Big Data Analytics-Selected Topics (60-475)

Frequent Itemset Mining and Association Rules

Lecture 4

School of Computer Science Faculty of Science University of Windsor

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Outline

- In last lecture, we talked about A-Priori algorithm for finding frequent itemsets
- In this lecture, we focus on how to find frequent **pairs** even more efficiently
 - First, we have a quick overview of hash tables



Hash Function

- A hash function is a function that:
 - When applied to a key, returns an integer, between 0 to N-1
 - Key could be one integer, two integers, or even five integers
 - Key could also be a String
 - When applied to equal keys, returns the same number
 - When applied to unequal keys, is unlikely to return the same number
- Hash functions are very important for searching, that is, looking things up fast

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Hash Function

- Consider the problem of searching an array for a given value
 - If the array is not sorted, the search requires O(n) time
 - If the array is sorted, we can do a binary search which requires O(log n) time
 - Can we do better?
 - How about an O(1) time?
 - O(1) is constant time!



Hash Function

- Suppose we have a magical function that, given a key to search for, it tells us exactly where in the array to look for the key
 - If it is in that location, it is in the array
 - If not, then it is not in the array
- That is the only purpose of this function
- This function is called a hash function

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Example

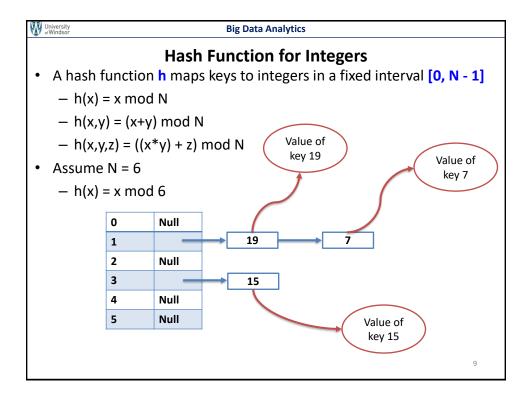
- Suppose we have this hash function:
 - hashCode("apple") = 5
 - hashCode("watermelon") = 3
 - hashCode("grapes") = 8
 - hashCode("orange") = 7
 - hashCode("blueberry") = 0
 - hashCode("strawberry") = 9
 - hashCode("mango") = 6
 - hashCode("banana") = 2

0	blueberry
_	

- 2 banana
- 3 watermelon4
- ⁵ apple
- 6 mango 7 orange
- 8 grapes
- 9 strawberry

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Example - Collision							
 Suppose we have this hash function: hashCode("apple") = 5 	0	blueberry					
hashCode("watermelon") = 3	1						
hashCode("grapes") = 8	2	banana					
hashCode("orange") = 7	3	watermelon					
hashCode("blueberry") = 0	4						
hashCode("strawberry") = 9 hashCode("mango") = 6	5	apple					
hashCode("banana") = 2	6	mango, <mark>kiwi</mark>					
hashCode("kiwi") = 6	7	orange					
There are different ways to deal	8	grapes					
with the collision in a hash table	9	strawberry					
		7					

W)	W University Big Data Analytics								
	Set vs. Map								
•	Sometimes we just want to store a set of keys		key	value					
	 Keys (objects) are either in the set or not 	141							
		142	James	James info					
	Sometimes we want a map — To look up for one object based on the value of its key	143	sparrow	sparrow info					
		144	BMW	BMW info					
		145	seagull	seagull info					
•	We use a key to find the place in the	146							
	map	147	bluejay	bluejay info					
•	The associated value is the	148	owl	owl info					
	information we want to look up			_					
•	Hashing works the same for sets								
	and maps			8					



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Example									
•	 Assume we want to keep the counts of pairs [i,j], but we do not have 								
	space in memory for all pairs								
•	We can put each pair in a bucket								
	 We do have space in memory for all buckets 								
	 Number of Buckets << Number of Pairs 								
	 We use a hash function h(i,j), to find the bucket for each pair 								
•	 Number of buckets (size of hash table) is 6 (N = 6) 								
•	 h(i,j) = (i+j) mod 6 								
•	He	re is ou	r pairs:			Count			
	•	[1,4]	h(1,4) = 5%6 = 5		_				
		- / -	h(3,5) = 8%6 = 2		0	0			
			h(1,4) = 5%6 = 5		1	0			
			h(2,3) = 5%6 = 5		2	2			
			h(1,4) = 5%6 = 5 h(2,6) = 8%6 = 2		3	2			
	•	[1,2]	h(1,2) = 3%6 = 3		4	1			
	•		h(2,7) = 9%6 = 3		-	_			
	•		h(1,3) = 4%6 = 4		5	5			
	•	[1,4]	h(1,4) = 5%6 = 5						
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Back to finding frequent itemsets

How to improve A-Priori?

