

CO1	Examine the basic concepts of data mining and machine learning concepts
Task 1:	Implement Apriori and FP-growth algorithm to find all frequent item sets for the chosen dataset and also generate Association Rules. Platform: Rapidminer, Language: Python

Tool: Rapidminer

Apriori Algorithm:

Use Case: Books Data

Objective:

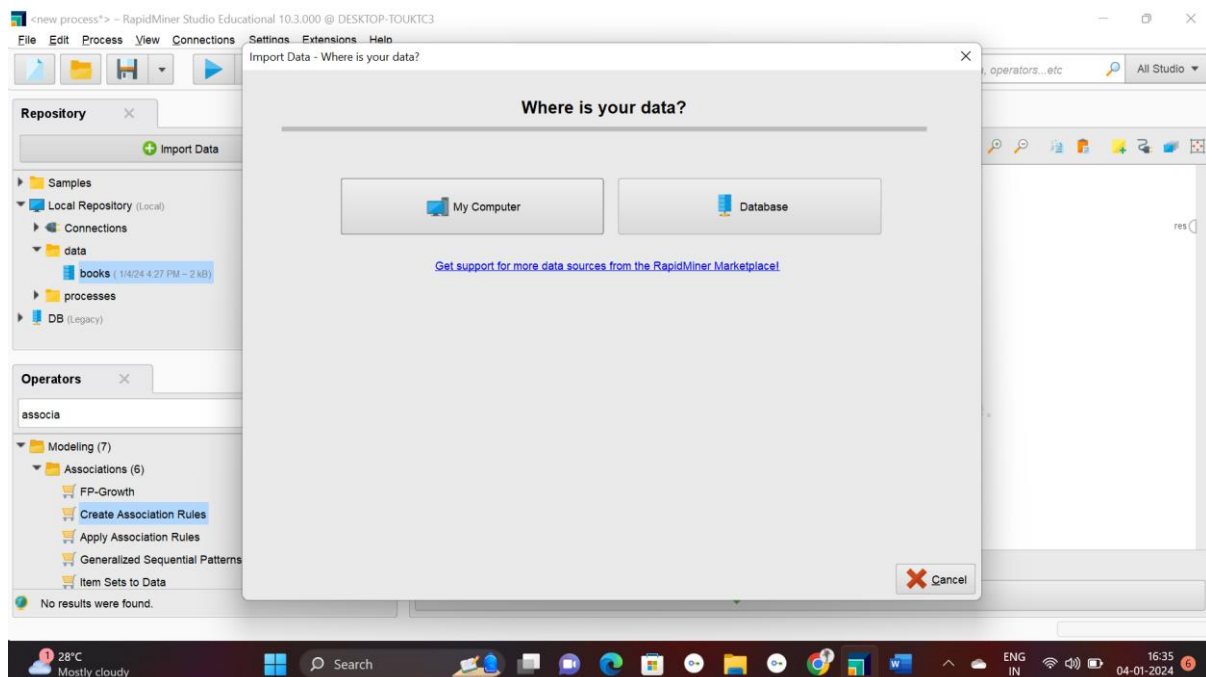
A shop wants to analyse customer purchase patterns of books to optimize product placement and run targeted promotions. The goal is to identify frequent item sets and association rules among purchased products.

