Hash-Based Improvements to A-Priori

Park-Chen-Yu Algorithm

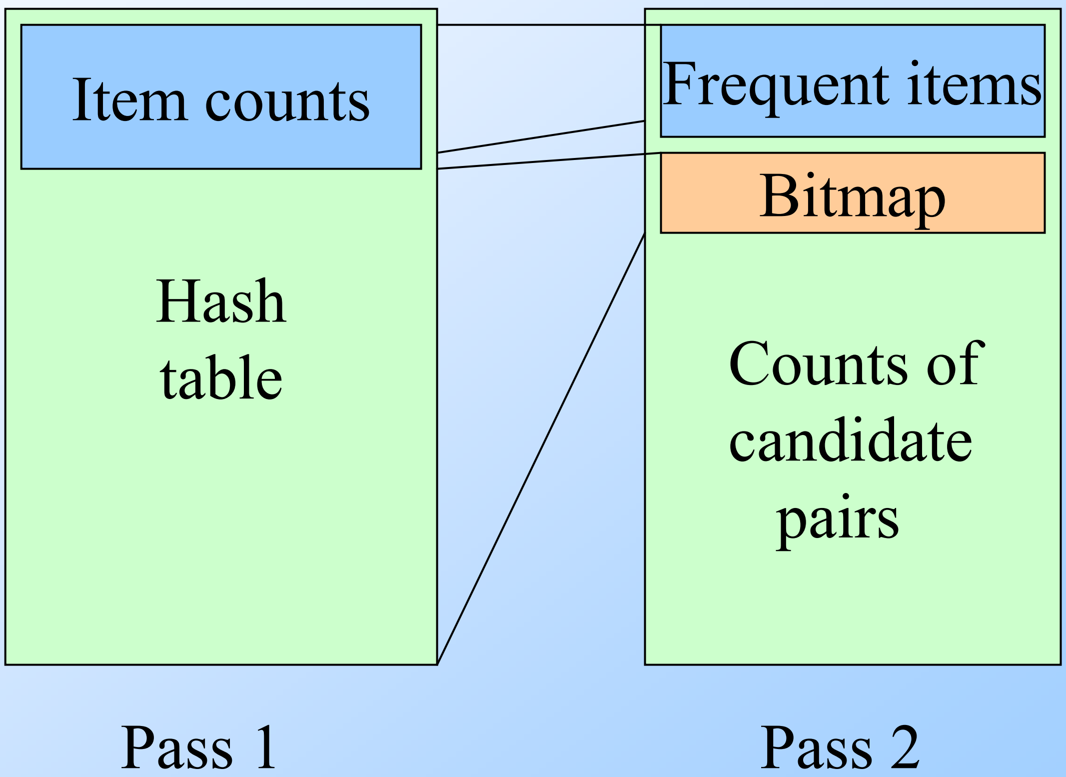
Multistage Algorithm

Approximate Algorithms

PCY Algorithm

- Hash-based improvement to A-Priori.
- During Pass 1 of A-priori, most memory is idle.
- Use that memory to keep counts of buckets into which pairs of items are hashed.
  - Just the count, not the pairs themselves.
- Gives extra condition that candidate pairs must satisfy on Pass 2.

Picture of PCY



PCY Algorithm --- Before Pass 1

- Organize main memory:
  - Space to count each item.
    - One (typically) 4-byte integer per item.
  - Use the rest of the space for as many integers, representing buckets, as we can.

PCY Algorithm --- Pass 1

```
FOR (each basket) {
    FOR (each item)
      add 1 to item's count;
    FOR (each pair of items) {
      hash the pair to a bucket;
      add 1 to the count for that
        bucket
    }
}
```

PCY Algorithm --- Between Passes

- Replace the buckets by a bit-vector:
  - 1 means the bucket count $\geq$ the support s (frequent bucket); 0 means it did not.
- Integers are replaced by bits, so the bit vector requires little second-pass space.
- Also, decide which items are frequent and list them for the second pass.

PCY Algorithm --- Pass 2

- Count all pairs $\{i,j\}$ that meet the conditions:
  1. Both i and j are frequent items.
  2. The pair $\{i,j\}$, hashes to a bucket number whose bit in the bit vector is 1.
- Notice all these conditions are necessary for the pair to have a chance of being frequent.

