Implementation and Code Usage

Apriori Algorithm Implementation

Abstract:

I studied and implemented the Apriori Algorithm, a data mining method for identifying association rules, in this midterm assignment. By designing and developing the code, I developed a unique approach to extract meaningful information from transaction data.

Introduction:

Data mining is the process of discovering patterns, correlations, and insights from large datasets to extract valuable information. It uses a variety of methods and algorithms to analyze data and find hidden patterns that can be predicted and utilized in decision-making. Association rules are one of the fundamental concepts in data mining, used to uncover relationships between variables in large datasets. They are typically represented as "if-then" statements that describe the co-occurrence of items in transactions. For example, an association rule might indicate that if a customer buys item A, they are likely to buy item B as well.

The Apriori algorithm is a popular algorithm used to mine association rules from transactional datasets. It works by generating frequent itemsets, which are sets of items that frequently occur together in transactions. The algorithm then creates association rules that satisfy user-specified requirements, including minimum support and minimum confidence, using these frequently occurring itemsets.

The algorithm scans the dataset to identify frequent itemsets, i.e., sets of items that occur together with a frequency greater than or equal to a specified minimum support. Based on the frequent itemsets found, the algorithm generates candidate itemsets by combining items to form larger itemsets. The algorithm prunes the candidate itemsets that cannot possibly be frequent based on the downward closure property. This reduces the number of candidate itemsets that need to be considered in subsequent iterations and is repeated iteratively until no new frequent itemsets can be found. Once all frequent itemsets are identified, the algorithm generates association rules from these itemsets by calculating their support and confidence. Association rules that meet the user-defined thresholds (minimum support and minimum confidence) are considered significant and are returned as the final output.

I implemented Apriori algorithm, FP-growth algorithm and Brute Force algorithm in this project. Following is the implementation of Apriori algorithm:

- We begin the implementation by finding itemsets containing only one item.
- Then, we verify the items and check their support, as it should be greater than or equal to minimum support. We eliminate all the items that have support less than minimum support.
- Then iteratively, we generate larger itemsets from the itemsets found in previous iteration.
- Candidates for the next iteration are generated by joining pairs of frequent itemsets found in previous iteration.
- Once all frequent itemsets are found, association rules are generated from these itemsets.
- The confidence of rule A -> B is defined as the support of the itemset {A,B} divided by the support of the antecedent {A}.

Core Concepts and Principles:

Frequent Itemset Discovery:

In the Apriori algorithm, discovering frequent itemsets involves iteratively finding itemsets that satisfy a minimum support threshold.

Support and Confidence:

In the Apriori algorithm, support and confidence are two key metrics used to identify meaningful patterns in transactional datasets. Support measures the frequency of occurrence of an itemset in the dataset. Confidence measures the reliability of the association between two itemsets in an association rule.

Association Rule:

In the Apriori algorithm, association rules are generated from frequent itemsets. An association rule is a relationship between two sets of items in a transactional dataset, often represented as "if-then" statements. The rule suggests that if the antecedent set of items is present in a transaction, then the consequent set of items is likely to be present as well.

Data Loading and Processing:

The code reads the transaction data of a retail store from a csv file. Each transaction consists of a list of items bought by a customer.

Determination of Minimum Support and Confidence:

The user is asked to enter values for minimum support and minimum confidence to filter out less significant patterns.

Results and Evaluation:

The project's effectiveness and efficiency are evaluated based on performance measures such as support, confidence, and the resulting association rules. We also compare our custom Apriori Algorithm implementation with the Apriori library to assess its reliability.