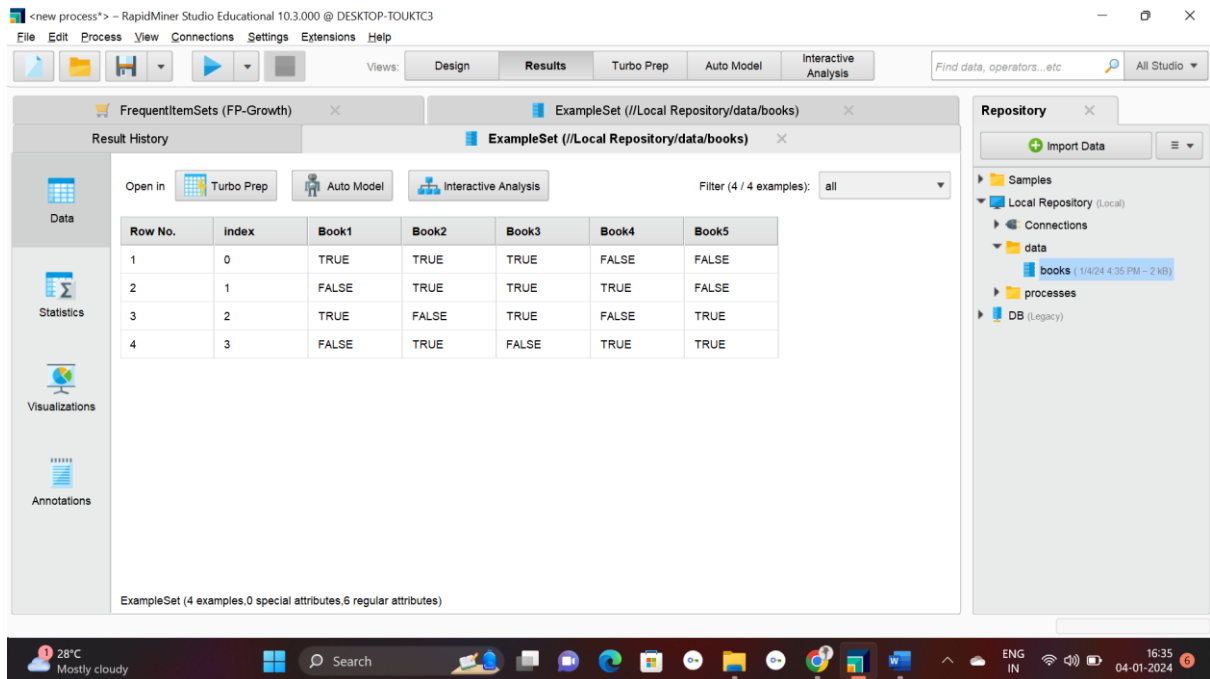
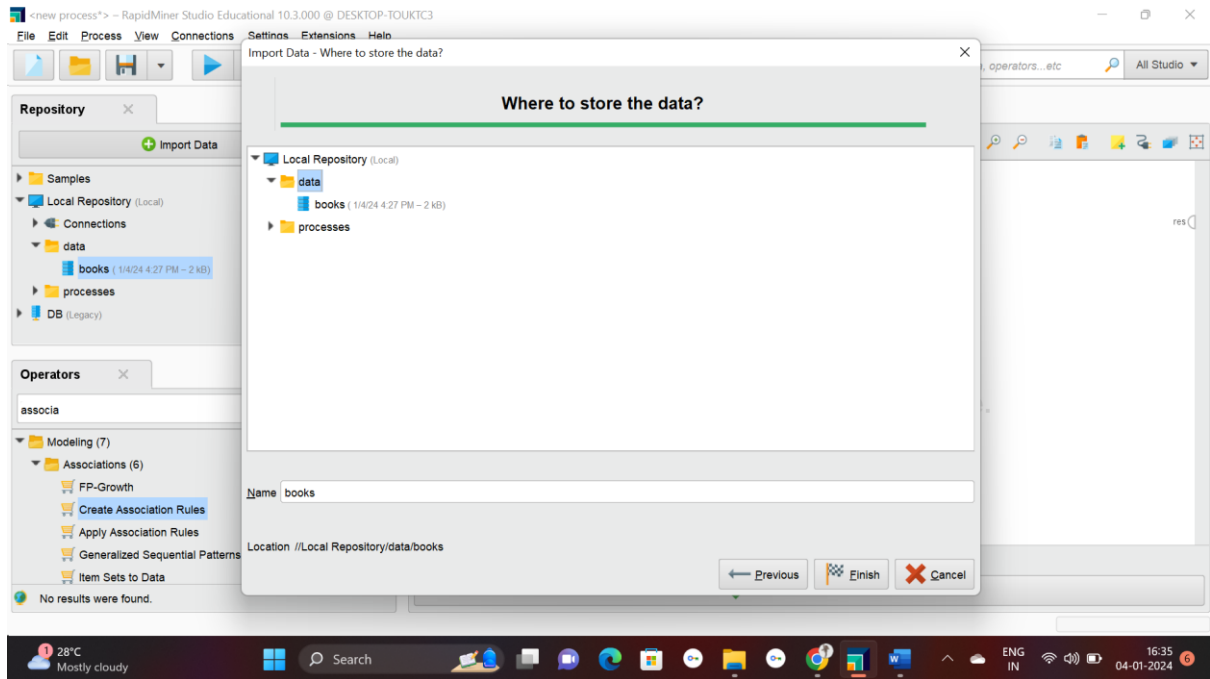
Implementation:

The Shop has a transaction history that includes the books purchased by customers. Using the Apriori algorithm and association rule mining, the supermarket aims to discover patterns of books that are frequently bought together.

