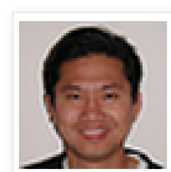
Pragmatic Programming Techniques

Today's presentation is largely stolen from Ricky Ho's Blog posting (But, any mistakes are assuredly mine!):

Sunday, August 29, 2010

Designing algorithms for Map Reduce

14-736, Monday, April 3rd (Gregory Kesden, Presenting)

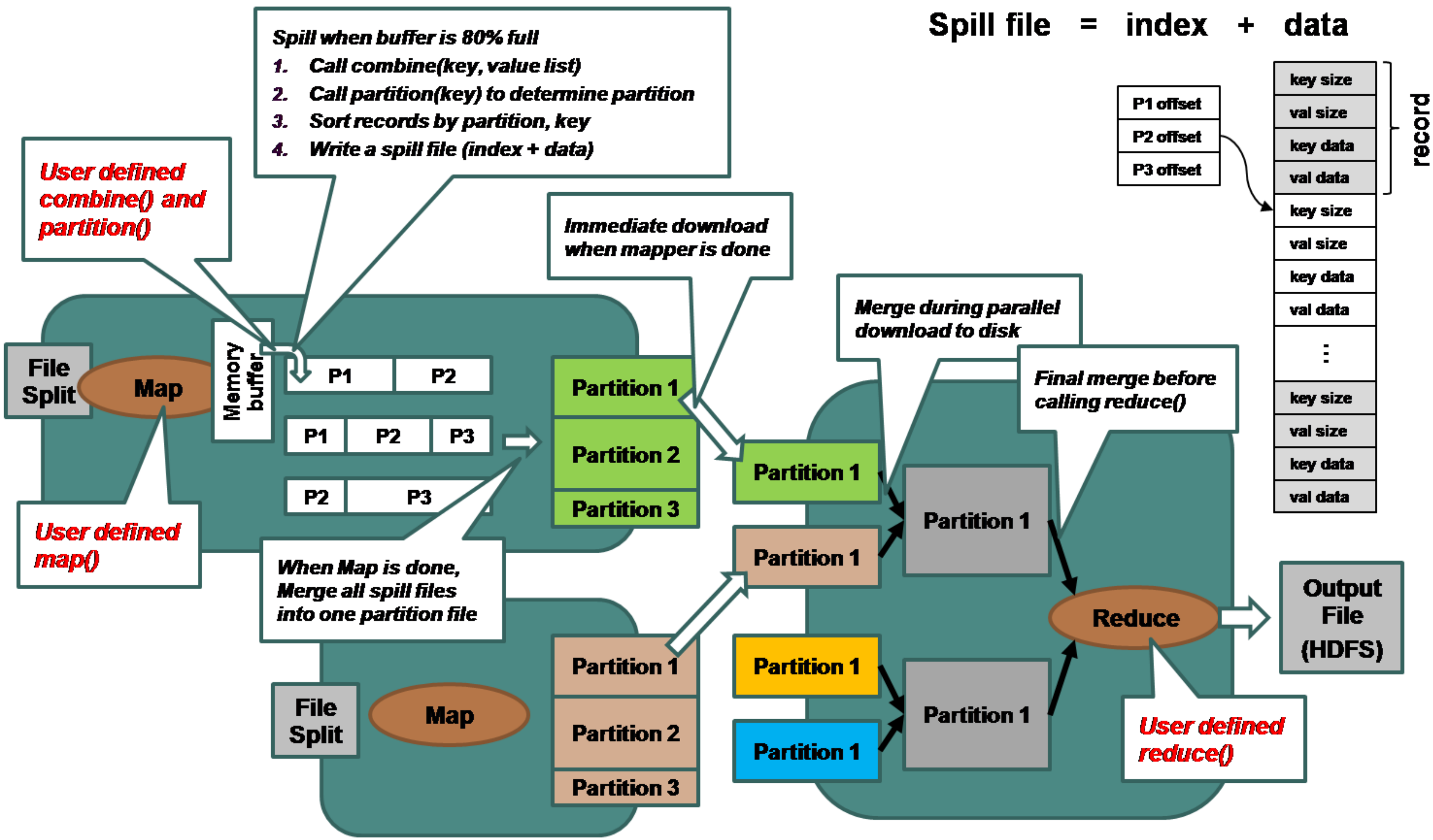


Ricky Ho

I am a software architect and consultant passionate in Distributed and parallel computing, Machine learning and Data mining, SaaS and Cloud computing.

