UEH UNIVERSITY

Application of the ECLAT Algorithm in Market Basket Analysis

Final report

1. LITERATURE REVIEW

Definition and Key Idea

ECLAT (Equivalence Class Clustering and bottom-up Lattice Traversal)

- Introduced by Zaki et al. (1997)
- Designed for association rule mining*
- Goal: Discover all frequent itemsets in a transaction database
- Constraint: Itemsets must satisfy a minimum support threshold

Key Idea of the ECLAT Algorithm in Frequent Itemset Mining

- Vertical Database Representation: Each item is associated with a set of Transaction IDs (TIDs) where it occurs.
- TID-List Intersection: Support is computed by intersecting TID-lists of candidate itemsets.
- Recursive Expansion: Starting from 1-itemsets, recursively extend itemsets by combining them to generate larger k-itemsets.

***Association rule mining:** Given a set of transactions, find rules that will predict the occurence of an item based on the occurences of other items in the transaction.

1. LITERATURE REVIEW

Pseudocode

INPUT: a file D consisting of baskets of items, a support threshold , and an item prefix I, such that I ⊆ J.

OUTPUT: A list of itemsets F[I](D,σ) for the specified prefix

METHOD:

F(i) ← {}

for all i ∈ J occurring in D **do**

$F[I] := F[I] \cup \{I \cup \{i\}\}$

#Create D_i

$D_i \leftarrow \{\}$

for all j ∈ J occurring in D such that j > i **do**

C ← cover({i}) ∩ cover({j})

if $|C| > \sigma$ **then**

$D_i \leftarrow D_i \cap \{j, C\}$

#Depth-first recursion

Compute $F[I \cap i](D_i, \sigma)$

$F[I] := F[I] \cup F[I \cup i]$

2. ALGORITHM ILLUSTRATION-

Step-by-step demonstration

Sample data

Transaction	Items
1	{A, B, C}
2	{A, C}
3	{A, B, D}
4	{B, E, F}
5	{A, B, C, E}

Step 1: Data preparation

Item	Transactions
A	{1, 2, 3, 5}
B	{1, 3, 4, 5}
C	{1, 2, 5}
D	{3}
E	{4, 5}
F	{4}

Step 2: Frequent itemset mining

Item	Transactions	Support
A	{1, 2, 3, 5}	4
B	{1, 3, 4, 5}	4
C	{1, 2, 5}	3
E	{4, 5}	2

With k = 1

Item	Transactions	Support
AB	{1,3,5}	3
AC	{1,2,5}	3
BC	{1,5}	2
BE	{4,5}	2

With k = 2

Item	Transactions	Support
ABC	{1,5}	2

With k = 3

2. ALGORITHM ILLUSTRATION

Step-by-step demonstration

Result

Items	Recommendation
A	B
A	C
B	C
B	E
A, B	C

Association Rules with Minimum Support = 2

- Given a minimum support threshold of 2, all frequent itemsets are identified.
- From these frequent itemsets, association rules can be derived.
- Ensures that only rules meeting the support constraint are retained.

3. ALGORITHM IMPLEMENTATION

Data Structures in ECLAT algorithm and Dataset information

Data structures

- Dictionary: Stores the vertical database; key = item, value = set of TIDs. Enables fast lookup of item occurrences.
- Set: Holds TIDs for each item; supports efficient intersection and removes duplicates.
- List: Represents original transactions before vertical transformation; each transaction = list of items.
- Tree (IT-tree): Node = itemset + its TID-set; built via depth-first search to organize and retrieve frequent itemsets efficiently.
- Recursion: Expands itemsets recursively; each call explores larger itemsets and backtracks via stack.