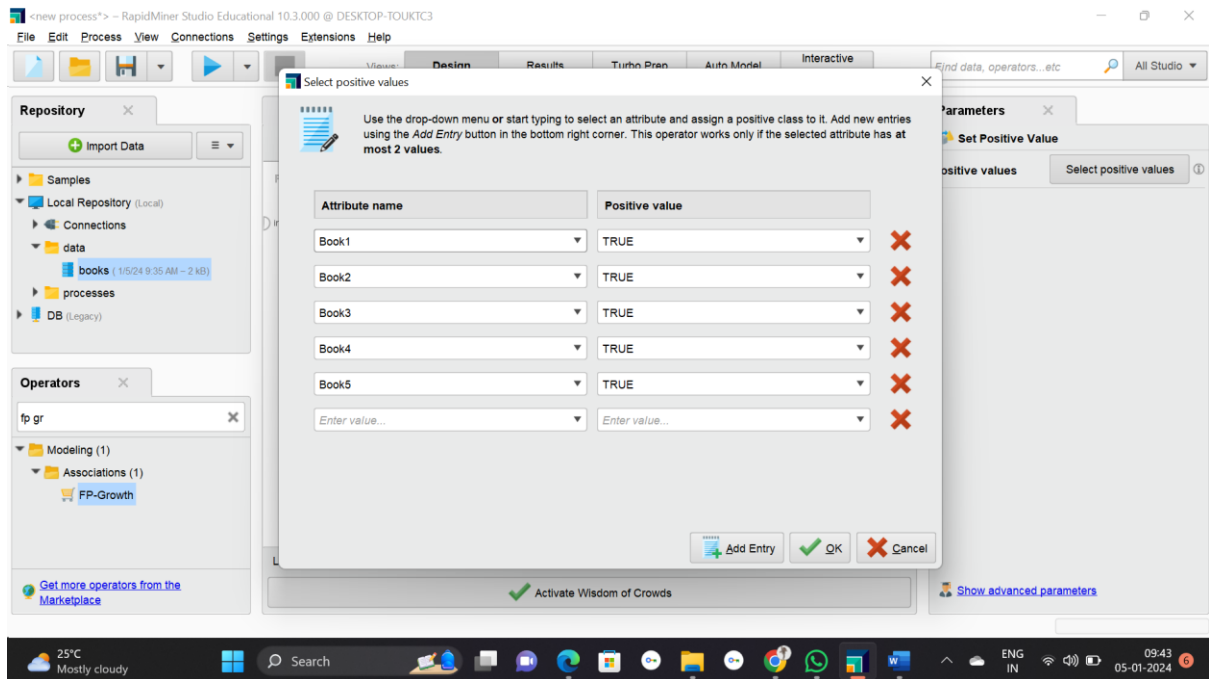
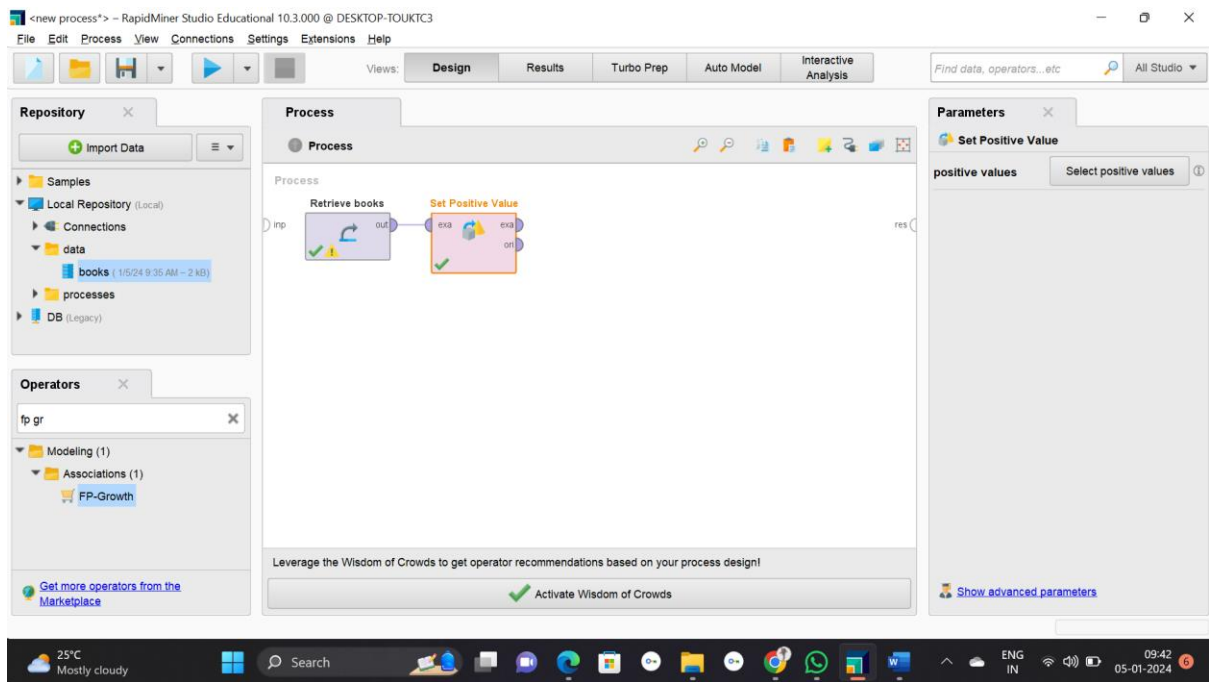
Step 1: Load Dataset