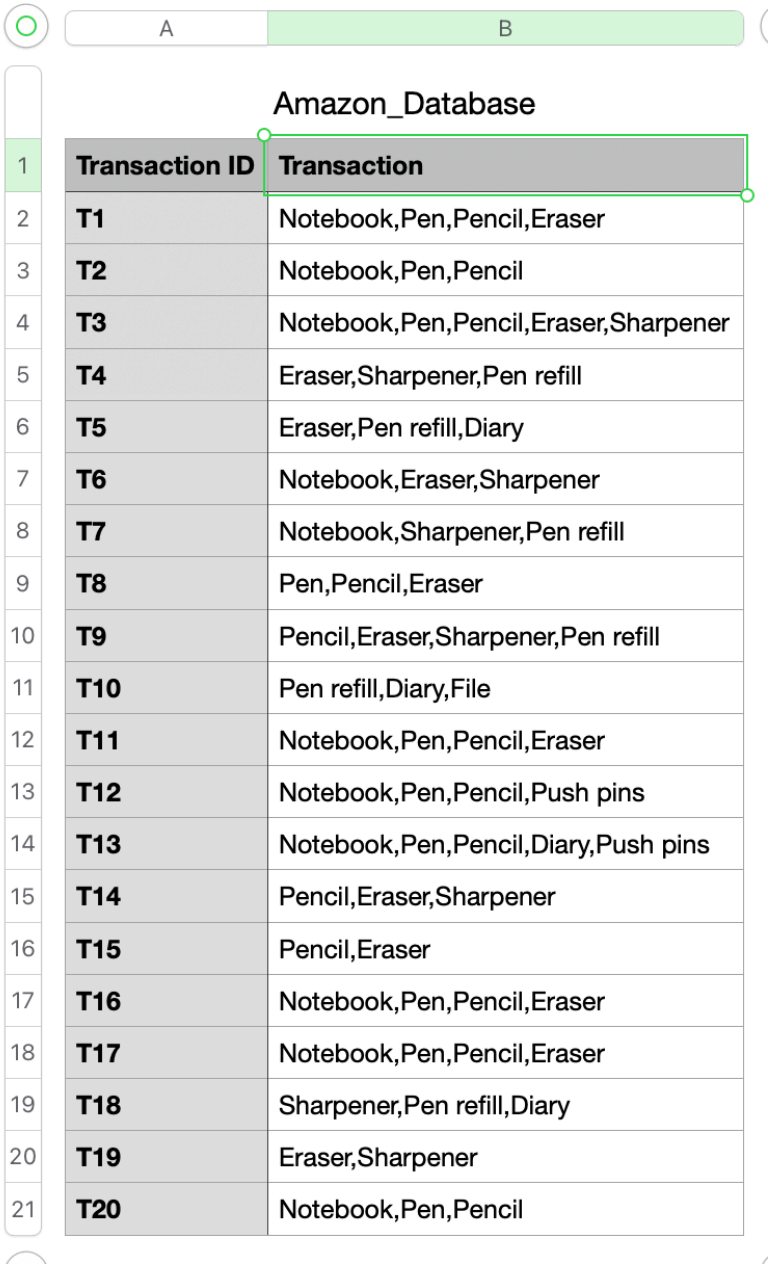
Conclusion:

To sum up, this project shows how data mining ideas, techniques, and principles can be applied. I successfully implemented the FP-growth algorithm, the Apriori method, and the Brute Force technique to extract useful association rules from transaction data from retail stores. The customization of algorithms, iterative "brute force" methodology, and strict adherence to user-specified criteria demonstrate the effectiveness of data mining in identifying significant patterns that support retail industry decision-making.

Screenshots:

Below are the screenshots of the csv files.

Figure 1: Amazon Database.



Amazon_Database

Transaction ID	Transaction
T1	Notebook,Pen,Pencil,Eraser
T2	Notebook,Pen,Pencil
T3	Notebook,Pen,Pencil,Eraser,Sharpener
T4	Eraser,Sharpener,Pen refill
T5	Eraser,Pen refill,Diary
T6	Notebook,Eraser,Sharpener
T7	Notebook,Sharpener,Pen refill
T8	Pen,Pencil,Eraser
T9	Pencil,Eraser,Sharpener,Pen refill
T10	Pen refill,Diary,File
T11	Notebook,Pen,Pencil,Eraser
T12	Notebook,Pen,Pencil,Push pins
T13	Notebook,Pen,Pencil,Diary,Push pins
T14	Pencil,Eraser,Sharpener
T15	Pencil,Eraser
T16	Notebook,Pen,Pencil,Eraser
T17	Notebook,Pen,Pencil,Eraser
T18	Sharpener,Pen refill,Diary
T19	Eraser,Sharpener
T20	Notebook,Pen,Pencil

Figure 2: Best Buy Database.

