Concurrent Apriori Data Mining Algorithms

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Outline

- Why it is important
- Introduction to Association Rule Mining (a Data Mining technique)
- Overview of Sequential Apriori algorithm
- The 3 Parallel Apriori algorithm implementations
- Future work

What is Data Mining?

- **Mining knowledge from data**
- **Data mining [Han, 2001]**
  - Process of extracting interesting (<u>non-trivial</u>, <u>implicit</u>, <u>previously unknown</u> and <u>potentially useful</u>) knowledge or patterns from data in large databases
- **Objectives of data mining:**
  - Discover knowledge that characterizes general properties of data
  - Discover patterns on the previous and current data in order to make predictions on future data

Source: Data Mining CSE6412

Big Data Era

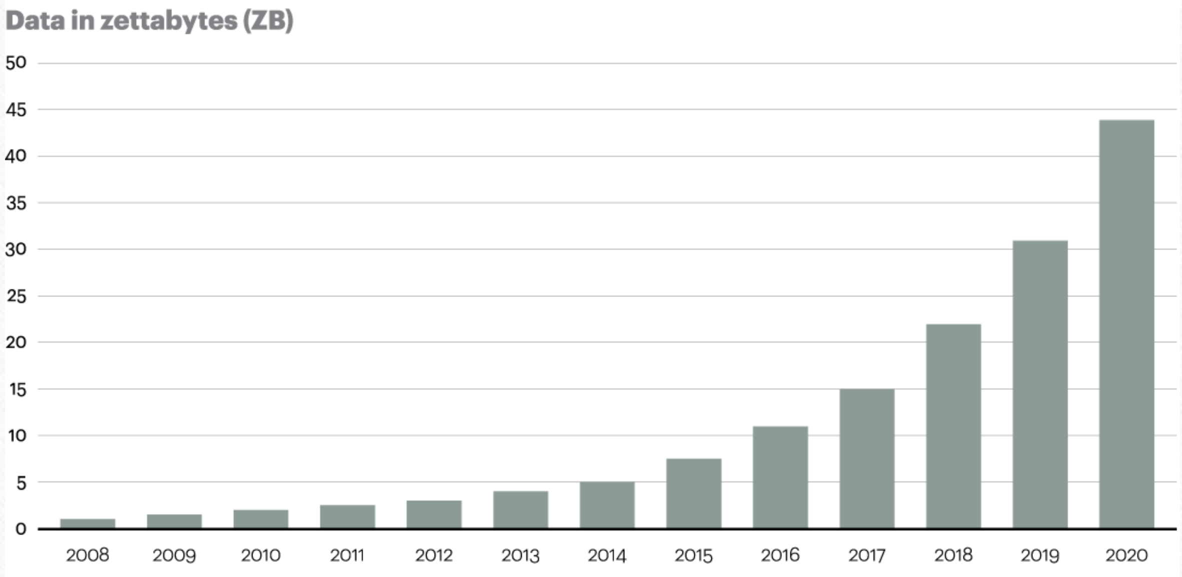
- Term introduced by Roger Magoulas in 2010
- "A massive volume of both structured and unstructured data that is so large it is difficult to process using traditional database and software techniques"- Webopedia
- Multicore machines allow for efficient concurrent computations, which require proper synchronization techniques, that can significantly reduce task completion times

Big Data Era

- 45 zettabytes (45 x 1000^3 gigabytes) of data produced in 2020

Figure 1

Data is growing at a 40 percent compound annual rate, reaching nearly 45 ZB by 2020



Source: Oracle, 2012

Why Mine Association Rules?

- Objective:
  - Finding interesting co-occurring items (or objects, events) in a given data set.
- Examples:
  - Given a database of transactions, each transaction is a list of items (purchased by a customer in a visit), you may find:

    computer → financial_management_software [support=2%, confidence=60%]
  - From a student database, you may find
    - major(x, “CS”) ^ gpa(x, “A”) → has_taken(x, “DB”) [1%, 75%]

Source: Data Mining CSE6412

Association Rule Mining Applications

- **Market basket analysis** (e.g. Stock market, Shopping patterns)
- **Medical diagnosis** (e.g. Causal effect relationship)
- **Census data** (e.g. Population Demographics)
- **Bio-sequences** (e.g. DNA, Protein)
- **Web Log** (e.g. Fraud detection, Web page traversal patterns)

What Kind of Databases?