Click ->Import-> select from My computer and load, Save under Local Repository

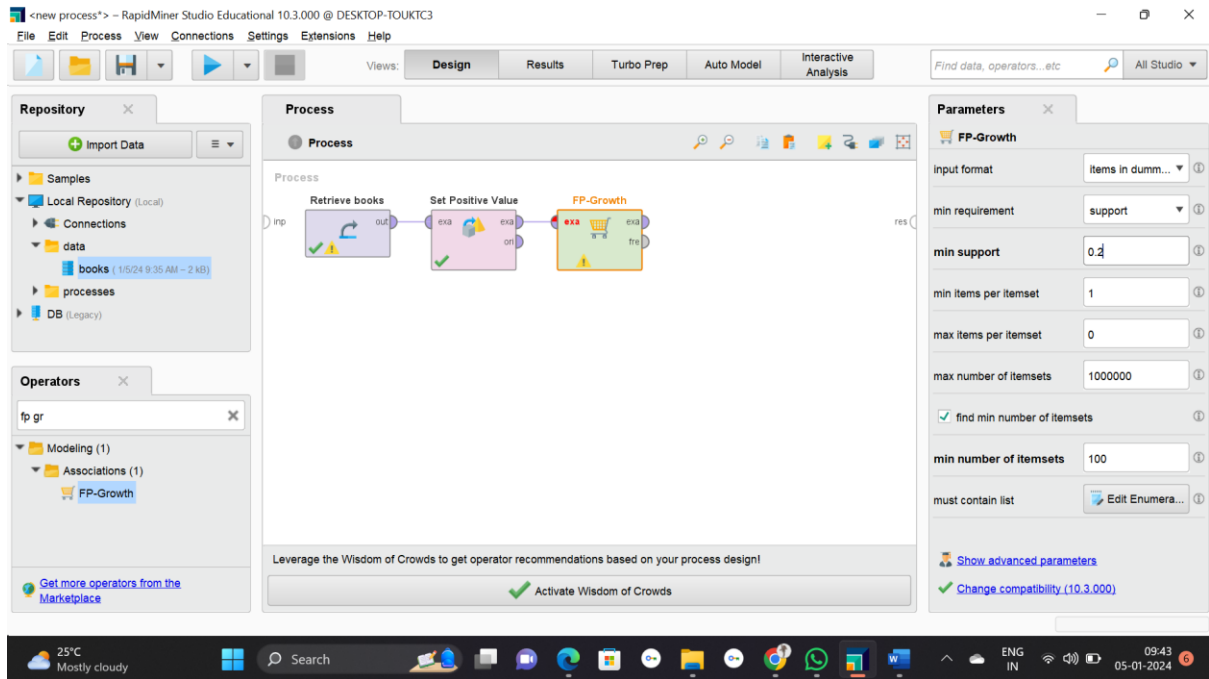




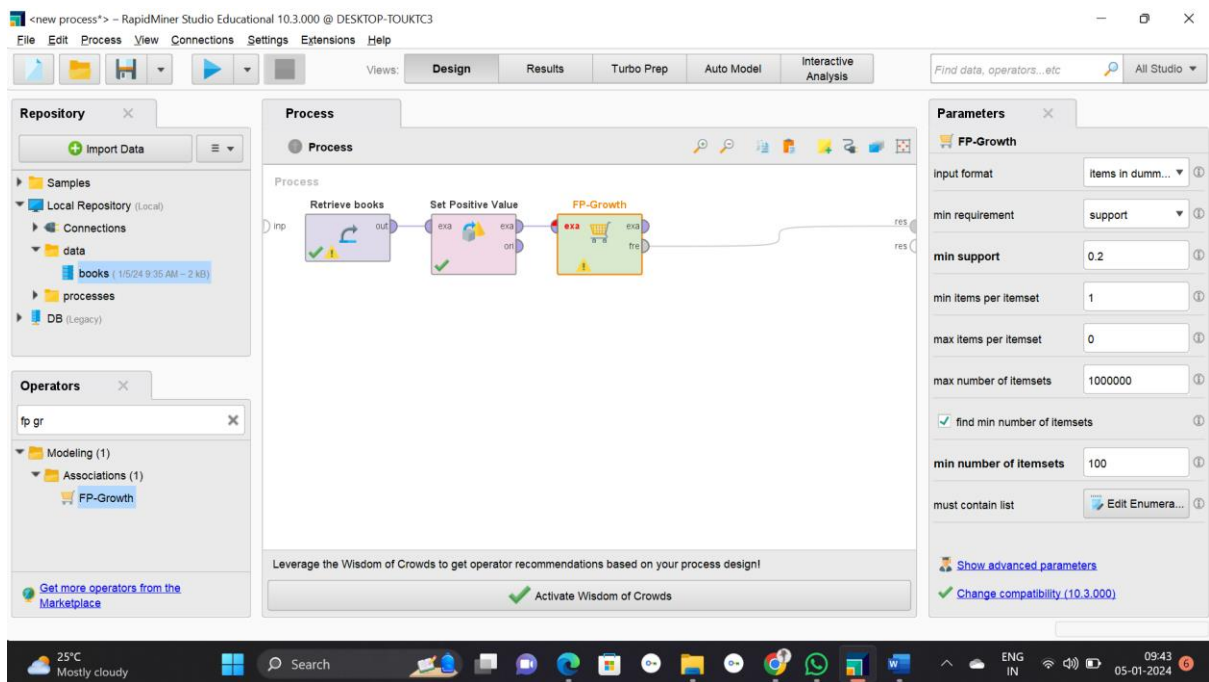
Step 2: Set Positive Values True to Positive