http://horicky.blogspot.com/2010/08/designing-algorithmis-for-map-reduce.html

Map-Reduce Overview



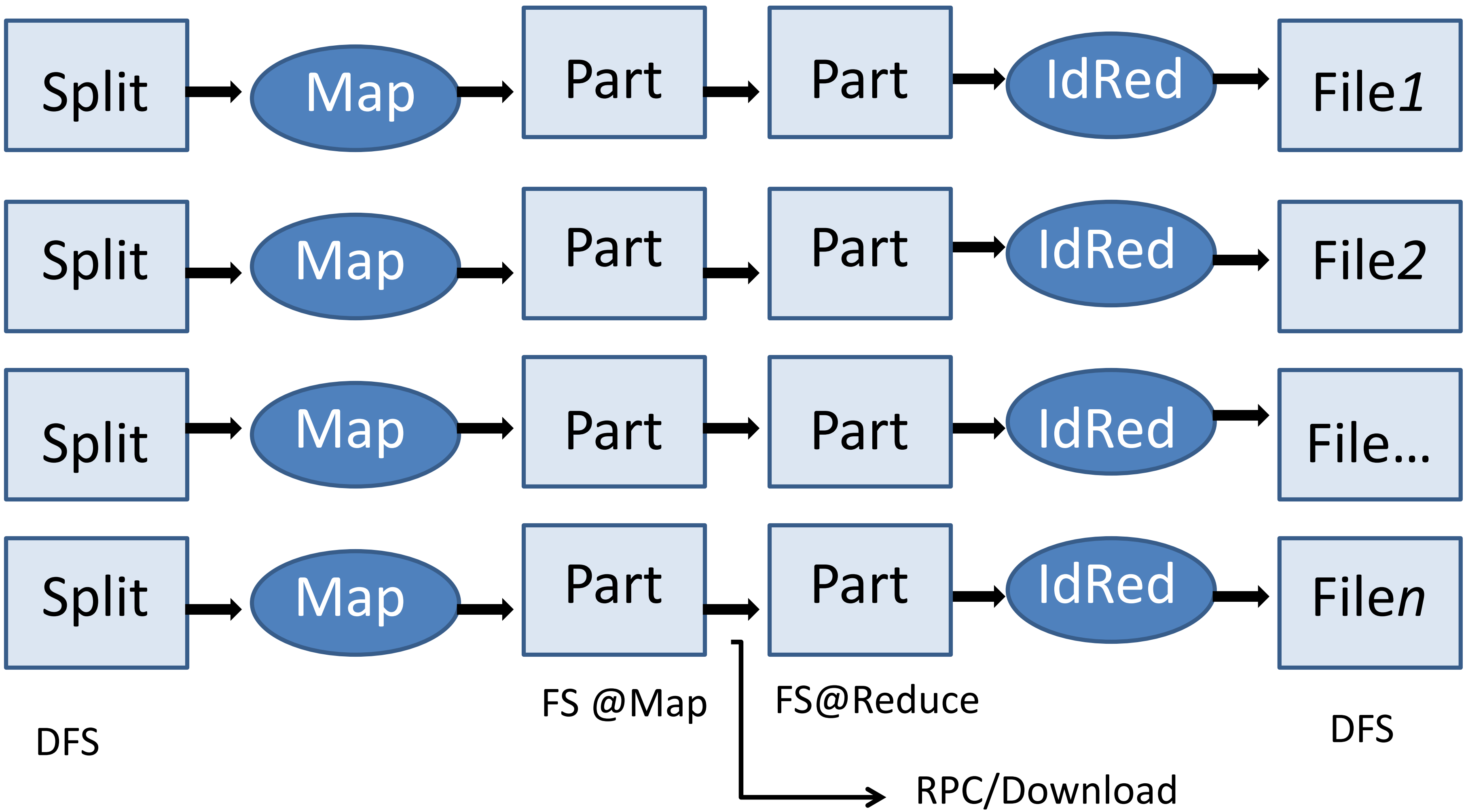
Where’s The Hype?

- Parallelism is (mostly) in the maps, which are independent (unsynchronized).
  - O(n) becomes O(1) with parallelism
- Merge sorts are Merge Sorts
  - O(n log n)
- Reduces are linear
  - O(n)

“Embarrassingly Parallel”

- Some things are essentially only Maps
  - Identity reduce
  - Massively parallel
  - No bottleneck
- Examples:
  - Filter to retain or exclude only certain patterns
  - Reduce data size by random sampling
  - Convert format, e.g. bold to italics
  - Flag bad data, e.g. negative, out of range, etc.