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PCY (Park-Chen-Yu) Algorithm

Observation:

In pass 1 of A-Priori, most memory is idle

- We store only individual item counts
- Can we use the idle memory to reduce memory required in pass 2?
- Pass 1 of PCY: In addition to item counts,
 maintain a hash table with as many buckets as fit
 in memory (why the maximum number of buckets that fits
 in memory?)
 - Keep a count for each bucket into which pairs of items are hashed
 - For each bucket just keep the count, not the actual pairs that hash to the bucket!

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PCY Algorithm - First Pass

FOR (each basket):

FOR (each item in the basket):

add 1 to item's count;

New in PCY

hash the pair to a bucket;

add 1 to the count for that bucket;
```

Few things to note:

- Pairs of items need to be generated from the input file; they are not present in the file
- We are not just interested in the presence of a pair, but we need to see whether it is present at least s (support) times

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Observations about Buckets

- Observation: If a bucket contains a frequent pair, then the bucket is surely frequent
- However, even without any frequent pair, a bucket can still be frequent ☺
 - So, we cannot use the hash to eliminate any member (pair) of a "frequent" bucket
- But, for a bucket with total count less than s, none of its pairs can be frequent ☺
 - Pairs that hash to this bucket can be eliminated as candidates (even if the pair consists of 2 frequent items)
- Pass 2:
 Only count pairs that hash to frequent buckets

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PCY Algorithm – Between Passes

- Replace the buckets by a bit-vector:
 - 1 means the bucket count exceeded the support s
 (call it a frequent bucket); 0 means it did not
- 4-byte integer counts are replaced by bits, so the bit-vector requires 1/32 of memory
- Also, decide which items are frequent and list them for the second pass

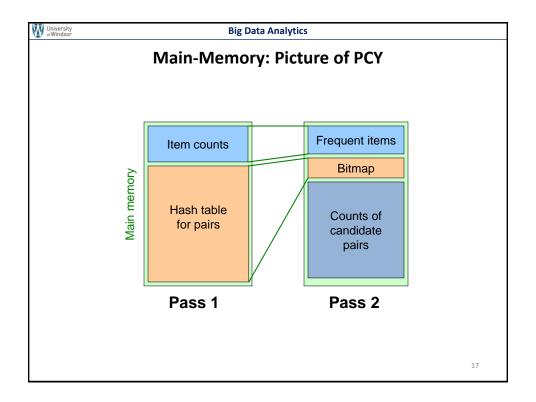
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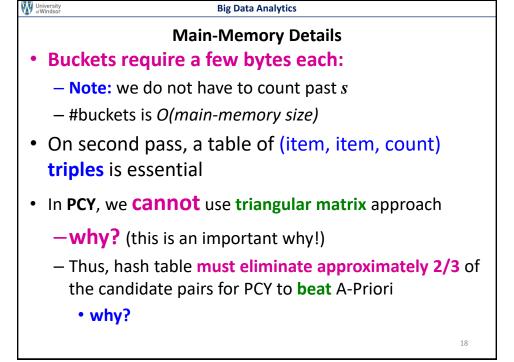


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PCY Algorithm – Pass 2

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

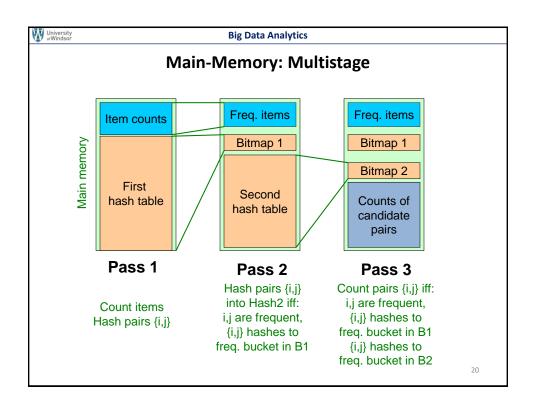






Refinement: Multistage Algorithm

- Limit the number of candidates to be counted
 - Remember: Memory is the bottleneck
 - Still need to generate all the itemsets but we only want to count/keep track of the ones that are frequent
- Key idea: After Pass 1 of PCY, rehash only those pairs that <u>qualify</u> for Pass 2 of PCY