Step 3: Add FP-Growth and set Support Value



Step 4: View the Frequent Itemset



<new process*> - RapidMiner Studio Educational 10.3.000 @ DESKTOP-TOUKTC3

File Edit Process View Connections Settings Extensions Help

Views: Design Results Turbo Prep Auto Model Interactive Analysis

Find data, operators... etc All Studio

Result History

FrequencyItemSets (FP-Growth)

ExampleSet (//Local Repository/data/books)

Repository

Import Data

Samples

Local Repository (Local)

Connections

data

books (1/5/24 9:35 AM - 2 kB)

processes

DB (Legacy)

No. of Sets: 18
Total Max. Size: 3

Min. Size: 1
Max. Size: 3
Contains item:

Update View

Size	Support	Item 1	Item 2	Item 3
1	0.750	Book2		
1	0.750	Book3		
1	0.500	Book1		
1	0.500	Book4		
1	0.500	Book5		
2	0.500	Book2	Book3	
2	0.250	Book2	Book1	
2	0.500	Book2	Book4	
2	0.250	Book2	Book5	
2	0.500	Book3	Book1	
2	0.250	Book3	Book4	
2	0.250	Book3	Book5	
2	0.250	Book1	Book5	
2	0.250	Book4	Book5	

25°C Mostly cloudy

Search

ENG IN

09:45 05-01-2024

Step 5: Add Create Association and set the confidence value

<new process*> - RapidMiner Studio Educational 10.3.000 @ DESKTOP-TOUKTC3

File Edit Process View Connections Settings Extensions Help

Views: Design Results Turbo Prep Auto Model Interactive Analysis

Find data, operators... etc All Studio

Repository

Import Data

Samples

Local Repository (Local)

Connections

data

books (1/5/24 9:35 AM - 2 kB)

processes

DB (Legacy)

Operators

assoc

Modeling (7)

Associations (6)

FP-Growth

Create Association Rules

Apply Association Rules

Get more operators from the Marketplace

Process

Process

Retrieve books

Select Attributes

Set Positive Value

FP-Growth

Create Association R...

Parameters

FP-Growth

input format: items in dumm...

min requirement: support

min support: 0.2

min items per itemset: 1

max items per itemset: 0

max number of itemsets: 1000000

find min number of itemsets

min number of itemsets: 100

must contain list: Edit Enumera...

Show advanced parameters

Change compatibility (10.3.000)

Leverage the Wisdom of Crowds to get operator recommendations based on your process design!

