffle and sort all the data to the reduce phase.
- Data need to be already organized or prepared in a very specific way:
  - Sorted by foreign key, partitioned by foreign key, and read in a very particular manner.
- Particularly useful if you want to join very large data sets together.

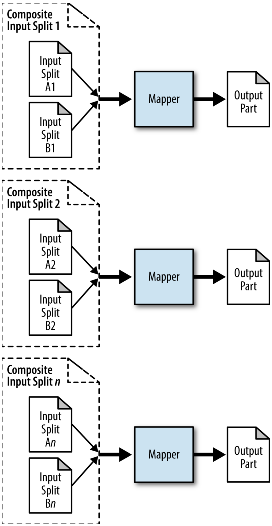
Composite Join Applicability

- All data sets can be read with the foreign key as the input key to the mapper.
- All data sets have the same number of partitions.
- Each partition is sorted by foreign key, and all the foreign keys reside in the associated partition of each data set.
- The data sets do not change often (if they have to be prepared).



Composite Join Structure

- Map-only
- Mapper is very trivial.
- Two values are retrieved from the input tuple and output to file system, e.g., `(key, value1, value2)`
- Most of the work is done by the driver code `CompositeInputFormat`
  - parses all the input files and outputs records to the mapper.



Composite Join Performance Analysis

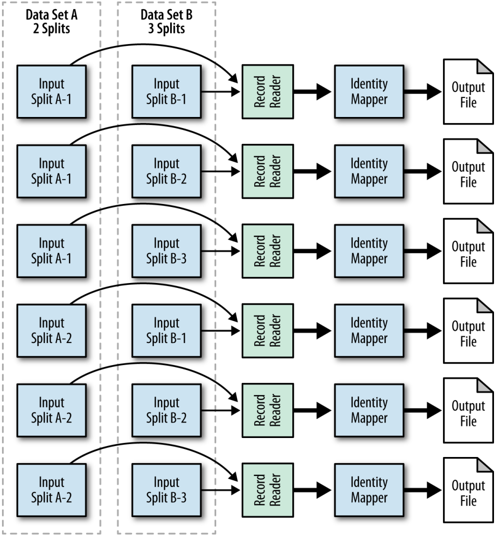
- Can be executed relatively quickly over large data sets.
- Data Preparation = sorting cost
- The cost of preparing the data is averaged out over all of the runs.

Cartesian Product

- Intent
  - Pair up and compare every single record with every other record in one or more data sets
- A Cartesian product does not fit nicely into the MapReduce paradigm
  - The operation is not intuitively splittable and cannot be parallelized very well
- Applications
  - You want to analyze relationships between all pairs of individual records.
- SQL Resemblance
  - `SELECT * FROM tableA, tableB;`

Cartesian Product Structure

- Map-only
- Essentially a RecordReader job
- Cross product of input splits is determined during job setup.
- Each record reader is responsible for generating the cross product of records from both input splits.



Cartesian Product Performance Analysis

- A massive explosion in data size $O(n^2)$
- If a single input split contains a thousand records $\rightarrow$ the right input split needs to be read a thousand times before the task can finish.
- If a single task fails for an odd reason, the whole thing needs to be restarted.

Summary

- MapReduce requires a new way of thinking and problem solving.
- Common pitfalls:
  - Mappers and reducers should be stateless.
  - Avoid your own IO and too much data to the same key.
- Design patterns are helpful for designing MapReduce algorithms.
  - Provide templates for solving common data manipulation problems.
  - Different categories of patterns.
- Filtering patterns are used to extract a small subset of the data.
  - Filter analyse each record individually, and data is not modified.
  - Sampling as a special form of filtering
  - Different filtering patterns: Filtering, Bloom filtering, Top Ten, Distinct.
- Numerical summarization patterns for calculating aggregate values.
- Join patterns combine data from different sources
  - Among the most complex patterns in MR
  - Combining data does not fit gracefully into the MR paradigm (which considers tuples individually)
  - Different join patterns: Reduce Side Join, Replicated Join, Composite Join, Cartesian Product