Best_Buy_Database

Transaction ID	Transaction
T1	Desktop,Printer,Flash Drive,Microsoft Office,Speakers,Anti-Virus
T2	Laptop,Flash Drive,Microsoft Office,Laptop Case,Anti-Virus
T3	Laptop,Printer,Flash Drive,Microsoft Office,Anti-Virus,Laptop Case,External Hard-Drive
T4	Laptop,Printer,Flash Drive,Anti-Virus,External Hard-Drive,Laptop Case
T5	Laptop,Flash Drive,Laptop Case,Anti-Virus
T6	Laptop,Printer,Flash Drive,Microsoft Office
T7	Desktop,Printer,Flash Drive,Microsoft Office
T8	Laptop,External Hard-Drive,Anti-Virus
T9	Desktop,Printer,Flash Drive,Microsoft Office,Laptop Case,Anti-Virus,Speakers,External Hard-Drive
T10	Digital Camera,Laptop,Desktop,Printer,Flash Drive,Microsoft Office,Laptop Case,Anti-Virus,External Hard-Drive,Speakers
T11	Laptop,Desktop,Laptop Case,External Hard-Drive,Speakers,Anti-Virus
T12	Digital Camera,Laptop,Laptop Case,External Hard-Drive,Anti-Virus,Speakers
T13	Digital Camera,Speakers
T14	Digital Camera,Desktop,Printer,Flash Drive,Microsoft Office
T15	Printer,Flash Drive,Microsoft Office,Anti-Virus,Laptop Case,Speakers,External Hard-Drive
T16	Digital Camera,Flash Drive,Microsoft Office,Anti-Virus,Laptop Case,External Hard-Drive,Speakers
T17	Digital Camera,Laptop,Laptop Case
T18	Digital Camera,Laptop Case,Speakers
T19	Digital Camera,Laptop,Printer,Flash Drive,Microsoft Office,Speakers,Laptop Case,Anti-Virus
T20	Digital Camera,Laptop,Speakers,Anti-Virus,Laptop Case

Figure 3: Walmart Database.

Walmart_Database

Transaction ID	Transaction
T1	Bananas,Pears,Apples
T2	Bananas,Pears,Apples
T3	Bananas,Pears,Apples,Oranges,Cucumber
T4	Bananas,Pears,Apples,Oranges,Blueberries
T5	Bananas,Pears,Oranges,Blueberries
T6	Bananas,Oranges,Blueberries
T7	Bananas,Blueberries
T8	Bananas,Blueberries,Cucumber
T9	Bananas,Apples,Blueberries
T10	Bananas,Apples,Blueberries
T11	Bananas,Apples,Blueberries,Cucumber

Figure 4: K-Mart Database.

K_Mart_Database

Transaction ID	Transaction
T1	Decorative Pillows,Quilts,Embroidered Bedspread
T2	Embroidered Bedspread,Shams,Kids Bedding,Bedding Collections,Bed Skirts,Bedspreads,Sheets
T3	Decorative Pillows,Quilts,Embroidered Bedspread,Shams,Kids Bedding,Bedding Collections
T4	Kids Bedding,Bedding Collections,Sheets,Bedspreads,Bed Skirts
T5	Decorative Pillows,Kids Bedding,Bedding Collections,Sheets,Bed Skirts,Bedspreads
T6	Bedding Collections,Bedspreads,Bed Skirts,Sheets,Shams,Kids Bedding
T7	Decorative Pillows,Quilts
T8	Decorative Pillows,Quilts,Embroidered Bedspread
T9	Bedspreads,Bed Skirts,Shams,Kids Bedding,Sheets
T10	Quilts,Embroidered Bedspread,Bedding Collections
T11	Bedding Collections,Bedspreads,Bed Skirts,Kids Bedding,Shams,Sheets
T12	Decorative Pillows,Quilts
T13	Embroidered Bedspread,Shams
T14	Sheets,Shams,Bed Skirts,Kids Bedding
T15	Decorative Pillows,Quilts
T16	Decorative Pillows,Kids Bedding,Bed Skirts,Shams
T17	Decorative Pillows,Shams,Bed Skirts
T18	Quilts,Sheets,Kids Bedding
T19	Shams,Bed Skirts,Kids Bedding,Sheets
T20	Decorative Pillows,Bedspreads,Shams,Sheets,Bed Skirts,Kids Bedding

Figure 5: Nike Database.