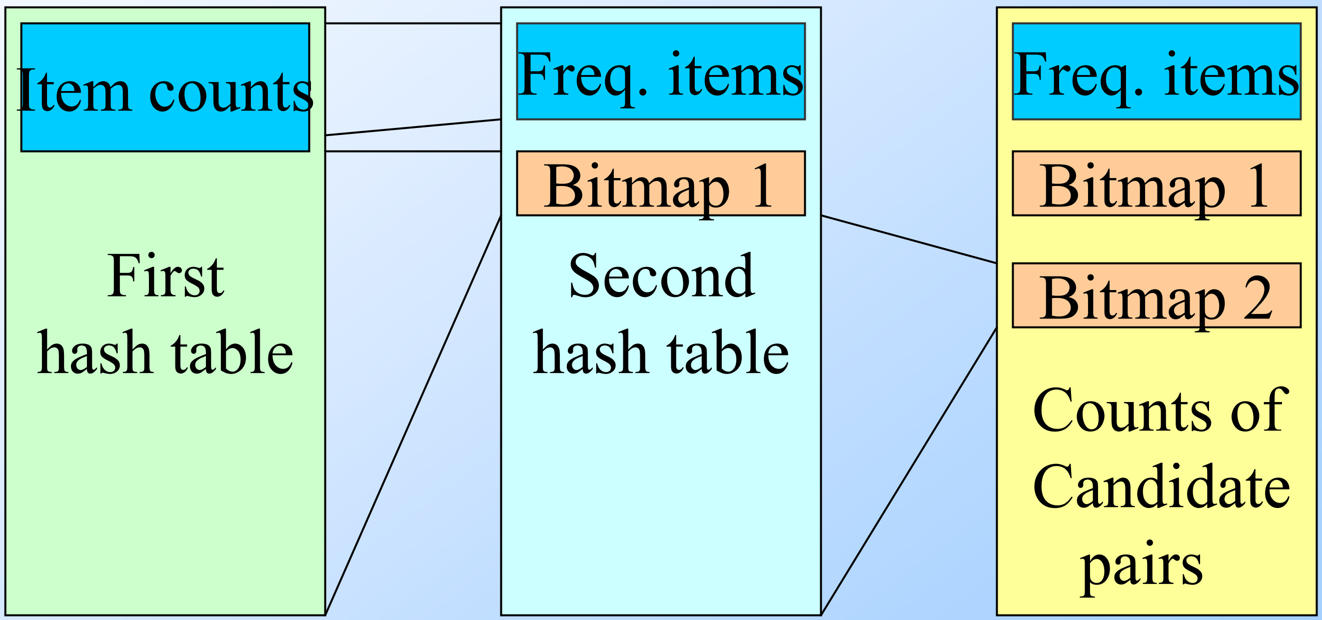
Memory Details

- Hash table requires buckets of 2-4 bytes.
  - Number of buckets thus almost 1/4-1/2 of the number of bytes of main memory.
- On second pass, a table of (item, item, count) triples is essential.
  - Thus, we need to eliminate 2/3 of the candidate pairs to beat a-priori.

Multistage Algorithm

- Key idea: After Pass 1 of PCY, rehash only those pairs that qualify for Pass 2 of PCY.
- On middle pass, fewer pairs contribute to buckets, so fewer *false drops* --- frequent buckets with no frequent pair.

Multistage Picture



Multistage --- Pass 3

- Count only those pairs $\{i,j\}$ that satisfy:
  1. Both i and j are frequent items.
  2. Using the first hash function, the pair hashes to a bucket whose bit in the first bit-vector is 1.
  3. Using the second hash function, the pair hashes to a bucket whose bit in the second bit-vector is 1.