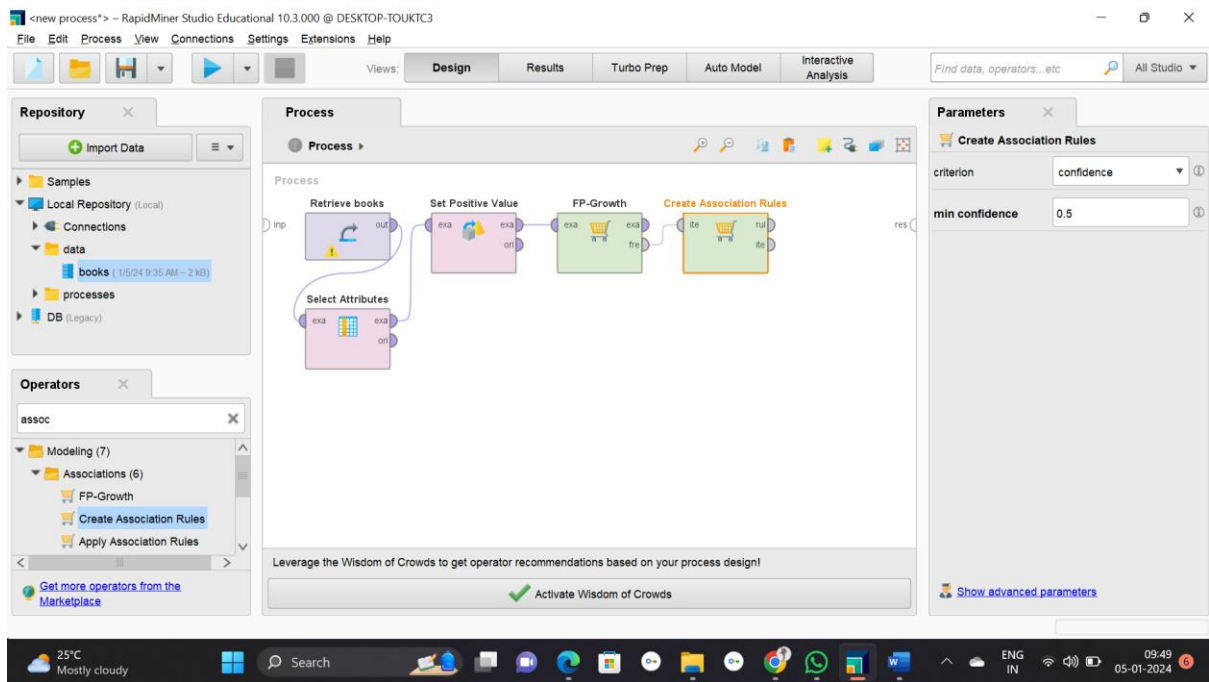
Activate Wisdom of Crowds

25°C Mostly cloudy

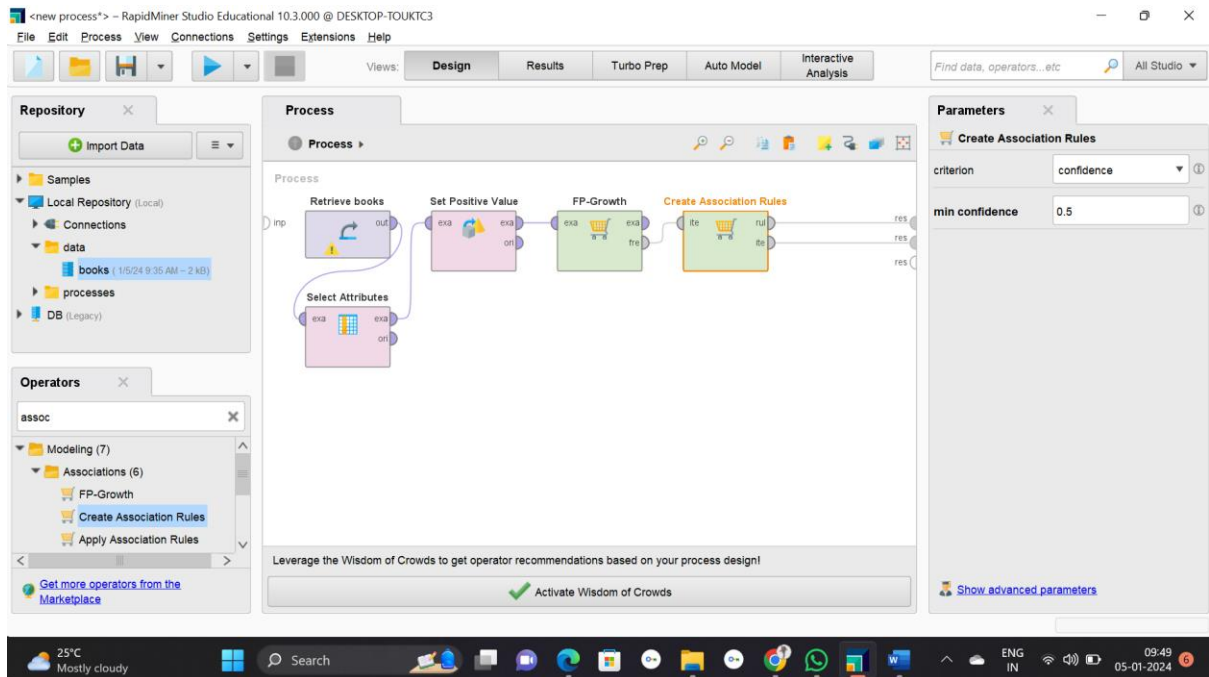
Search

ENG IN

09:47 05-01-2024



Step 6: View both rules and Item set



Step 7: Execute the Model

The screenshot displays the RapidMiner 10.3.0 interface. The top menu bar includes File, Edit, Process, View, Connections, Settings, Extensions, and Help. The top toolbar contains icons for file operations and execution. The main workspace is divided into several panes:

- Left Sidebar:** Contains icons for Data, Graph, Description, and Annotations.
- Top Bar:** Shows the current process as "ExampleSet (/Local Repository/data/books)".
- Process View:** Displays the "AssociationRules (Create Association Rules)" process. The "Result History" pane shows the output of the process.
- Results Pane:** Displays the "FrequentItemSets (FP-Growth)" results. The table below shows the output of the association rules process.
- Right Sidebar:** Shows the "Repository" pane with a tree view of the data sources.

