Pairs Design Pattern


```
map(docID a, doc d)
 for all term w in doc d do
  for all term u NEAR w do
   Emit(pair (w, u), count 1)

reduce(pair p, counts [c1, c2,…])
 sum = 0
 for all count c in counts do
  sum += c
 Emit(pair p, count sum)
```

- Can use combiner or in-mapper combining
- Good: easy to implement and understand
- Bad: huge intermediate-key space (shuffling/sorting cost!)
  - Quadratic in number of distinct terms

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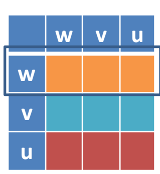
Stripes Design Pattern




```
map(docID a, doc d)
 for all term w in doc d do
  H = new hashMap
  for all term u NEAR w do  H{u} ++
  Emit(term w, stripe H)

reduce(term w, stripes [H1, H2,…])
 Hout = new hashMap
 for all stripe H in stripes do  Hout = ElementWiseSum(Hout, H)
 Emit(term w, stripe Hout)
```

- Can use combiner or in-mapper combining
- Good: much smaller intermediate-key space
  - Linear in number of distinct terms
- Bad: more difficult to implement, Map needs to hold entire stripe in memory

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Beyond Pairs and Stripes

- In general, it is not clear which approach is better
  - Some experiments indicate stripes win for co-occurrence matrix computation
- Pairs and stripes are special cases of shapes for covering the entire matrix
  - Could use sub-stripes, or partition matrix horizontally and vertically into more square-like shapes etc.
- Can also be applied to higher-dimensional arrays
- Will see interesting version of this idea for joins

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(3) Relative Frequencies

- Important for data mining
- E.g., for each species and color, compute probability of color for that species
  - Probability of Northern Cardinal being red, P(color = red | species = N.C.)
    - Count f(N.C.), the frequency of observations for N.C. (marginal)
    - Count f(N.C., red), the frequency of observations for red N.C.'s (joint event)
    - P(red | N.C.) = f(N.C., red) / f(N.C.)
- Similarly: normalize word co-occurrence vector for word w by dividing it by w's frequency

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Bird Probabilities Using Stripes

- Use species as intermediate key
  - One stripe per species, e.g., stripe[N.C.]
- (stripe[species])[color] stores f(species, color)
- Map: for each observation of (species S, color C) in an observation event, increment (stripe[S])[C]
  - Output (S, stripe[S])
- Reduce: for each species S, add all stripes for S
  - Result: stripeSum[S] with total counts for each color for S
  - Can get f(S) by adding all stripeSum[S] values together
  - Get probability P(color = C | species = S) as (stripeSum[S])[C] / f(S)

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Discussion, Part 1

- Stripe is great fit for relative frequency computation
- All values for computing the final result are in the stripe
- Any smaller unit would miss some of the joint events needed for computing f(S), the marginal for the species
- So, this would be a problem for the pairs pattern

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Bird Probabilities Using Pairs

- Intermediate key is (species, color)
- Map produces partial counts for each species-color combination in input
- Reduce can compute f(species, color), the total count of each species-color combination
- But: cannot compute marginal f(S)
  - Reduce needs to sum f(S, color) for all colors for species S

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Pairs-Based Solution, Take 1

- Make sure all values f(S, color) for the same species end up in the same reduce task
  - Define custom partitioning function on species
- Maintain state across different keys in same reduce task
- This essentially simulates the stripes approach in the reduce task, creating big reduce tasks when there are many colors
- Can we do better?

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Discussion, Part 2

- Pairs-based algorithm would work better, if marginal f(S) was known already
  - Reducer computes f(species, color) and then outputs f(species, color) / f(species)
- We can compute the species marginals f(species) in a separate MapReduce job first
- Better: fold this into a single MapReduce job
  - Problem: easy to compute f(S) from all f(S, color), but how do we compute f(S) before knowing f(S, color)?

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Bird Probabilities Using Pairs, Take 2

- Map: for each observation event, emit ((species S, color C), 1) and ((species S, dummyColor), 1) for each species-color combination encountered
- Use custom partitioner that partitions based on the species component only
- Use custom key comparator such that (S, dummyColor) is before all (S, C) for real colors C
  - Reducer computes f(S) before the f(S, C)
    - Reducer keeps f(S) in state for duration of entire task
  - Reducer then computes f(S, C) for each C, outputting f(S, C) / f(S)
- Advantage: avoids having to manage all colors for a species together

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Order Inversion Design Pattern

- Occurs surprisingly often during data analysis
- Solution 1: use complex data structures that bring the right results together
  - Array structure used by stripes pattern
- Solution 2: turn synchronization into ordering problem
  - Key sort order enforces computation order
  - Partitioner for key space assigns appropriate partial results to each reduce task
  - Reducer maintains task-level state across Reduce invocations
  - Works for simpler pairs pattern, which uses simpler data structures and requires less reducer memory

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(4) Secondary Sorting

- Recall the weather data: for simplicity assume observations are (date, stationID, temperature)
- Goal: for each station, create a time series of temperature measurements
- Per-station data: use stationID as intermediate key
- Problem: reducers receive huge number of (date, temp) pairs for each station
  - Have to be sorted by user code

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Can Hadoop Do The Sorting?

