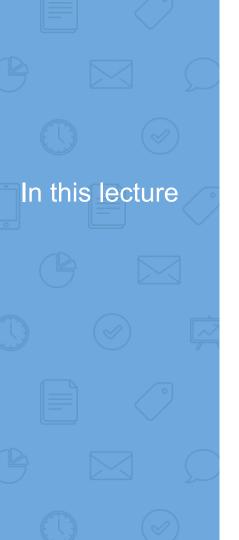


Systems design



1. Quick recap of scale

- 2. A full systems example putting things together
 - How to compute data sizes?
 - Computing a large join?
 - Building an index

Structured

(e.g. ads, purchases, product tables)
[aka relational tables]

Data models



Semi-structured

(e.g. user profile, web site activity) [aka JSON documents]



rst_name	last_name	cell	city	year_of_birth	location_x	location_y
'Mary'	'Jones'	'516-555-2048'	'Long Island'	1986	'-73.9876'	'40.7574'

1			
i	10	1	'Developer'
	11	1	'Engineer'

20	1	'MyApp'	1.0.4
21	1	'DocFinder'	2.5.7

30	1	'Bentley'	1973
31	1	'Rolls Royce'	1965

```
last_name: "Jones",
cell: "516-555-2048",
city: "Long Island",
year_of_birth: 1986,
location: {
        type: "Point",
        coordinates: [-73.9876, 40.7574
profession: ["Developer", "Engineer"],
apps: [
 { name: "MyApp",
  version: 1.0.4 },
 { name: "DocFinder",
  version: 2.5.7 }
cars: [
  { make: "Bentley",
   year: 1973 },
  { make: "Rolls Royce",
   year: 1965 }
```

In reality, a mix of systems -- e.g., Amazon/e-commerce site

Hybrid Data Systems

Data

Structured

(e.g. ads, purchases, product table

Relational

Semi-structured

(e.g. user profile, web site activity) **Key-Value**

Unstructured



Language/Tools

Hybrid future

- Built on same Lego blocks
- Past: SQL → noSQL → newSQL
- Now: hybrid SQL + pandas/ML

Example: Alibaba's data analysis design

DB Service

Cassandra Mongo Memcached

DynamoDB BigTable

BigQuery Aurora

MySql Oracle **SQL Server**

Semi-structured

Structured Relational

Algorithms

JOINs, Aggregates

Indexing, Map-Reduce



Hashing, Sorting



Key Starter Questions for:

Scale, Scale, Scale

- 1. How to scale to large data sets?
 - Is data relational, or unstructured or ...?
 - Is data in Row or Column store?
 - Is data sorted or not?

- 2. How do we organize search values?
 - ▶ E.g., Hash indices, B+ trees

- 3. How to JOIN multiple datasets?
 - E.g., SortMerge, HashJoins

Primary data structures/algorithms

Big Scale Lego Blocks

Roadmap



Hashing

Sorting

HashTables (hash_i(key) --> location)

HashFunctions (hash;(key) --> location)

HashFunctions (hash_i(key) --> location)

BucketSort, QuickSort MergeSort

MergeSortedFiles

MergeSort

MergeSort

IO analysis

Recap

Sorting of relational T with N pages

$$\sim 2N(\left[\log_B \frac{N}{2(B+1)}\right] + 1)$$

~ 2 N

~ 4 N

SortMerge and HashJoin for R & S

(vs n log n, for n tuples in RAM. Negligible for large data, vs IO -- much, much slower)

Sort N pages when N ~= B

(because $(Log_R 0.5) < 0$)

Sort N pages when N \sim = 2*B^2

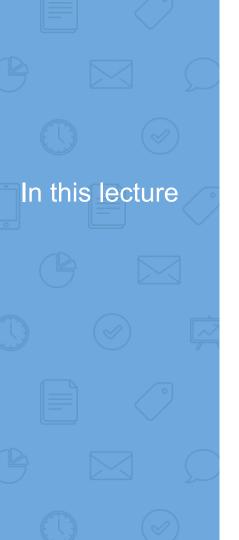
(because $(Log_R B) = 1$)