Transactional database TDB

TID	Items
100	f, a, c, d, g, i, m, p
200	a, b, c, f, l,m, o
300	b, f, h, j, o
400	b, c, k, s, p
500	a, f, c, e, l, p, m, n

- Itemset: a set of items
- A ***transaction*** is a tuple (tid, X)
  - Transaction ID tid
  - Itemset X
- A ***transactional database*** is a set of transactions
  - In many cases, a transaction database can be treated as a set of itemsets (ignore TIDs)
- Association rule from TDB (relates two itemsets):
  - $\{a, c, m\} \rightarrow \{l\}$ [support=40%, confidence=66.7%]

Source: Data Mining CSE6412

Definition of Association Rule

- An association rule is of the form:

  $$X \rightarrow Y \text{ [support, confidence]}$$

  where
  - $X \subset I$, $Y \subset I$, $X \cap Y = \varnothing$ and I is a set of items (objects or events).
  - support: probability that a transaction (or a record) contains X and Y, i.e.,

    $$\text{support } (X \rightarrow Y) = P(X \cup Y)$$

  - confidence: conditional probability that a transaction (or a record) having X also contains Y, i.e.,

    $$\text{confidence}(X \rightarrow Y) = P(Y|X)$$

- A rule associates one set of items (events) with another set of items (events)

Source: Data Mining CSE6412

Support and Confidence: Example

$$\text{support}(X \rightarrow Y) = P(X \cup Y)$$

$$\text{confidence}(X \rightarrow Y) = P(Y|X)$$

Transaction ID	Items Bought
2000	A,B,C
1000	A,C
4000	A,D
5000	B,E,F

Relative frequency is used to estimate the probability.

- $\{A\} \rightarrow \{C\}$ (50%, 66.7%)
- $\{C\} \rightarrow \{A\}$ (50%, 100%)
- $\{A, C\} \rightarrow \{B\}$ (25%, 50%)
- $\{A, B\} \rightarrow \{E\}$ (0%, 0%)

Source: Data Mining CSE6412

Mining Association Rules

- Problem statement

  Given a *minimum support* (*min_sup*), also called *support threshold*, and a *minimum confidence* (*min_conf*), also called *confidence threshold*, find all association rules that satisfy both *min_sup* and *min_conf* from a data set *D*.

Source: Data Mining CSE6412

How to Mine Association Rules

- A two-step process:
  - Find all frequent itemsets ---- the key step
  - Generate strong association rules from frequent itemsets.
- Example: given min_sup=50% and min_conf=50%

Transaction ID	Items Bought
2000	A,B,C
1000	A,C
4000	A,D
5000	B,E,F

Frequent Itemset	Support
{A}	75%
{B}	50%
{C}	50%
{A, C}	50%

- Generate strong rules:
  - {A} → {C} [support=50%, confidence=66.6%]
  - {C} → {A} [support=50%, confidence=100%]

Source: Data Mining CSE6412

Candidate Generation

How to Generate Candidates?
(i.e. How to Generate C_{k+1} from L_k)

- Given L_k = the set of frequent k-itemsets
- List the items in each itemset of L_k in an order

$$L_3 = \begin{array}{|c|}\hline \{1\ 2\ 3\} \\ \{1\ 2\ 4\} \\ \{1\ 3\ 4\} \\ \{1\ 3\ 5\} \\ \{2\ 3\ 4\} \\ \hline\end{array}$$

- Given L_k , generate C_{k+1} in two steps:
  - Join Step: Join L_k with L_k by joining two k-itemsets in L_k. Two k-itemsets are joinable if their first (k-1) items are the same and the last item in the first itemset is smaller than the last item in the second itemset (the condition for joining two members of L_k).

    Now, C_4={{1 2 3 4}, {1 3 4 5}}
  - Prune Step: Delete all candidates in C_{k+1} that have a non-frequent subset by checking all length-k subsets of a candidate
    - Now, C_4={{1 2 3 4}}