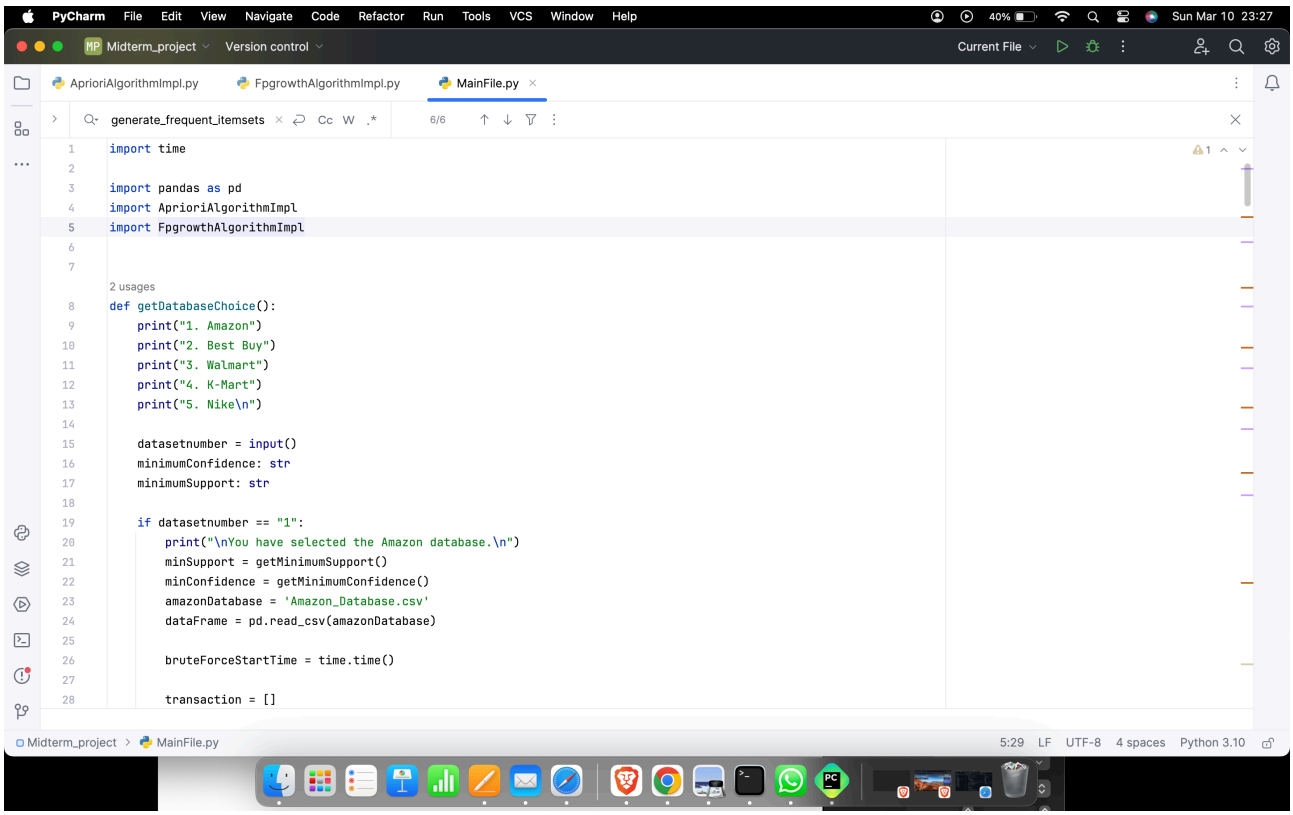
Nike_Database

Transaction ID	Transaction
T1	Running Shoe,Socks,Sweatshirts,Modern Pants
T2	Running Shoe,Socks,Sweatshirts
T3	Running Shoe,Socks,Sweatshirts,Modern Pants
T4	Running Shoe,Sweatshirts,Modern Pants
T5	Running Shoe,Socks,Sweatshirts,Modern Pants,Soccer Shoe
T6	Running Shoe,Socks,Sweatshirts
T7	Running Shoe,Socks,Sweatshirts,Modern Pants,Tech Pants,Rash Guard,Hoodies
T8	Swimming Shirt,Socks,Sweatshirts
T9	Swimming Shirt,Rash Guard,Dry Fit V-Nick,Hoodies,Tech Pants
T10	Swimming Shirt,Rash Guard,Dry
T11	Swimming Shirt,Rash Guard,Dry Fit V-Nick
T12	Running Shoe,Swimming Shirt,Socks,Sweatshirts,Modern Pants,Soccer Shoe,Rash Guard,Hoodies,Tech Pants,Dry Fit V-Nick