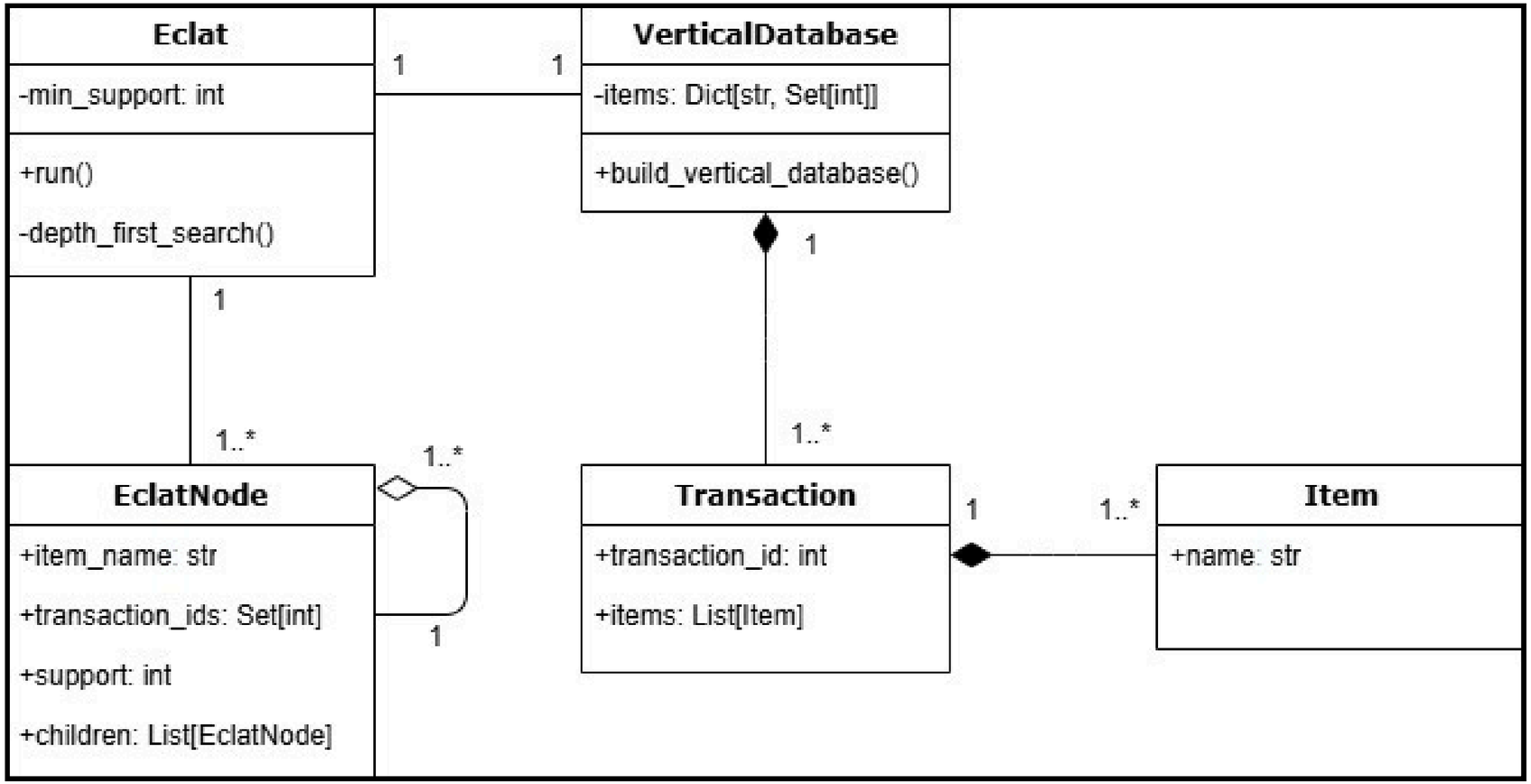
Dataset information

- Contains transaction records of store members from Jan 21, 2015 – Apr 30, 2015
- Includes 38,765 rows and 3 attributes
- Dataset is complete with no missing values

Variable	Type	Description	Unique	Blank
Member_number	Int64	Member ID	3989	0
Date	Object	Purchased date	728	0
ItemDescription	Object	Product name	167	0

3. ALGORITHM IMPLEMENTATION

Class diagram



3. ALGORITHM IMPLEMENTATION

Class diagram (Implementation)

```python
class Item:
    def __init__(self, name):
        self.name = name

class Transaction:
    def __init__(self, transaction_id, items):
        self.transaction_id = transaction_id
        self.items = items

class VerticalDatabase:
    def __init__(self, transactions):
        self.items = {}
        self.build_vertical_database(transactions)

    def build_vertical_database(self, transactions):
        for transaction in transactions:
            for item in transaction.items:
                if item.name not in self.items:
                    self.items[item.name] = set()
                self.items[item.name].add(transaction.transaction_id)

class EclatNode:
    def __init__(self, item_name, transaction_ids, support):
        self.item_name = item_name
        self.transaction_ids = transaction_ids
        self.support = support
        self.children = []
```