Example of Candidate Generation

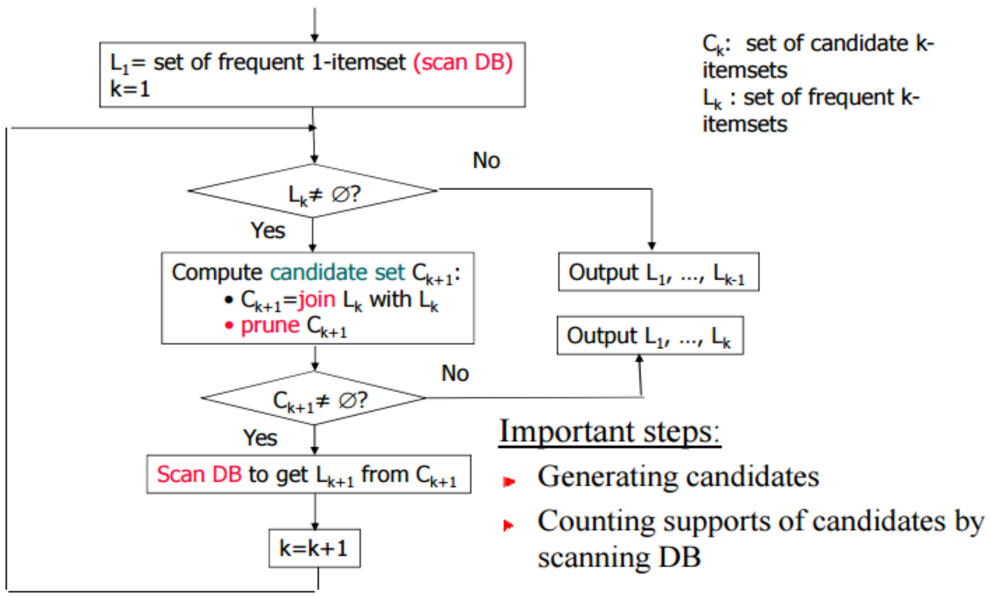
- L_4={*abcd, abcg, abdg, abef, abeh, acdg, bcdg*}
- Self-joining: L_4*L_4
  - *abcdg* from *abcd* and *abcg*
  - *abefh* from *abef* and *aceh*
- Pruning:
  - *abefh* is removed because *abfh or aefh or befh* is not in L_4
- C_5={*abcdg*}

Source: Data Mining CSE6412

Apriori Algorithm

- Proposed by Agrawal and Srikant in 1994

Apriori Algorithm (Flow Chart)



Important steps:

- Generating candidates
- Counting supports of candidates by scanning DB

Apriori Algorithm Example

Database D

TID	Items
100	1 3 4
200	2 3 5
300	1 2 3 5
400	2 5

Scan D → C_1

itemset	sup.
{1}	2
{2}	3
{3}	3
{4}	1
{5}	3

→ L_1

itemset	sup.
{1}	2
{2}	3
{3}	3
{5}	3

→ C_2

itemset
{1 2}
{1 3}
{1 5}
{2 3}
{2 5}
{3 5}

Scan D → C_2

itemset	sup
{1 2}	1
{1 3}	2
{1 5}	1
{2 3}	2
{2 5}	3
{3 5}	2

→ L_2

itemset	sup
{1 3}	2
{2 3}	2
{2 5}	3
{3 5}	2

→ C_3

itemset
{2 3 5}

Scan D → L_3

itemset	sup
{2 3 5}	2

Assume:
min_sup_count = 2

Source: Data Mining CSE6412

My Paper

- Rakesh Agrawal and John C. Shafer. Parallel mining of association rules: Design, implementation and experience. Technical report, IBM, 1996.
- Rakesh Agrawal and John C Shafer. Parallel mining of association rules. *IEEE Transactions on Knowledge and Data Engineering*, (6):962–969, 1996.

Rakesh Agrawal

Source: Google Scholar

3 Parallel Apriori Algorithms

IMPORTANT: Algorithms implemented on a **shared-nothing multiprocessor** communicating via a **Message Passing Interface** (MPI)

- **Count Distribution**
  - Each processor calculates its **Candidate Set Counts** from its local Database and end of each pass sends out **Candidate Set Counts** to all other processors.
- **Data Distribution**
  - Each processor is assigned a **mutually exclusive partition of the Candidate Set** on which it computes the count and end of pass sends out **Candidate Set Tuple** to all other processors.
- **Candidate Distribution**
  - **Both Candidate Set and Database is partitioned during some pass k**, so that each processor can operate independently.

Notations

k-itemset	An itemset having *k* items.
L_k	Set of frequent *k*-itemsets (those with minimum support). Each member of this set has two fields: i) itemset and ii) support count.
C_k	Set of candidate *k*-itemsets (potentially frequent itemsets). Each member of this set has two fields: i) itemset and ii) support count.
P^i	Processor with id *i*.
D^i	The dataset local to the processor P^i.
DR^i	The dataset local to the processor P^i after repartitioning.
C_k^i	The candidate set maintained with the Processor P^i during the *k*th pass (there are *k* items in each candidate).

Source: My Paper

Count Distribution Algorithm

Pass k = 1:

1. Processor P^i scans over its data partition D_i; reads one tuple transaction (i.e. (TID,X)) at a time and building its local C_1^i and storing it in a hash-table (new entry is created if necessary).
2. At end of the pass every P^i loads contents of into a buffer and sends it out to all other processors.
3. At the same time each P^i receives the send buffer from another processor and increments the count value of every element in its local C_1^i hash-table if this element is present in the buffer otherwise a new entry would be created.
4. P^i will now have the entire candidate set C_1 with global support counts for each candidate/element/itemset.

Step 2 and 3 require synchronization

Count Distribution Algorithm Cont.