~1 * (P(R) + P(S)) + OUT

Where P(R) and P(S) are number of pages in R and S, when you have enuf RAM

For SortMerge, if already sorted

For HashJoin, if already partitioned



1. Quick recap of scale

- 2. A full systems example putting things together
 - How to compute data sizes?
 - Execute a large join?
 - Build an index

Product Search & CoOccur

Billion products

User searches for "coffee machine"





Product recommendations

Customers who viewed this item also viewed these products











Weber One Touch Gold **Premium Charcoal** Grill-57cm









Add to cart





Product Search & CoOccur

Counting popular product-pairs



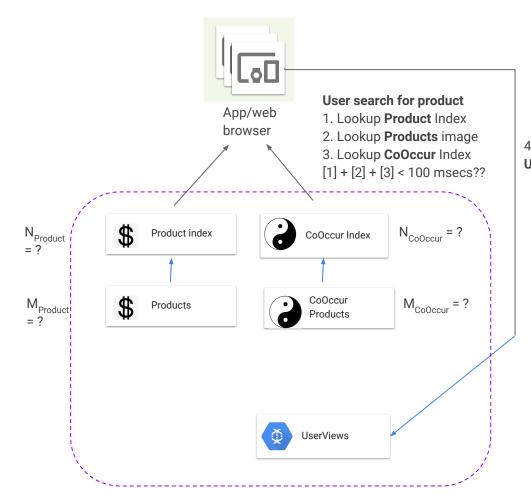
Story: Amazon/Walmart/Alibaba (AWA) want to sell products

- AWA wants fast user searches for product
- 2. AWA shows 'related products' for all products so users can explore
 - Using <u>collaborative filtering</u> ('wisdom of crowds') from historical website logs.
 - Each time a user views a set of products, those products are related (co-occur)
- ⇒ Goal: compute product pairs and their co-occur count, across all users

Data input:

- AWA has 1 billion products. Each product record is ~1MB (descriptions, images, etc.).
- AWA has 10 billion UserViews each week, from 1 billion users. Stored in UserViews, each row has <userID, productID, viewID, viewTime>.

Product Search& CoOccur



4. Capture user browsing info to **UserViews**









Counting product views for billion product PAIRs

UserViews(UserId, ProductID, ..., ...) CoOccur(ProductID1, ProductID2, count)

Nespresso Coffee
Bread maker
Kenwood Espresso

Nespresso Coffee	Bread Maker	301
Bread maker	Kenwood Espresso	24597
Kenwood Espresso	Bike	22

 $\frac{\text{Algorithm}\text{: For each user, product }p_{_{i}}\ p_{_{j}}{\text{CoOccur}[p_{_{i}}\ p_{_{i}}]\ +=\ 1}$

Counting in RAM (pre-CS145)

Pre-cs145

Compute in RAM

(Engg approximations)

Counting product views

Input size (4 bytes for user, 4 bytes for productid)	~1Bil * [4 + 4] = 8 GB
Output size (4 bytes for productid, 4 bytes for count)	~1Bil * [4 + 4] = 8 GB

Trivial

Counting product pair views

'Trivial?'
(if you have ~25 Billion\$, at 100\$/16GB RAM)

Plan #1: P * P matrix for counters in RAM (4 bytes for count)

- RAM size = 1 Billion * 1Billion * 4 = 4 Million TBs
- \circ [Note: We'll keep counter(p_i , p_j) and counter(p_j , p_i) in these examples. Why? We want to lookup cooccur counters both ways]

Plan #1 (on disk): Let OS page into memory as needed

 Worst case #1 > 100 million years (if you seek to update each counter)

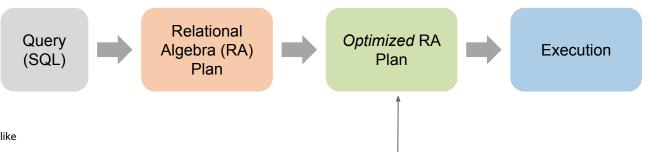




Product CoOccur <u>Your mission:</u> Design an efficient system to compute co-occur counts on *Sundays* from weekly logs and produce a <u>CoOccurCount</u> table cproductID, productID, count>