 - i and j are frequent, and
 - {i, j} hashes to a frequent bucket from Pass 1
- On middle pass, fewer pairs contribute to buckets, so fewer false positives
- Requires 3 passes over the data





Multistage - Pass 3

- Count only those pairs $\{i, j\}$ that satisfy these candidate pair conditions:
 - 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**

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Important Points

- 1. The two hash functions have to be independent
- 2. We need to check both hashes on the third pass
 - If not, we would end up counting pairs of items that hashed first to an infrequent bucket but happened to hash second to a frequent bucket



Example - Multistage

- Assume we have two hash functions h1 and h2
- h1 maps only pairs (1,2) and (3,6) to bucket #5 in the first hash table
- h2 maps only pairs (1,2) and (8,9) to bucket #7 in the second hash table
- Here are frequency of each pair:
 - freq(1,2) = 50, freq(3,6) = 50, freq(8,9) = 400
- Assume the support threshold s is set to 200
- In the first hash table, the frequency of bucket #5 is 100
 - bucket #5 is not frequent in the first hash table
- In the second hash table, the frequency of bucket #7 is 400
 - bucket #7 is frequent in the second hash table
- If we only check the second hash table, we would count pair (1,2) although we shouldn't have!

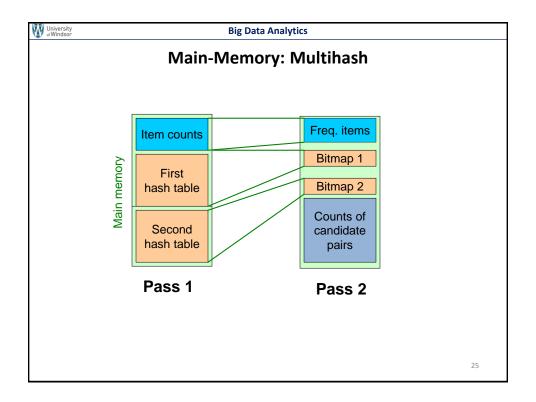
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Refinement: Multihash

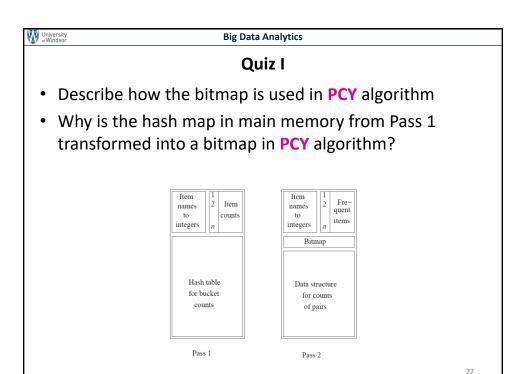
- Key idea: Use several independent hash tables on the first pass
- The danger of using two hash tables on one pass is that each hash table has half as many buckets as the one large hash table of PCY
 - We have to be sure most buckets will still not reach count s
- If so, we can get a benefit like multistage, but in only 2 passes



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PCY: 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 occupy exactly what one PCY bitmap does, but too many hash functions makes all counts > s





Answer to Quiz I

- Describe how the bitmap is used in PCY algorithm
- Why is the hash map in main memory from Pass 1 transformed into a bitmap in PCY algorithm?
- Answer:
 - Between the passes of PCY, the hash table is summarized as a bitmap, with one bit for each bucket.
 The bit is 1 if the bucket is frequent and 0 if not.
 - Thus, integers of 32 bits are replaced by single bits, and the bitmap shown in the second pass in the figure takes up only 1/32 of the space that would otherwise be available to store counts.