"Embarrassingly Parallel"



Sorting

- Map-Reduce is, in many ways, a distributed sorting engine that can some useful work along the way
  - The merge sort and reduce perform the sort
- We can leverage this if we actually want to sort
  - Identity map
  - Identity reduce
- One possibly trick: Partition by range
  - Simplifies merge.

```
partition(key) {
  range = (KEY_MAX - KEY_MIN) / NUM_OF_REDUCERS
  reducer_no = (key - KEY_MIN) / range
  return reducer_no
}
```

Inverted Indexes

- Common index from key to location, e.g. word to <fileName:line#>
- Map emits key, e.g. <word, fileName:line#>
- Reduce produces <key, list<metadata>>, e.g. <word, list<fileName:line#>>

```
map(key, container) {
  for each element in container {
      element_meta =
           extract_metadata(element, container)
      emit(element, [container_id, element_meta])
  }
}

reduce(element, container_ids) {
  element_stat =
       compute_stat(container_ids)
  emit(element, [element_stat, container_ids])
}
```

Simple Statistics

- Where operation is *both* commutative and associative
- Map does local computation
- Reduce forms global computation
- Examples: Min, max, count, sum (What about average?)

```
class Mapper {
  buffer

  map(key, number) {
      buffer.append(number)
      if (buffer.is_full) {
          max = compute_max(buffer)
          emit(1, max)
      }
  }
}
```

```
class Reducer {
  reduce(key, list_of_local_max) {
      global_max = 0
      for local_max in list_of_local_max {
          if local_max > global_max {
              global_max = local_max
          }
      }       emit(1, global_max)
  }
}
```

```
class Combiner {
  combine(key, list_of_local_max) {
      local_max = maximum(list_of_local_max)
      emit(1, local_max)
  }
}
```

Histograms

- Divide into different intervals.
- Maps compute the count per interval.
- Reduce will compute the per interval.
- Note power is in map: Ability to classify in parallel

```
class Mapper {
  interval_start = [0, 20, 40, 60, 80]

  map(key, number) {
      i = 0;
      while (i < NO_OF_INTERVALS) {
          if (number < interval_start[i]) {
              emit(i, 1)
              break
          }
      }
  }
}
```

```
class Reducer {
  reduce(interval, counts) {
      total_counts = 0
      for each count in counts
          total_counts += count
      }
      emit(interval, total_coun
  }
```

```
class Combiner {
  combine(interval, occurrence) {
      emit(interval, occurrence.size)
  }
}
```

SELECT

- Filter: *result = SELECT c1, c2, c3, c4 FROM source WHERE conditions*
  - Implement in Map
- Aggregation: *SELECT sum(c3) as s1, avg(c4) as s2 ... FROM result GROUP BY c1, c2 HAVING conditions*
  - Implement in Reduce

```
class Mapper {
  map(k, rec) {
      select_fields =
          [rec.c1, rec.c2, rec.c3, rec.c4]
      group_fields =
          [rec.c1, rec.c2]
      if (filter_condition == true) {
          emit(group_fields, select_fields)
      }
  }
}
```

```
class Reducer {
  reduce(group_fields, list_of_rec) {
      s1 = 0
      s2 = 0
      for each rec in list_of_rec {
          s1 += rec.c3
          s2 += rec.c4
      }
      s2 = s2 / rec.size
      if (having_condition == true) {
          emit(group_fields, [s1, s2])
      }
  }
}
```

Simple Join

```
map(k1, rec) {
  emit(rec.key, [rec.type, rec])
}

reduce(k2, list_of_rec) {
  list_of_typeA = []
  list_of_typeB = []
  for each rec in list_of_rec {
      if (rec.type == 'A') {
          list_of_typeA.append(rec)
      } else {
          list_of_typeB.append(rec)
      }
  }

  # Compute the catesian product
  products = []
  for recA in list_of_typeA {
      for recB in list_of_typeB {
          emit(k2, [recA, recB])
      }
  }
}
```

Kesden’s Additional Slides

- The next few slides are from me, rather than the cited source for the rest of the presentation.

Normalize Format For Join

- Map records to common Format
- Identity reduce
- Identity Map
- Reduce to form cross-product
- Filter to get results

Shortest Path

- Form Graph as Adjacency List
  - Map: <Node, <Node, Distance>> for each adjacency
  - Reduce:<Node, Shortest<Node, Distance>>

- Work from each node in parallel
- Map
  - Node *n* as a key and *(D, points-to)* as its value
    - *D* is the distance form the start
    - *Points-to* is a list of Nodes reachable from *n*, initially direct adjacencies
    - Emits all points reachable from *n* via each node in *points-to*
- Reduce
  - Emits one Node n for each key, the one with the shortest D

- Repeat Map and Reduce phases until no shorter distances found (nothing learned, nothing can be learned, convergance)