- 1. AWA's data quality magicians recommend
 - (a) keep only <u>top billion</u> popular pairs, and (b) drop pairs with co-occur counts less than million.
 - (c) Also, assume users view ten products on average each week (User is interested in ~10 products/week, not 1000s).
- 2. For simplicity, <u>SortedUserViews</u> is stored sorted by <userID, productID>.
 - You can sequentially scan the log and produce co-occurring product pairs for each user. In other words, output (p_i, p_i) if a user viewed products p_i and p_i .
 - This "stream" of tuples (<u>TempCoOccur</u>) may then be (a) stored on disk or (b) discarded after updating any data structures.

Post CS 145



Write a query like

SELECT TOP(..)... FROM SortedUserViews v1, SortedUserViews v2 WHERE ... GROUP BY v1.productId, v2.productId HAVING count(*) > 1 million

Optimize,

Evaluate design plans



Build Query Plans

- S BENEFITS Analyze Plans

- For SFW, Joins queries
 - Sort? Hash? Count? Brute-force?
 - Pre-build an index? B+ tree, Hash? b.
- What statistics can I keep to optimize?
 - E.g. Selectivity of columns, values

Cost in I/O, resources? To query, maintain?

Product CoOccur

Plans?

Plan#1: With 1 machine, use RAM to count (Cost = 25B\$ or > 100 million years).

Plan#2: With 1 machine

Plan 2

- Scan SortedUserViews. For each user, append <p_i, p_j> to a file TempCoOccurLog if the user has viewed p_i and p_j. (i.e., produce per-user co-occur product pair. Append to log ⇒ No seek...)
- 2. Externally sort TempCoOccurLog on disk, so identical product pairs are adjacent to each other in the sorted file
- 3. Scan sorted TempCoOccurLog. With a single pass, you can count co-occur pairs. Drop co-occur pairs with < 1 million.

Nespresso	Iphone
Nespresso	Iphone

Nespresso	Iphone

Nespresso	Iphone
Nespresso	Iphone
Nespresso	Iphone
respiesso	ipriorit

Nespresso Iphone

TempCoOccurLog (After Step 1)

Sorted TempCoOccurLog (After Step 2)

Count sorted TempCoOccurLog (After Step 3)

Product CoOccur

Pre-design

		Size	Why?
	ProductId	4 bytes	1 Billion products ⇒ Need at least 30 bits (2^30 ~= 1 Billion) to represent each product uniquely. So use 4 bytes.
	UserID	4 bytes	ш
	ViewID	8 bytes	10 Billion product views.
0	Product	1 PB	1 Billion products of 1 MB each
	SortedUserViews	240 GB (4 M pages)	Each record is <userid, productid,="" viewid,="" viewtime="">. Assume: we use 8 bytes for viewTime. So that's 24 bytes per record. 10 Billion*24 bytes = 240 GBs.</userid,>
<u> </u>	CoOccur (for top 1 Billion)	12 GB	The output should be <pre>productID</pre> , productID, count> for the co-occur counts. That is, 12 bytes per record (4 + 4 + 4 for the two productIDs and 4 bytes for count). To keep top billion product pairs (as recommended by AWA data quality), you need 1 billion * 12 bytes = 12 GBs.
	TempCoOccurLog (assume: ~10 product views/user)	800 GB (12.5 M pages)	# product pairs produced: 1 billion users * 10^2 = 100 billion Size @8 bytes/record (productID, productID) = 800 GBs

Product CoOccur

Plan #2

Steps	Cost (time)	Why?
Scan SortedUserViews		
Append <p_i, p_j=""> to TempCoOccurLog</p_i,>		
Externally sort TempCoOccurLog on disk		
(Assume sort cost is ~2N, where N is number of pages for table and B is number of buffers, and B ~~ N)		
Scan TempCoOccurLog (sorted) and keep counts in CoOccur		