- Use (stationID, date) as intermediate key
  - Problem: records for the some station might end up in different reduce tasks
  - Solution: custom partitioner, using only stationID component of key for partitioning
- General value-to-key conversion design pattern
  - To partition by X and then sort each X-group by Y, make (X, Y) the key
  - Define key comparator to order by composite key (X, Y)
  - Define partitioner and grouping comparator for (X, Y) to consider only X for partitioning and grouping
    - Grouping part is necessary if all dates for a station should be processed in the same Reduce invocation (otherwise each station-date combination ends up in a different Reduce invocation)

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Design Pattern Summary

- In-mapper combining: do work of combiner in mapper
- Pairs and stripes: for keeping track of joint events
- Order inversion: convert sequencing of computation into sorting problem
- Value-to-key conversion: scalable solution for secondary sorting, without writing own sort code

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Tools for Synchronization

- Cleverly-constructed data structures for key and values to bring data together
- Preserving state in mappers and reducers, together with capability to add initialization and termination code for entire task
- Sort order of intermediate keys to control order in which reducers process keys
- Custom partitioner to control which reducer processes which keys

Issues and Tradeoffs

- Number of key-value pairs
  - Object creation overhead
  - Time for sorting and shuffling pairs across the network
- Size of each key-value pair
  - (De-)serialization overhead
- Local aggregation
  - Opportunities to perform local aggregation vary
  - Combiners can make a big difference
  - Combiners vs. in-mapper combining
  - RAM vs. disk vs. network

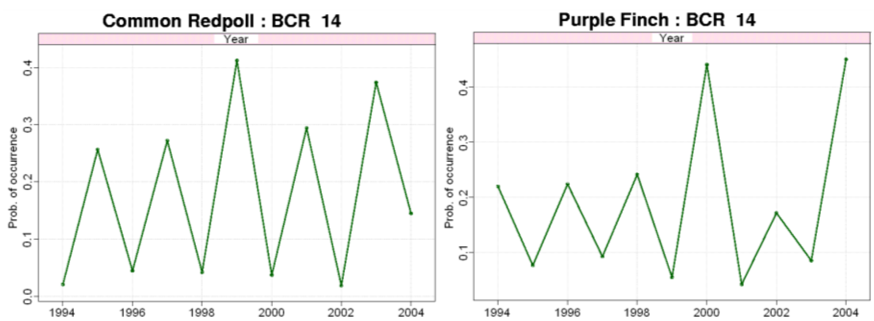
Now that we have seen important design patterns and MapReduce algorithms for simpler problems, let's look at some more complex problems.

Joins in MapReduce

- Data sets $S=\{s_1,\ldots, s_{|S|}\}$ and $T=\{t_1,\ldots, t_{|T|}\}$
- Find all pairs (s_i, t_j) that satisfy some predicate
- Examples
  - Pairs of similar or complementary function summaries
  - Facebook and Twitter posts by same user or from same location
- Typical goal: minimize job completion time

Function-Join Pattern

- Find groups of summaries with certain properties of interest
  - Similar trends, opposite trends, correlations
  - Groups not known a priori, need to be discovered



Existing Join Support

- Hadoop has some built-in join support, but our goal is to design our own algorithms
  - Built-in support is limited
  - We want to understand important algorithm design principles
- “Join” usually just means equi-join, but we also want to support other join predicates
- Note: recall join discussion from earlier lecture

Joining Large With Small

- Assume data set T is small enough to fit in memory
- Can run Map-only join
  - Load T onto every mapper
  - Map: join incoming S-tuple with T, output all matching pairs
    - Can scan entire T (nested loop) or use index on T (index nested loop)
- Downside: need to copy T to all mappers
  - Not so bad, since T is small

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Distributed Cache

- Efficient way to copy files to all nodes processing a certain task
  - Use it to send small T to all mappers
- Part of the job configuration
- Hadoop still needs to move the data to the worker nodes, so use this with care
  - But it avoids copying the file for every task on the same node

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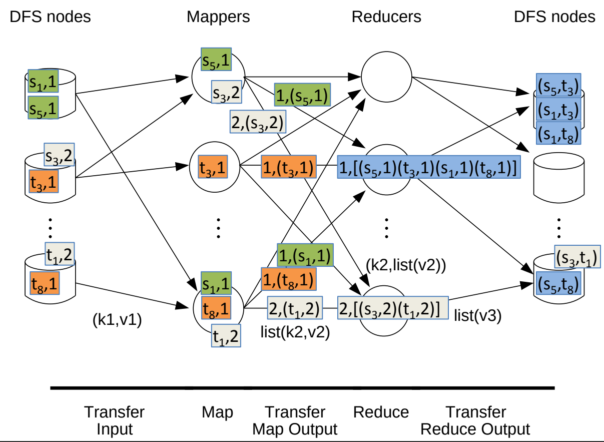
Recall: Standard Equi-Join Algorithm