The "Results" pane displays the following table:

Premises	Conclusion	Support	Confidence	LaPlace	Gain	p-s	Lift	Convict...
Book2	Book3	0.500	0.667	0.857	-1	-0.062	0.889	0.750
Book3	Book2	0.500	0.667	0.857	-1	-0.062	0.889	0.750
Book2	Book4	0.500	0.667	0.857	-1	0.125	1.333	1.500
Book3	Book1	0.500	0.667	0.857	-1	0.125	1.333	1.500
Book4	Book2	0.500	1	1	-0.500	0.125	1.333	∞
Book1	Book3	0.500	1	1	-0.500	0.125	1.333	∞
Book2, Book1	Book3	0.250	1	1	-0.250	0.062	1.333	∞
Book3, Book4	Book2	0.250	1	1	-0.250	0.062	1.333	∞
Book2, Book5	Book4	0.250	1	1	-0.250	0.125	2	∞
Book4, Book5	Book2	0.250	1	1	-0.250	0.062	1.333	∞
Book3, Book5	Book1	0.250	1	1	-0.250	0.125	2	∞
Book1, Book5	Book3	0.250	1	1	-0.250	0.062	1.333	∞

The "Repository" pane on the right shows the data sources: Samples, Local Repository (Local), Connections, data, books (1/5/24 9:35 AM - 2 KB), processes, and DB (Legacy).

Apriori Algorithm:

Tool : Google Colab

Use Case: Books Data

Objective:

The main objective is to identify sets of books that frequently occur together in the dataset. These sets are known as frequent itemsets, from the frequent itemsets, generate association rules that express relationships between different sets of books and Visualize the generated association rules as a directed graph.

Implementation:

Using the Apriori algorithm and association rule mining, the prediction is brought to discover patterns that are frequently happens together.

Program:

```
# Install necessary libraries
!pip install mlxtend
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules

# Sample dataset (replace this with your actual dataset)
buying_books_data = [
    ['Book1', 'Book2', 'Book3'],
    ['Book2', 'Book3', 'Book4'],
    ['Book1', 'Book3', 'Book5'],
    ['Book2', 'Book4', 'Book5'],
]

# Convert the dataset to a one-hot encoded format
te = TransactionEncoder()
te_ary = te.fit(buying_books_data).transform(buying_books_data)
df_buying_books = pd.DataFrame(te_ary, columns=te.columns_)

# Apply the Apriori algorithm
min_support = 0.2 # Adjust as needed
frequent_itemsets = apriori(df_buying_books, min_support=min_support,
                             use_colnames=True)

# Generate association rules
min_confidence = 0.5 # Adjust as needed
rules = association_rules(frequent_itemsets, metric='confidence',
                          min_threshold=min_confidence)

# Display frequent itemsets
```



```

print("Frequent Itemsets:")
print(frequent_itemsets)

# Display association rules
print("\nAssociation Rules:")
print(rules)

```

OUTPUT:

```

Frequent Itemsets:
support      itemsets
0      0.50      (Book1)
1      0.75      (Book2)
2      0.75      (Book3)
3      0.50      (Book4)
4      0.50      (Book5)
5      0.25      (Book2, Book1)
6      0.50      (Book3, Book1)
7      0.25      (Book5, Book1)
8      0.50      (Book3, Book2)
9      0.50      (Book4, Book2)
10     0.25      (Book5, Book2)
11     0.25      (Book4, Book3)
12     0.25      (Book5, Book3)
13     0.25      (Book5, Book4)
14     0.25      (Book3, Book2, Book1)
15     0.25      (Book5, Book3, Book1)
16     0.25      (Book4, Book3, Book2)
17     0.25      (Book4, Book5, Book2)

```

```

Association Rules:
support antecedents consequents antecedent support consequent
0      0.50      (Book1)      (Book2)      0.50
0.75
1      0.50      (Book3)      (Book1)      0.75
0.50
2      0.75      (Book1)      (Book3)      0.50
0.75
3      0.50      (Book5)      (Book1)      0.50
0.50
4      0.50      (Book1)      (Book5)      0.50
0.50
5      0.75      (Book3)      (Book2)      0.75
0.75
6      0.75      (Book2)      (Book3)      0.75
0.75
7      0.75      (Book4)      (Book2)      0.50
0.75
8      0.50      (Book2)      (Book4)      0.75
0.50
9      0.75      (Book5)      (Book2)      0.50
0.75
10     0.50      (Book4)      (Book3)      0.50
0.75

```

11	(Book5)	(Book3)	0.50
0.75			
12	(Book5)	(Book4)	0.50
0.50			
13	(Book4)	(Book5)	0.50
0.50			
14	(Book2, Book3)	(Book1)	0.50
0.50			
15	(Book3, Book1)	(Book2)	0.50
0.75			
16	(Book2, Book1)	(Book3)	0.25
0.75			
17	(Book1)	(Book2, Book3)	0.50
0.50			
18	(Book5, Book3)	(Book1)	0.25
0.50			
19	(Book5, Book1)	(Book3)	0.25
0.75			
20	(Book3, Book1)	(Book5)	0.50
0.50			
21	(Book5)	(Book3, Book1)	0.50
0.50			
22	(Book1)	(Book5, Book3)	0.50
0.25			
23	(Book3, Book4)	(Book2)	0.25
0.75			
24	(Book2, Book4)	(Book3)	0.50
0.75			
25	(Book2, Book3)	(Book4)	0.50
0.50			
26	(Book4)	(Book2, Book3)	0.50
0.50			
27	(Book5, Book4)	(Book2)	0.25
0.75			
28	(Book2, Book4)	(Book5)	0.50
0.50			
29	(Book5, Book2)	(Book4)	0.25
0.50			
30	(Book4)	(Book5, Book2)	0.50
0.25			
31	(Book5)	(Book2, Book4)	0.50
0.50			