Product CoOccur

Plan #2

Steps	Cost (IO)	Why?
Scan SortedUserViews	4 M	240GB (4 M pages)
Append <p_i, p_j=""> to TempCoOccurLog</p_i,>	12.5M	800 GB (12.5M pages)
Externally sort TempCoOccurLog on disk	25M	IO cost is (appx) = 2*N = 2*12.5M
(Assume sort cost is ~2N, where N is number of pages for table and B is number of buffers, and B ~~ N)		
Scan TempCoOccurLog (sorted) and keep counts in CoOccur	12.5M	800 GB

Total IO cost = (4M+ 12.5M + 25M + 12.5M) = 54MRecall: Scan at 100 MBps, then time (secs) [assume, files are stored sequentially] = (54M * 64 KB) / 100 MBps = ~34.5K secs

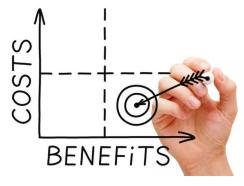
Optimize,

Evaluate design plan 1, plan 2, plan 3, ...



Build Query Plans

- 1. For SFW, Joins queries
 - a. Sort? Hash? Count? Brute-force?
 - b. Pre-build an index? B+ tree, Hash?
- 2. What statistics can I keep to optimize?
 - a. E.g. Selectivity of columns, values



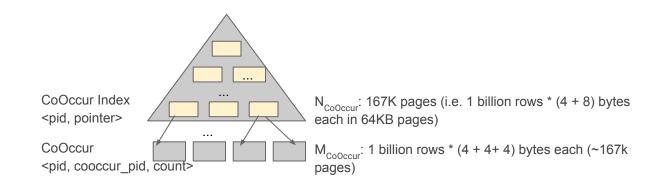
Analyze Plans

Cost in I/O, resources? To query, maintain?

Product CoOccur

B+ tree index

Build indexes with search key=productId. (Assume: CoOccur data may not be clustered)



For Index on Product data? [Recall: 1 billion tuples * 1 M B each = 1 PB]

- $M_{Product}$: 1 PB/64 KB = 15.6 Billion pages
- N_{Product}: <pid, pointer> = 167K pages

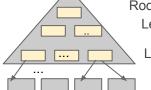
Product CoOccur

B+ tree index

N	167,000	From previous page
How large is f?		4 bytes for productId + 8 bytes for pointers @ 64KB/page f * 4 + f*8 <= 64k ⇒ f ~= 5460

Recall We need a B+ tree of height h = \[\llog_f \ned{N1} \]

CoOccur Index
<pid, pointer>
CoOccur
<pid, cooccur_pid, count>



Root: 1 page, with 5460 pointers

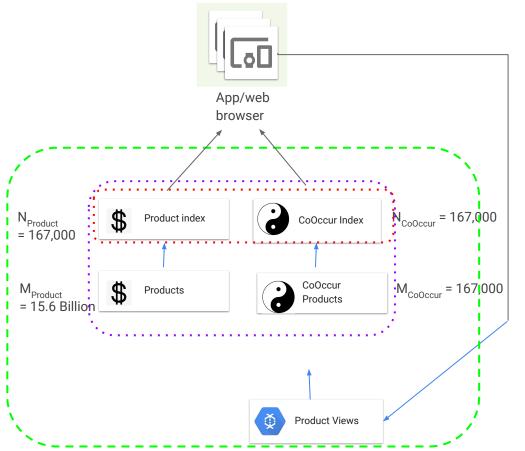
Level 1: <= 5460 pages, with 5460 ptrs each to next level

Leaf: N = 167,000 pages

(h = 2, Each leaf can point upto 5460 search keys; Note: can grow upto 5460^2 before needing h=3)

Data: 1 billion records with 12 bytes each

Product CoOccur



User latency?

- 1. Lookup Product Index
- 2. Lookup Products image
- 3. Lookup CoOccur Index

[1] + [2] + [3] < 100 msecs





Bigger Product CoOccur

Problem so far

 AWA's product catalog is 1 billion items. AWA has 10 billion product views each week, from 1 billion users. Each log record stores <userID, productID, viewID, viewtime>

Consider 1000x Bigger problem!

 Product catalog is <u>1 trillion</u> items. AWA has 10 billion product views. Rest stays same

⇒ What changes?