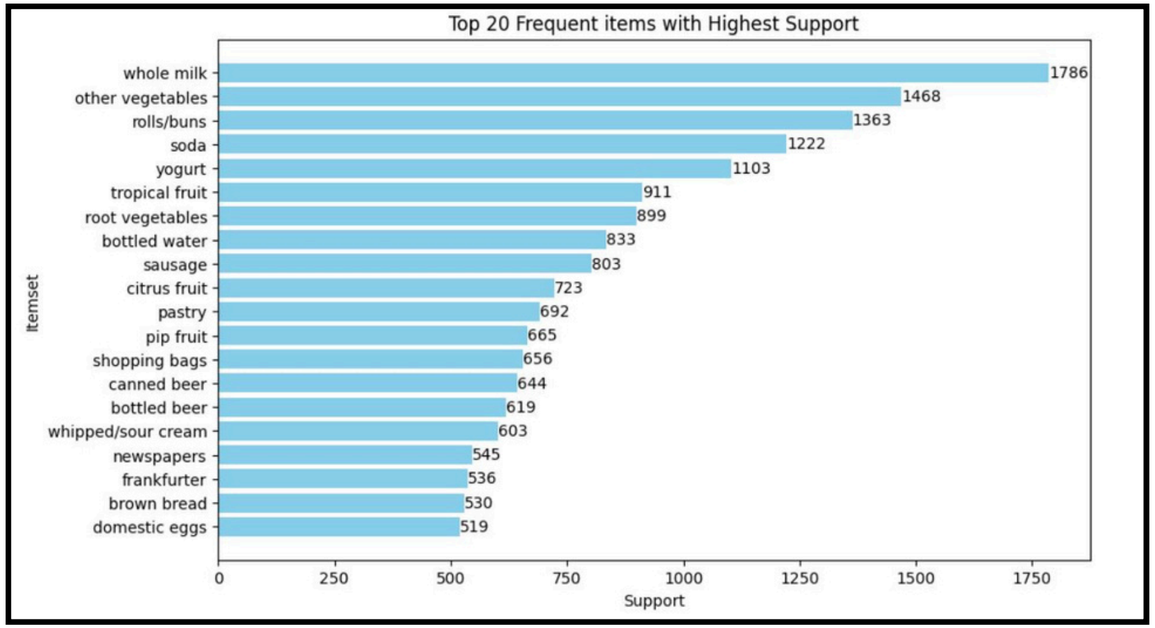
3. ALGORITHM IMPLEMENTATION

Class diagram (Implementation)

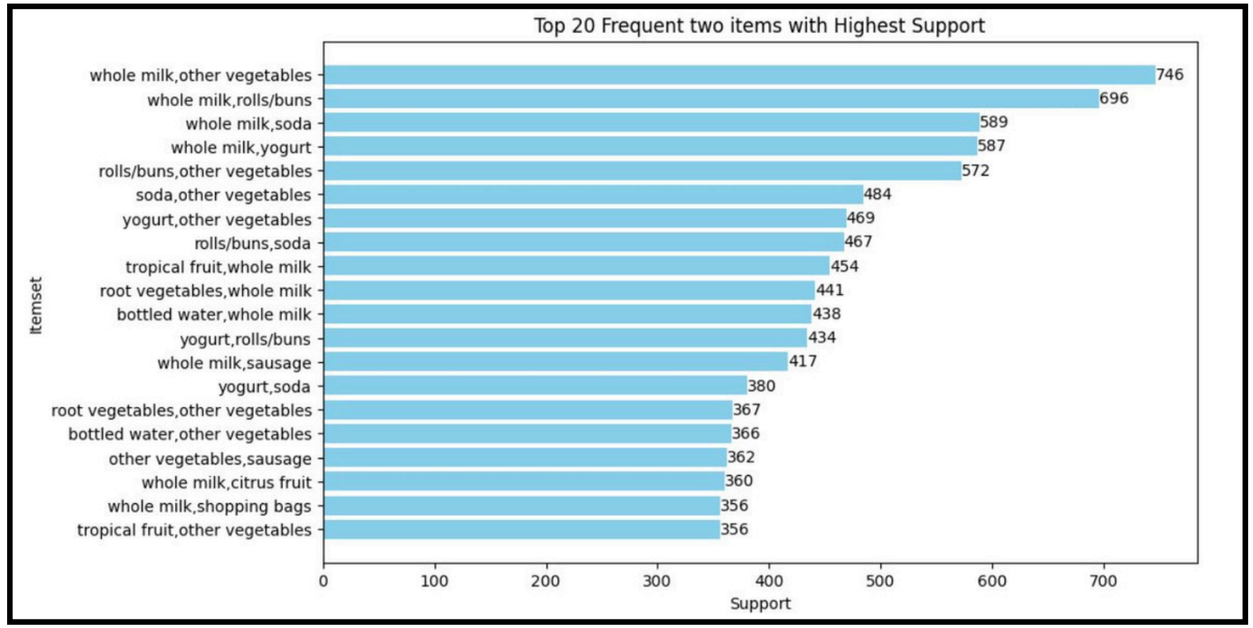
```
class Eclat:
    def __init__(self, min_support):
        self.min_support = min_support

    def run(self, vertical_db):
        frequent_itemsets = []
        for item_name, transaction_ids in vertical_db.items.items():
            support = len(transaction_ids)
            if support >= self.min_support:
                frequent_itemsets.append(EclatNode(item_name, transaction_ids, support))
        self.depth_first_search(frequent_itemsets, vertical_db)
        return frequent_itemsets

    def depth_first_search(self, itemsets, vertical_db):
        for i in range(len(itemsets)):
            for j in range(i + 1, len(itemsets)):
                intersection = itemsets[i].transaction_ids & itemsets[j].transaction_ids
                support = len(intersection)
                if support >= self.min_support:
                    new_itemset = EclatNode(
                        itemsets[i].item_name + "," + itemsets[j].item_name,
                        intersection,
                        support
                    )
                    itemsets[i].children.append(new_itemset)
                    self.depth_first_search([new_itemset], vertical_db)
```