	support	confidence	lift	leverage	conviction	zhangs_metric
0	0.25	0.500000	0.666667	-0.1250	0.50	-0.500000
1	0.50	0.666667	1.333333	0.1250	1.50	1.000000
2	0.50	1.000000	1.333333	0.1250	inf	0.500000
3	0.25	0.500000	1.000000	0.0000	1.00	0.000000
4	0.25	0.500000	1.000000	0.0000	1.00	0.000000
5	0.50	0.666667	0.888889	-0.0625	0.75	-0.333333
6	0.50	0.666667	0.888889	-0.0625	0.75	-0.333333
7	0.50	1.000000	1.333333	0.1250	inf	0.500000
8	0.50	0.666667	1.333333	0.1250	1.50	1.000000
9	0.25	0.500000	0.666667	-0.1250	0.50	-0.500000
10	0.25	0.500000	0.666667	-0.1250	0.50	-0.500000
11	0.25	0.500000	0.666667	-0.1250	0.50	-0.500000
12	0.25	0.500000	1.000000	0.0000	1.00	0.000000
13	0.25	0.500000	1.000000	0.0000	1.00	0.000000

14	0.25	0.500000	1.000000	0.0000	1.00	0.000000
15	0.25	0.500000	0.666667	-0.1250	0.50	-0.500000
16	0.25	1.000000	1.333333	0.0625	inf	0.333333
17	0.25	0.500000	1.000000	0.0000	1.00	0.000000
18	0.25	1.000000	2.000000	0.1250	inf	0.666667
19	0.25	1.000000	1.333333	0.0625	inf	0.333333
20	0.25	0.500000	1.000000	0.0000	1.00	0.000000
21	0.25	0.500000	1.000000	0.0000	1.00	0.000000
22	0.25	0.500000	2.000000	0.1250	1.50	1.000000
23	0.25	1.000000	1.333333	0.0625	inf	0.333333
24	0.25	0.500000	0.666667	-0.1250	0.50	-0.500000
25	0.25	0.500000	1.000000	0.0000	1.00	0.000000
26	0.25	0.500000	1.000000	0.0000	1.00	0.000000
27	0.25	1.000000	1.333333	0.0625	inf	0.333333
28	0.25	0.500000	1.000000	0.0000	1.00	0.000000
29	0.25	1.000000	2.000000	0.1250	inf	0.666667
30	0.25	0.500000	2.000000	0.1250	1.50	1.000000
31	0.25	0.500000	1.000000	0.0000	1.00	0.000000

FP-growth algorithm

Tool : Google Colab

Program:

```
!pip install pyfpgrowth

import pyfpgrowth

# Sample dataset (replace this with your actual dataset)
buying_books_data = [
    ['Book1', 'Book2', 'Book3'],
    ['Book2', 'Book3', 'Book4'],
    ['Book1', 'Book3', 'Book5'],
    ['Book2', 'Book4', 'Book5'],
]

# Convert the dataset to a list of transactions
transactions = [tuple(transaction) for transaction in
buying_books_data]

# Apply the FP-growth algorithm
min_support = 2 # Adjust as needed
patterns = pyfpgrowth.find_frequent_patterns(transactions, min_support)

# Generate association rules
min_confidence = 0.5 # Adjust as needed
rules = pyfpgrowth.generate_association_rules(patterns, min_confidence)

# Display frequent itemsets
print("Frequent Itemsets:")
print(patterns)
```

```
# Display association rules
print("\nAssociation Rules:")
print(rules)
```

```
itemset_labels = [' ', ' '.join(map(str, itemset)) for itemset in
patterns.keys()]
```

```
plt.figure(figsize=(36, 24))
plt.subplot(2, 2, 1)
plt.barh(itemset_labels, list(patterns.values()))
plt.xlabel('Support')
plt.ylabel('Itemsets')
plt.title('Frequent Itemsets')
```

```
import seaborn as sns
```

```
plt.subplot(2, 2, 2)
sns.histplot(list(patterns.values()), bins=10, kde=True)
plt.xlabel('Support')
plt.ylabel('Frequency')
plt.title('Support Distribution')
```

OUTPUT:

Frequent Itemsets:

```
{('Book1',): 2, ('Book1', 'Book3'): 2, ('Book4',): 2, ('Book2',
'Book4'): 2, ('Book5',): 2, ('Book2',): 3, ('Book3',): 3, ('Book2',
'Book3'): 2}
```

Association Rules:

```
{('Book1',): (('Book3',), 1.0), ('Book3',): (('Book2',),
0.6666666666666666), ('Book2',): (('Book3',), 0.6666666666666666),
('Book4',): (('Book2',), 1.0)}
```

