

Hadoop MapReduce (part b)

ECE 454 / 750: Distributed Computing

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Slides are derived from online materials:

<https://highlyscalable.wordpress.com/2012/02/01/mapreduce-patterns/>

Learning objectives

MapReduce programming patterns in pseudo-code:

- counting and summing
- selection
- projection
- inverted index
- cross-correlation

Counting and summing

The simplest solution outputs a (key, 1) tuple for every instance of a key.

```
class Mapper
  method Map(docid id, doc d)
    for all term t in doc d do
      Emit(term t, count 1)
```

```
class Reducer
  method Reduce(term t, counts [c1, c2,...])
    sum = 0
    for all count c in [c1, c2,...] do
      sum = sum + c
    Emit(term t, count sum)
```

Counting and summing (cont.)

Instead of emitting one key-value pair for each word in the input, the mapper can aggregate the counts for each document. This requires additional memory for the map task.

```
class Mapper
  method Map(docid id, doc d)
    H = new AssociativeArray
    for all term t in doc d do
      H{t} = H{t} + 1
    for all term t in H do
      Emit(term t, count H{t})
```

Counting and summing (cont.)

Alternatively, a combiner can be used to aggregate counters across all the documents processed by a map task. The combiner is executed before the shuffle phase, and is usually identical to the reducer.

```
class Mapper
  method Map(docid id, doc d)
    for all term t in doc d do
      Emit(term t, count 1)

class Combiner
  method Combine(term t, counts [c1, c2,...])
    sum = 0
    for all count c in [c1, c2,...] do
      sum = sum + c
    Emit(term t, count sum)
```

Selection

Selection returns a subset of the input elements that satisfy some predicate (e.g., $x < 10$). Only a mapper is required, and it is possible to run the job without a reducer at all, in which case the framework will generate one output file per map task.

```
class Mapper
  method Map(rowkey key, tuple t)
    if t satisfies the predicate
      Emit(tuple t, null)
```

Projection

Projection returns a subset of the fields of each input element (e.g., from $\langle x, y, z \rangle$ to $\langle x, y \rangle$). The reducer is needed only to eliminate duplicates.

```
class Mapper
```

```
    method Map(rowkey key, tuple t)
```

```
        tuple g = project(t)  // extract required fields to tuple g
```

```
        Emit(tuple g, null)
```

```
class Reducer
```

```
    method Reduce(tuple t, array n)  // n is an array of nulls
```

```
        Emit(tuple t, null)
```

Inverted index

Given a set of text documents with distinct identifiers, produce a mapping from term to document ID.

```
class Mapper
```

```
    method Map(docid id, doc d)
```

```
        for all term t in doc d do
```

```
            Emit(term t, docid id)
```

```
class Reducer
```

```
    method Reduce(term t, docids [id1, id2, ...])
```

```
        Emit(term t, list of docids)
```


Cross-correlation

Problem statement:

- There is a set of tuples of items (e.g., sentences of words). For each possible pair of items, calculate **the number of tuples where these items co-occur**. If the total number of items is N , then N^2 values should be reported.
- This problem appears in text analysis (say, items are words and tuples are sentences), market analysis (customers who buy *this* tend to also buy *that*). If N^2 is quite small and such a matrix can fit in the memory of a single machine, then the implementation is straightforward.
- Otherwise, it is possible to scale out the computation using MR.

Cross-correlation (cont.)

Pairs Approach: simplest and generally slowest (**why?**)

```
class Mapper
  method Map(void, items [i1, i2,...] )
    for all item i in [i1, i2,...]
      for all item j in [i1, i2,...] such that j > i
        Emit(pair [i j], count 1)
```

```
class Reducer
  method Reduce(pair [i j], counts [c1, c2,...])
    s = sum([c1, c2,...])
    Emit(pair[i j], count s)
```

Cross-correlation (cont.)

Stripes Approach: faster (**why?**) but more complex and requires more memory for map-side aggregation (i.e., computing H).

```
class Mapper
  method Map(void, items [i1, i2,...] )
    for all item i in [i1, i2,...]
      H = new AssociativeArray : item -> counter
      for all item j in [i1, i2,...] such that j > i
        H{j} = H{j} + 1
      Emit(item i, stripe H)
```

```
class Reducer
  method Reduce(item i, stripes [H1, H2,...])
    H = new AssociativeArray : item -> counter
    H = merge-sum( [H1, H2,...] )
    for all item j in H.keys()
      Emit(pair [i j], H{j})
```

Cross-correlation (cont.)

- Two examples are given shortly. For simplicity, the first example uses short records with two items per record. The second example uses longer records with three items per record.
- The examples assume that the mapper function in the previous two slides is optimized as follows:
 1. The mapper emits nothing if $i = j$ because we are not interested in cross-correlations between an item and itself.
 2. The mapper eliminates duplicates by ensuring that $i < j$.
- Both examples assume that a combiner is not used. To prepare for the midterm and final exam, repeat this exercise on your own assuming that a combiner is used.

Example 1: pairs

R1 = “a dog”, R2 = “a cat”

Mapper:

Input: R1
 R2

Output: <[a, dog], 1>
 <[a, cat], 1>

Reducer:

Input: <[a, dog], [1]>
 <[a, cat], [1]>

Output: <[a, dog], 1>
 <[a, cat], 1>

Example 1: stripes

R1 = “a dog”, R2 = “a cat”

Mapper:

Input: R1
 R2

Output: <[a], {dog:1}>
 <[a], {cat:1}>

Reducer:

Input: <[a], [{dog:1}, {cat:1}]>
Output: <[a, dog], 1>
 <[a, cat], 1>

Example 2: pairs

R1 = “a big dog”, R2 = “a small cat”

Mapper:

Input: R1
R2

Output: <[a, big], 1> <[a, dog], 1> <[big, dog], 1>
<[a, small], 1> <[a, cat], 1> <[cat, small], 1>

Reducer:

Input: <[a, big], [1]> <[a, dog], [1]> <[big, dog], [1]>
<[a, small], [1]> <[a, cat], [1]> <[cat, small], [1]>

Output: <[a, big], 1> <[a, cat], 1> <[a, dog], 1>
<[a, small], 1> <[big, dog], 1> <[cat, small], 1>

Example 2: stripes

R1 = “a big dog”, R2 = “a small cat”

Mapper:

Input: R1
R2

Output: $\langle [a], \{big:1, dog:1\} \rangle \langle [big], \{dog:1\} \rangle$
 $\langle [a], \{small:1, cat:1\} \rangle \langle [cat], \{small:1\} \rangle$

Reducer:

Input: $\langle [a], [\{big:1, dog:1\}, \{small:1, cat:1\}] \rangle$
 $\langle [big], [\{dog:1\}] \rangle \quad \langle [cat], [\{small:1\}] \rangle$

Output: $\langle [a, big], 1 \rangle \langle [a, cat], 1 \rangle \langle [a, dog], 1 \rangle$
 $\langle [a, small], 1 \rangle \langle [big, dog], 1 \rangle \langle [cat, small], 1 \rangle$