Product CoOccur

Pre-design

	Size	Why?
ProductId	8 bytes (vs 4bytes)	1 trillion products ⇒ Need at least 40 bits (2^40 ~= 1 Trillion) to represent each product uniquely. So use 8 bytes (i.e 64 bits).
UserID	4 bytes	ш
UserViewsID	8 bytes	10 Billion product views.
Product	1000 PB	1 Trillion products of 1 MB each
Users	Unknown	Each record is <userid, productid,="" viewid,="" viewtime="">.</userid,>
SortedUserViews	280 GB (vs 240 GB)	Assume: we use 8 bytes for viewTime. So that's 28 bytes per record. 10 Billion*28 bytes = 280 GBs.
CoOccur	20 GBs (vs 12 GB)	The output should be <pre>productID</pre> , productID, count> for the co-occur counts. That is, 20 bytes per record (8 + 8 + 4 for the two productIDs and 4 bytes for count). To keep top billion product pairs (as recommended by AWA data quality), you need 1 billion * 20 bytes = 20 GBs.
TempCoOccur (with UserSession assumption, of ~10 views/user)	1600 GB (vs 800 GB)	# product pairs produced: 1 billion users * 10^2 = 100 billion Size @16 bytes/record = 1600 GBs.

1000x larger catalog? < 2x increase in run time!

Data Systems Design

Popular Systems design pattern

- 1. Efficiently compute 'batch' of data (sort, hash, count)
- 2. Build Lookup index on result (b+ tree, hash table)
- 3. For 'streaming' data, update with 'micro batches'

Popular problems

- 1. Related videos (youtube), people (Facebook), pages (web)
- 2. Security threats, malware (security), correlation analysis

Key Goal:

Scale, Scale, Scale

- 1. How to scale to large data sets?
 - Is data in Row or Column store?
 - Is data sorted or not?

- 2. How do we organize search values?
 - ▷ E.g., Hash indices, B+ trees

- 3. How to JOIN multiple datasets?
 - ▷ E.g., SortMerge, HashJoins



Optimization

Roadmap



Build Query Plans

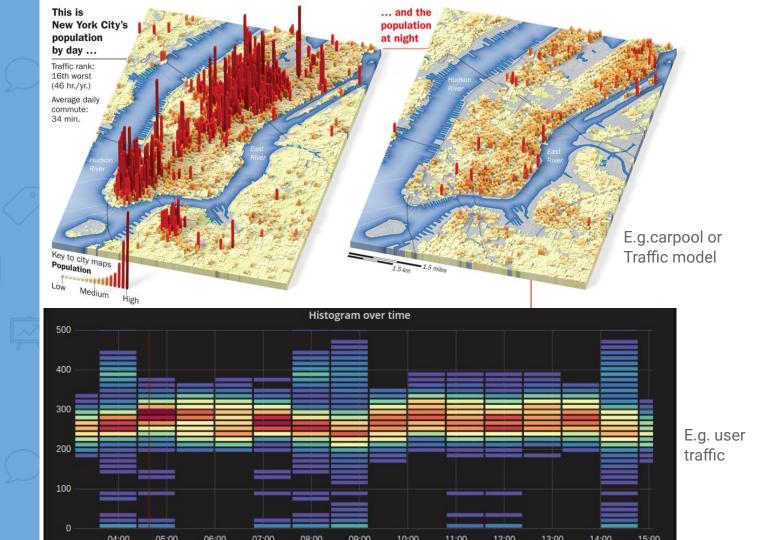
- SLSOD
 BENEFITS
 - Analyze Plans

- 1. For SFW, Joins queries
 - a. Brute-force? Sort? Hash? Count?
 - b. Pre-build an index? B+ tree, Hash?
- 2. What statistics can I keep to optimize?
 - a. E.g. Selectivity of columns, values

Cost in I/O, resources? To query, maintain?

