



HICAP

Hierarchical Clustering with PAttern Preservation

RIT2013061 Soumya Agrawal

RIT2013062 Gaurav Goyal

RIT2013063 Vamsi Sangam

RIT2013064 Kumar Abhishek

RIT2013086 Viswakanth Korada



Problem statement

To introduce a new approach in clustering algorithms, which is
Hierarchical **C**lustering with **P**attern **P**reservation (HICAP) .




Hyperclique Pattern

- Hyperclique pattern is a type of association pattern that contains items that are highly affiliated with each other. By high affiliation, we mean that the presence of an item in a transaction strongly implies the presence of every other item that belongs to the same hyperclique pattern.
- h-confidence measure is specifically designing need to measure the strength of association .

The **h-confidence** of the itemset $P = \{i_1, i_2, \dots, i_n\}$ denoted as $hconf(P)$, is a measure that reflects the overall affinity among items within the itemset. This measure is defined as:

$$hconf(P) = \min \{ \text{conf} \{ i_1 \rightarrow i_2, i_3, \dots, i_n \}, \text{conf} \{ i_2 \rightarrow i_1, i_3, \dots, i_n \}, \dots, \text{conf} \{ i_n \rightarrow i_1, i_2, \dots, i_{n-1} \} \},$$

where conf is the conventional definition of association rule confidence.

- 
- Given a transaction database and the set of all item set $I = \{ i_1, i_2, \dots i_n \}$ of an item set P is a hyperclique pattern if and only if

1. $P \subseteq I$ and $|P| > 0$.
2. $hconf(P) \geq h_c$, where h_c is the minimum h -confidence threshold.

- A Hyperclique pattern is a **maximal** hyperclique pattern if no superset of this pattern is a hyperclique pattern.
- 

ALGORITHM

➤ The algorithm consist of two phases :

1st phase: HICAP finds maximal hyperclique pattern which we want to preserve in HICAP algorithm.

2nd phase : HICAP conducts hierarchical clustering and output the clustering results.

Maximal hyperclique patterns cover only 10% - 20 % of all objects and thus HICAP also includes uncovered objects as a separate initial cluster.

Finally the similarity between the cluster is calculated using average of the pairwise cosine similarity.

HICAP Algorithm

Input: D : a document data set.
 θ : a minimum h-confidence threshold.
 α : a minimum support threshold.

Output: CR: the hierarchical clustering result.

Variables: S: the hyperclique pattern set.
MS: the maximal hyperclique pattern set.
PD: The output set of preprocessing
LS: a set of objects which are not covered by identified maximal hyperclique patterns
CS: a set containing target clustering objects

Method

Phase I: Maximum Hyperclique Dattern Discovery

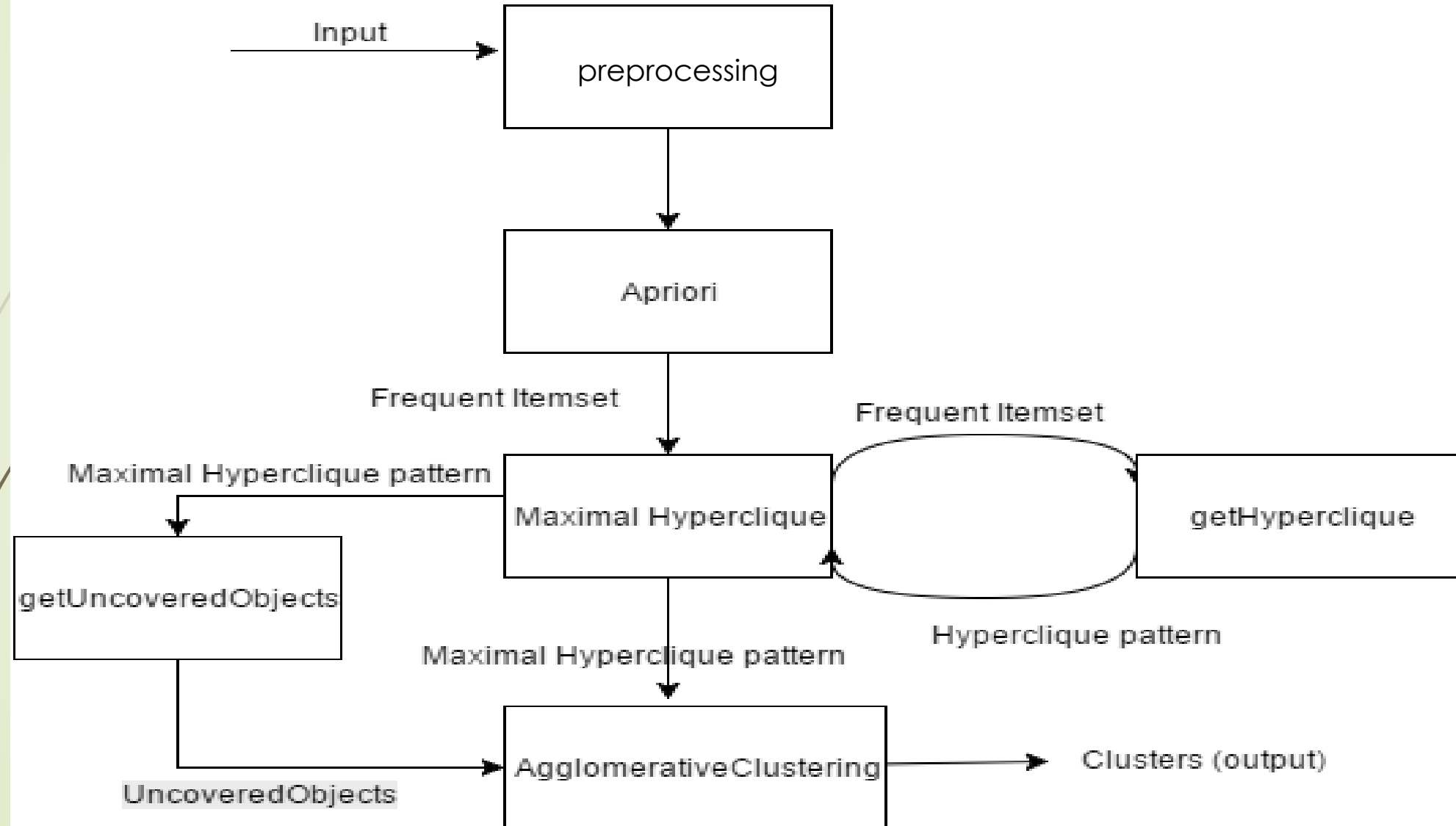
1. $S = \text{hyperclique_miner}(\theta, \alpha, D)$
2. $MS = \text{maximal_hyperclique_pattern}(S)$