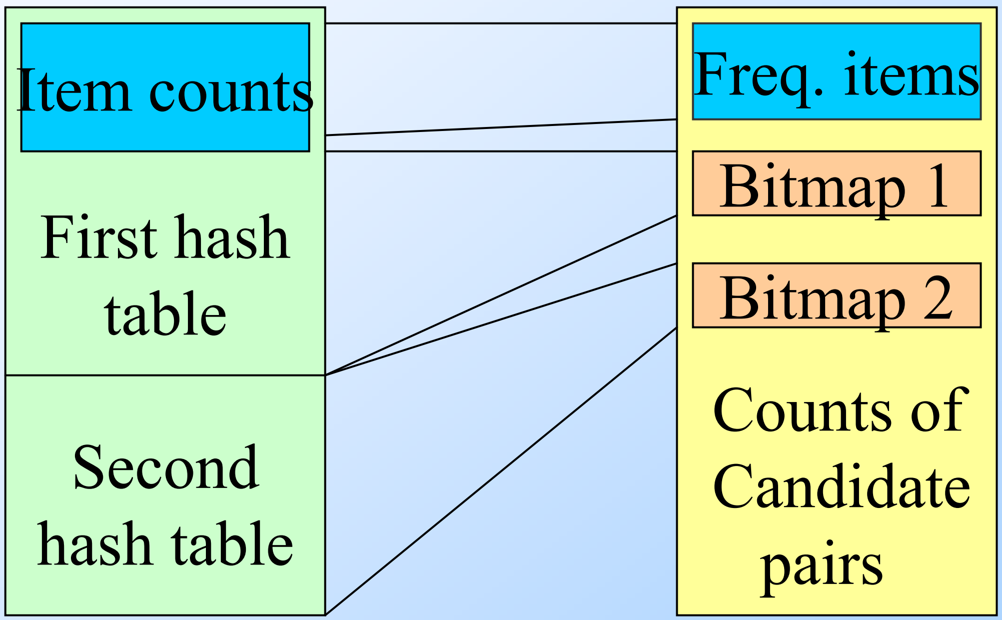
Important Points

1. The two hash functions have to be independent.
2. We need to check both hashes on the third pass.
   - If not, the pair could pass tests (1) and (3), yet it was never hashed on the second pass because it was in a low-count bucket on the first pass.

Multihash

- Key idea: use several independent hash tables on the first pass.
- Risk: halving the number of buckets doubles the average count. We have to be sure most buckets will still not reach count *s*.
- If so, we can get a benefit like multistage, but in only 2 passes.

Multihash Picture



Extensions

- Either multistage or multihash can use more than two hash functions.
- In multistage, there is a point of diminishing returns, since the bit-vectors eventually consume all of main memory.
- For multihash, the bit-vectors total exactly what one PCY bitmap does, but too many hash functions makes all counts $\geq s$.

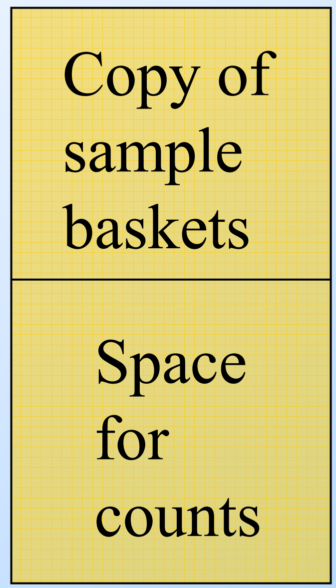
All (Or Most) Frequent Itemsets In $\leq$ 2 Passes

- Simple algorithm.
- SON (Savasere, Omiecinski, and Navathe).
- Toivonen.

Simple Algorithm --- (1)

- Take a main-memory-sized random sample of the market baskets.
- Run a-priori or one of its improvements (for sets of all sizes, not just pairs) in main memory, so you don't pay for disk I/O each time you increase the size of itemsets.
  - Be sure you leave enough space for counts.

The Picture



Simple Algorithm --- (2)

- Use as your support threshold a suitable, scaled-back number.
  - E.g., if your sample is 1/100 of the baskets, use s/100 as your support threshold instead of s.
- Verify that your guesses are truly frequent in the entire data set by a second pass.
- But you don't catch sets frequent in the whole but not in the sample.
  - Smaller threshold, e.g., s/125, helps.

SON Algorithm --- (1)

- Repeatedly read small subsets of the baskets into main memory and perform the first pass of the simple algorithm on each subset.
- An itemset becomes a candidate if it is found to be frequent in *any* one or more subsets of the baskets.

SON Algorithm --- (2)

- On a second pass, count all the candidate itemsets and determine which are frequent in the entire set.
- Key "monotonicity" idea: an itemset cannot be frequent in the entire set of baskets unless it is frequent in at least one subset.

Toivonen's Algorithm --- (1)

- Start as in the simple algorithm, but lower the threshold slightly for the sample.
  - Example: if the sample is 1% of the baskets, use $s/125$ as the support threshold rather than $s/100$.
  - Goal is to avoid missing any itemset that is frequent in the full set of baskets.

Toivonen’s Algorithm --- (2)

- Add to the itemsets that are frequent in the sample the *negative border* of these itemsets.
- An itemset is in the negative border if it is not deemed frequent in the sample, but all its immediate subsets are.

Example

- *ABCD* is in the negative border if and only if it is not frequent, but all of *ABC*, *BCD*, *ACD*, and *ABD* are.

Toivonen's Algorithm --- (3)

- In a second pass, count all candidate frequent itemsets from the first pass, and also count the negative border.
- If no itemset from the negative border turns out to be frequent, then the candidates found to be frequent in the whole data are *exactly* the frequent itemsets.

Toivonen's Algorithm --- (4)

- What if we find something in the negative border is actually frequent?
- We must start over again!
- Try to choose the support threshold so the probability of failure is low, while the number of itemsets checked on the second pass fits in main-memory.