(Pass K = 1 Example)

Processor/Node 1

Itemset	Support
{a}	15
{b}	5
{c}	7
{d]	2

Processor/Node 2

Itemset	Support
{a}	5
{b}	2
{c}	1
{d]	3
{e}	6

Processor/Node 3

Itemset	Support
{a}	2
{b}	1
{c}	4
{d]	9

Processor/Node 1 at end of pass

Itemset	Support
{a}	22
{b}	8
{c}	12
{d]	14
{e}	6

Count Distribution Algorithm Cont.

Pass k > 1:

1. Every processor P^i generates C_k using frequent itemset L_{k-1} created at pass k - 1
2. Processor P^i goes over local database partition D^i and develops local support count for candidates in C_k
3. Processor P^i exchange local C_k counts with all other processor to develop global C_k counts. **Processors are forced to synchronize in this step.**
4. Each processor P^i now computes L_k from C_k.
5. Each processor P^i decides to continue to next pass or terminate (The decision will be identical as the processors all have identical L_k).

Data Distribution Algorithm

- **Pass k = 1:** Same as the Count Distribution Algorithm
- **Pass k > 1:**

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1. Processor P^i generates C_k from L_{k-1}. Retaining only $1/N^{th}$ of the itemsets forming the candidates subset C_k^i that it will count. The C_k^i sets are all disjoint and the union of all C_k^i sets is the original C_k.
2. Processor P^i develops support counts for the itemsets in its local candidate set C_k^i using both local data pages and data pages received from other processors.
3. At end of the pass, each processor P^i calculates L_k^i using the local C_k^i. Again, all L_k^i sets are disjoint and the union of all L_k^i is L_k.
4. Processors exchange L_k^i so that every processor has the complete L_k to generate C_{k+1} for next pass. **Processors are forced to synchronize in this step.**
5. Each processor P^i can independently (but identically) decide whether to terminate or continue.

Candidate Distribution Algorithm

Pass $k < m$: Use either Count or Data distribution algorithm.
Pass $k = m$:

1. Partition L_{k-1} among the N processors such that L_{k-1} sets are "well balanced". **Important:** For each itemset remember which processor was assigned to it.
2. Processor P^i generates C_k^i using only the L_{k-1} partition assigned to it.
3. P^i develops global counts for candidates in C_k^i and the database is repartitioned into DR^i at the same time.
4. After P^i has processed local data and data received from other processors it posts N – 1 asynchronous receive buffer to receive L_k^j from all other processors needed for the **pruning C_{k+1}^i** in the prune step of candidate generation.
5. Processor P^i computes L_k^i from C_k^i and asyncronosly broadcasts it to the other N – 1 processors using N – 1 asynchronous sends.

Candidate Distribution Algorithm Cont.

Pass k > m:

1. Processor P^i collects all frequent itemsets sent by other processors. They are used for the **pruning step**. Itemsets from some processor j can be not of length k – 1 due to processors being fast or slow, but **P^i keeps track of the longest length of itemsets received for every single processor**.
2. **P^i generates C_k^i using local L_{k-1}^i**. P^i has to be careful during the pruning process as it could be that not all the L_{k-1}^j from all other processors. So when examining if a candidate should be pruned it needs to go back to the pass k = m and find out which processor was assigned to the current itemset when its length was m – 1 and check if L_{k-1}^j has been received from this processor.
(e.g. Let m = 2; L_4 = {abcd, abce,abde} and we are looking at itemset {abcd} then we have to go back to when the itemset was {ab} (i.e. at pass k = m) to determine which processor was assigned to this itemset).
3. P^i makes a pass over DR^i and counts C_k^i. From C_k^i computes L_k^i and broadcast it to every other process via N – 1 **asynchronous sends**.

Pros and Cons of the Algorithms

- **Count Distribution**
  - **Pro:** Minimizes heavy data transfer between processors
  - **Con:** Redundant Candidate Set counting
- **Data Distribution**
  - **Pro:** Utilizes Aggregate Memory by assigning each processor a mutually exclusive subset of the Candidate set
  - **Con:** Requires good communication network(high bandwidth/low latency) due to large size of data needed to be broadcast at each pass
- **Candidate Distribution**
  - **Pro:** Maximizes use of aggregate memory while limiting communication to a single redistribution pass. Eliminates synchronization costs that Count and Data must pay at end of every pass
  - **Con**(Post testing): it turns out the single redistribution pass takes its toll on the system

Looking Ahead

- Plan
  - Implement all three algorithm
  - Compare their performance (with each other; with sequential Apriori; with other sequential frequent pattern mining algorithms)
  - Find out synchronization capabilities of the MPI (Message Protocol Interface) in a multithreaded environment
  - Find out synchronization modifications needed of implementing the algorithms on a system that does not have a **shared-nothing multiprocessor** infrastructure.

Thank You!

Questions?