- Join condition: S.A=T.A
- Map(s) = (s.A, s); Map(t) = (t.A, t)
- Reduce combines S-tuples and T-tuples with same key

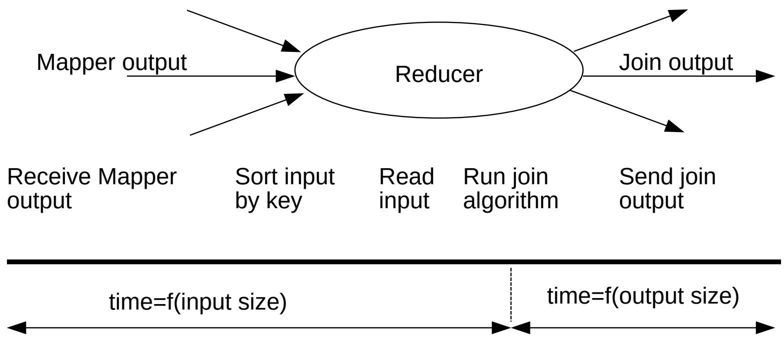


Problems With Standard Approach

- Degree of parallelism limited by number of distinct A-values
- Data skew
  – If one A-value dominates, reducer processing that key will become bottleneck
- Does not generalize to other joins

Reducer-Centric Cost Model

- Difference between join implementations starts with Map output

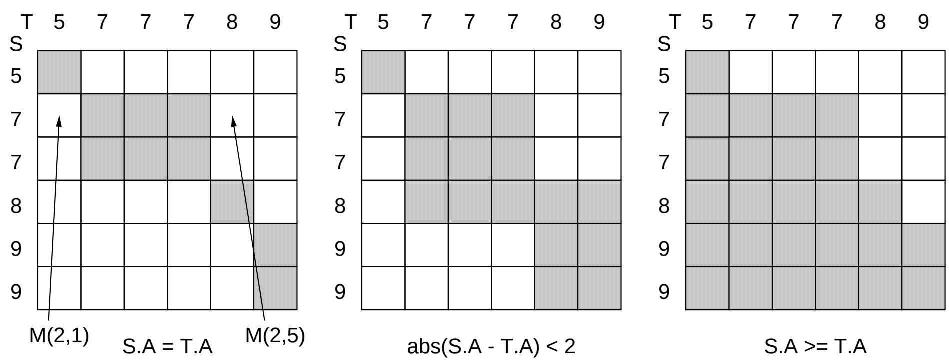


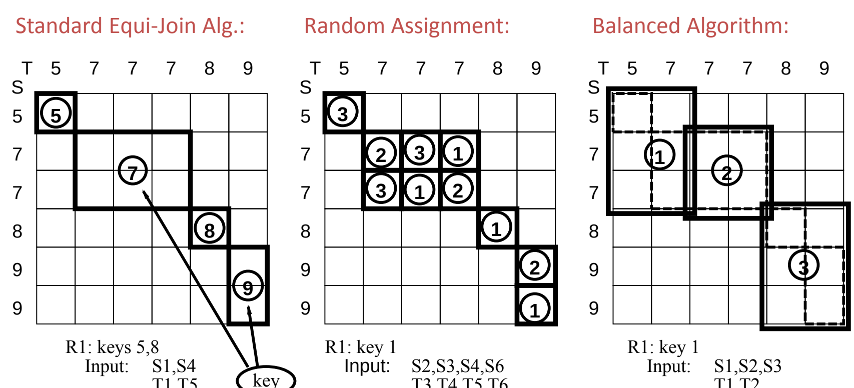
Optimization Goal: Minimal Job Completion time

- Assume all reducers are similarly capable
- Processing time at reducer is approximately monotonic in input and output size
- Hence need to minimize:
  - Max-reducer-input and/or
  - Max-reducer-output
- Join problem classification
  - Input-size dominated: minimize max-reducer-input
  - Output-size dominated: minimize max-reducer-output
  - Input-output balanced: minimize combination of both

Join Model

- Join-matrix M: M(i, j) = *true*, if and only if (s_i, t_j) in join result
- Cover each *true*-valued cell by exactly one reducer





Standard Equi-Join Alg.:

R1: keys 5,8
Input: S1,S4
T1,T5
Output: 2 tuples

R2: key 7
Input: S2,S3
T2,T3,T4
Output: 6 tuples

R3: key 9
Input: S5,S6
T6
Output: 2 tuples

max-reducer-input = 5
max-reducer-output = 6

Random Assignment:

R1: key 1
Input: S2,S3,S4,S6
T3,T4,T5,T6
Output: 4 tuples

R2: key 2
Input: S2,S3,S5
T2,T4,T6
Output: 3 tuples

R3: key 3
Input: S1,S2,S3
T1,T2,T3
Output: 3 tuples

max-reducer-input = 8
max-reducer-output = 4

Balanced Algorithm:

R1: key 1
Input: S1,S2,S3
T1,T2
Output: 3 tuples

R2: key 2
Input: S2,S3
T3,T4
Output: 4 tuples

R3: key 3
Input: S4,S5,S6
T5,T6
Output: 3 tuples

max-reducer-input = 5
max-reducer-output = 4