Phase II: Hierarchical Clustering

3. $PD = \text{preprocessing}(D)$
4. $LS = \text{uncovered_objects}(MS, D)$
5. $CS = LS \cup MS$
6. **for** $i=1$ to $|CS|-1$
7. find the pair of elements with max group average cosine value from the set CS,
8. merge the identified pair, and update CS and CR accordingly
9. **endfor**
10. **OUTPUT** CR
11. **End**

HICAP

FLOW CHART





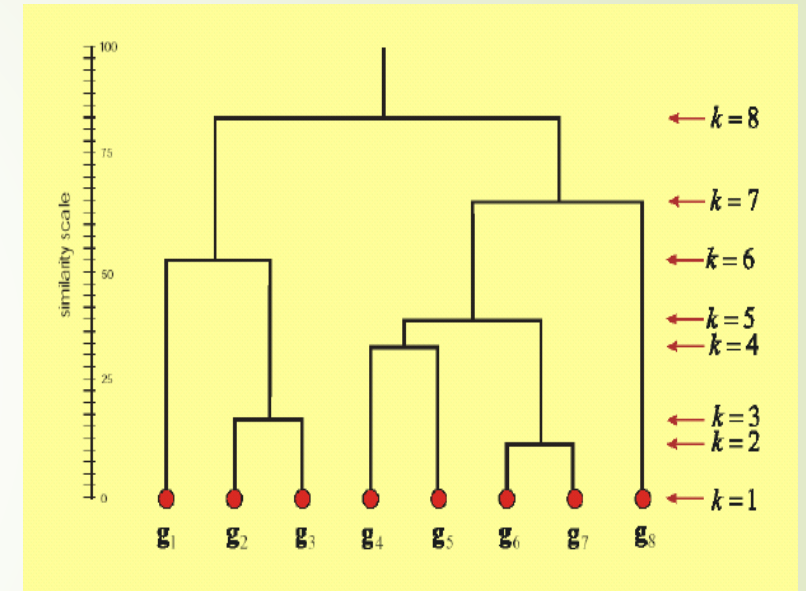
Hyperclique pattern v/s Frequent Itemset

- Hyperclique pattern include objects which are strongly similar to each other with respect to the cosine measure ,in contrast many pair of objects from a frequent item set may have very poor cosine measure.
- Hyperclique pattern have better performance at low level of support than the frequent item set .

Finally , the size of the maximal hyperclique pattern is significantly smaller than the size of the maximal frequent item sets.

Hierarchical clustering

- There are two styles of hierarchical clustering algorithms to build a tree from the input set S :
 - **Agglomerative (bottom-up):**
 - Beginning with singletons (sets with 1 element)
 - Merging them until S is achieved as the root.
 - It is the most common approach.
 - **Divisive (top-down):**
 - Recursively partitioning S until singleton sets are reached.



DataSet

- There are 9835 transaction records. There were at most 32 items purchased on one of its transactions. The total number of unique items is 169.

Data	
# Transactions in Input Data	9835
# Columns in Input Data	32
# Items in Input Data	169

1	citrus fruit	semi-finished bread	margarine	ready soups	
2	tropical fruit	yogurt	coffee		
3	whole milk				
4	pip fruit	yogurt	cream cheese	meat spreads	
5	other vegetables	whole milk	condensed milk	long life bakery product	
6	whole milk	butter	yogurt	rice	abrasive cleaner
7	rolls/buns				
8	other vegetables	UHT-milk	rolls/buns	bottled beer	liquor (appetizer)
9	pot plants				
10	whole milk	cereals			
11	tropical fruit	other vegetables	white bread	bottled water	chocolate
12	citrus fruit	tropical fruit	whole milk	butter	curd
13	beef				
14	frankfurter	rolls/buns	soda		
15	chicken	tropical fruit			
16	butter	sugar	fruit/vegetable juice	newspapers	
17	fruit/vegetable juice				
18	packaged fruit/vegetables				
19	chocolate				
20	specialty bar				
21	other vegetables				



Thank you...