3. ALGORITHM IMPLEMENTATION

Find Frequent Items



k-itemsets with k = 1



k-itemsets with k = 2

3. ALGORITHM IMPLEMENTATION

Generate Association Rules using the association_rules() Function

```
# Convert itemsets to frozenset
df_one['itemsets'] = df_one['Itemset'].apply(lambda x: frozenset([x]))
df_two['itemsets'] = df_two['Itemset'].apply(lambda x: frozenset(x.split(',')))
# Convert itemsets to frozenset and calculate support as a decimal
df_one['itemsets'] = df_one['Itemset'].apply(lambda x: frozenset([x]))
df_one['support'] = df_one['Support'] / total_transactions
df_two['itemsets'] = df_two['Itemset'].apply(lambda x: frozenset(x.split(',')))
df_two['support'] = df_two['Support'] / total_transactions
# Create a DataFrame with itemsets and support
itemsets_df = pd.concat([df_one[['itemsets', 'support']], df_two[['itemsets', 'support']]], axis=0)
# Generate association rules
rules = association_rules(itemsets_df, metric="confidence", min_threshold=0.53)
```

3. ALGORITHM IMPLEMENTATION

Threshold Setting & Rule Evaluation

Metric	Theshold
MinSup	0.03
MinConf	0.53
MinLift	1.16

3. ALGORITHM IMPLEMENTATION

Threshold Setting & Rule Evaluation

Rules with highest Support

antecedents	consequents	support	confidence	lift
(yogurt)	(whole milk)	0.150590	0.532185	1.161510
(shopping bags)	(whole milk)	0.091329	0.542683	1.184422
(bottled beer)	(whole milk)	0.085428	0.537964	1.174124
(beef)	(whole milk)	0.064135	0.536481	1.170886
(frozen vegetables)	(whole milk)	0.055156	0.537500	1.173110

3. ALGORITHM IMPLEMENTATION

Threshold Setting & Rule Evaluation

Rules with highest Confidence & Lift

antecedents	consequents	support	confidence	lift
(ham)	(whole milk)	0.036942	0.582996	1.272407
(hamburger meat)	(whole milk)	0.045408	0.565495	1.234211
(sugar)	(whole milk)	0.036942	0.560311	1.222897
(chocolate)	(whole milk)	0.047973	0.554896	1.211078
(waffles)	(whole milk)	0.037968	0.550186	1.200798

3. ALGORITHM IMPLEMENTATION

Conclusions, limitations and future work

Conclusions

- Whole milk emerges as the dominant product, strongly associated with multiple items
- Lift values for rules (ham → whole milk), (hamburger meat → whole milk), (sugar → whole milk) range 1.22–1.27, exceeding the baseline 1.16
- Interpretation: Presence of ham, hamburger meat, or sugar increases the likelihood of purchasing whole milk by 22–27% compared to random chance

Limitations & Future Work

- Current study focuses only on 2-item association rules, potentially overlooking complex, multi-dimensional relationships among products.
- Future research should explore multi-item association rules.
- Integration with advanced techniques such as clustering, time-series analysis, and deep learning can provide more comprehensive and accurate recommendations.

THANK YOU