Example

Stats for spatial and temporal data



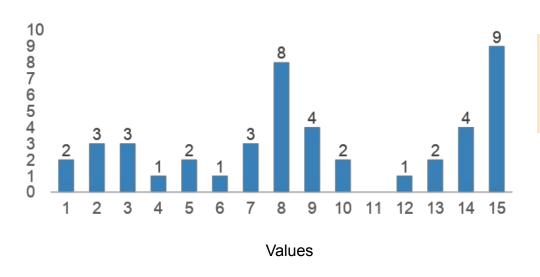


Histograms

- A histogram is a set of value ranges ("buckets") and the frequencies of values in those buckets
- How to choose the buckets?
 - Equi-width & Equi-depth
- High-frequency values are very important(e.g, related products)

Example

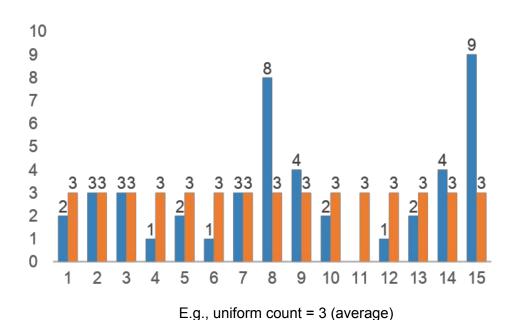
Frequency



How do we compute how many values between 8 and 10? (Yes, it's obvious)

Problem: counts take up too much space!

What if we kept average only?



How much space do the full counts (bucket_size=1) take?

How much space do the uniform counts (bucket_size=ALL) take?

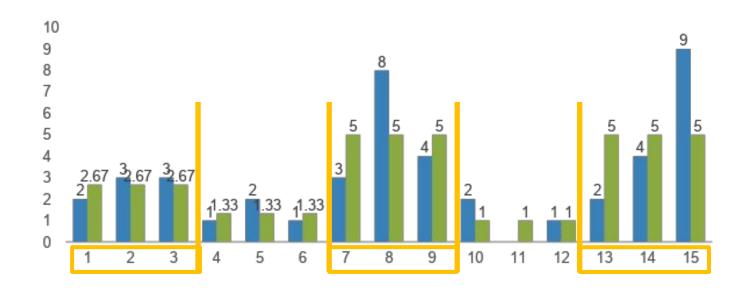
And Average Error?

Fundamental Tradeoffs

- Want high resolution (like the full counts)
- Want low space (like uniform)
- Histograms are a compromise!

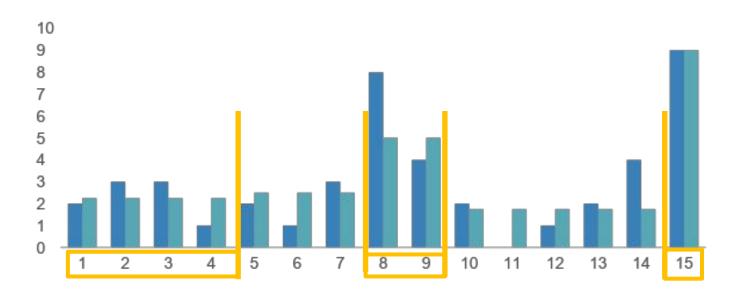
So how do we compute the "bucket" sizes?

Equi-width



Partition buckets into roughly same width (value range)

Equi-depth



Partition buckets for roughly same number of items (total frequency)



Histograms

- Simple, intuitive and popular
- Parameters: # of buckets and type
- Can extend to many attributes (multidimensional)

Maintaining Histograms

- Histograms require that we update them!
 - Typically, you must run/schedule a command to update statistics on the database
 - Out of date histograms can be terrible!

Research on self-tuning histograms and the use of query feedback

Compressed Histograms

One popular approach

- 1. Store the most frequent values and their counts explicitly
- 2. Keep an equiwidth or equidepth one for the rest of the values

People continue to try fancy techniques here *wavelets*, *graphical models*, *entropy models*, ...

Optimization

Roadmap



Build Query Plans

- SLSOD BENEFITS
 - Analyze Plans

- I. For SFW, Joins queries
 - a. Brute-force? Sort? Hash? Count?
 - b. Pre-build an index? B+ tree, Hash?
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Cost in I/O, resources? To query, maintain?