T13	Running Shoe,Swimming Shirt,Socks,Sweatshirts,Modern Pants,Soccer Shoe,Rash Guard,Tech Pants,Dry Fit V-Nick,Hoodies
T14	Running Shoe,Swimming Shirt,Rash Guard,Tech Pants,Hoodies,Dry Fit V-Nick
T15	Running Shoe,Swimming Shirt,Socks,Sweatshirts,Modern Pants,Dry Fit V-Nick,Rash Guard,Tech Pants
T16	Swimming Shirt,Soccer Shoe,Hoodies,Dry Fit V-Nick,Tech Pants,Rash Guard
T17	Running Shoe,Socks
T18	Socks,Sweatshirts,Modern Pants,Soccer Shoe,Hoodies,Rash Guard,Tech Pants,Dry Fit V-Nick
T19	Running Shoe,Swimming Shirt,Rash Guard
T20	Running Shoe,Swimming Shirt,Socks,Sweatshirts,Modern Pants,Soccer Shoe,Hoodies,Tech Pants,Rash Guard,Dry Fit V-Nick

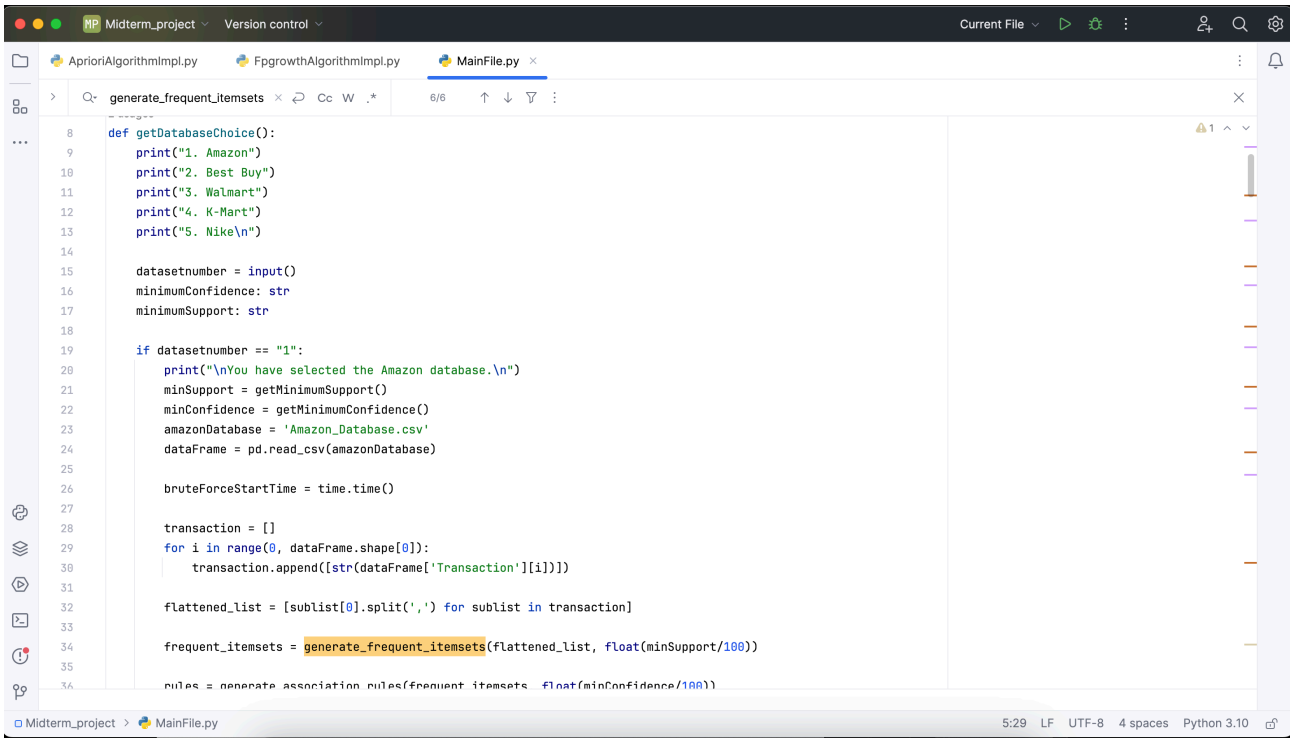
Below are screenshots form my code:

We have to execute the MainFile.py in command prompt using command

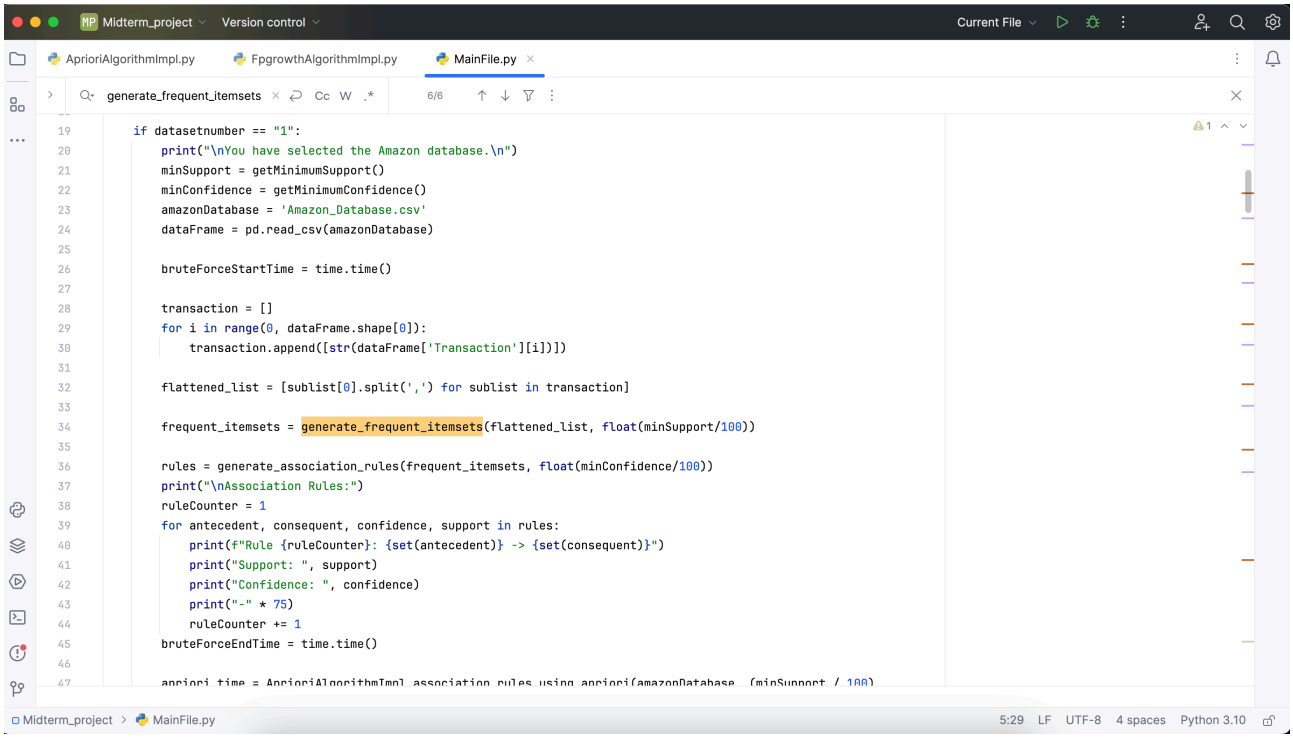
python MainFile.py



Selecting Database and entering minimum support and confidence:



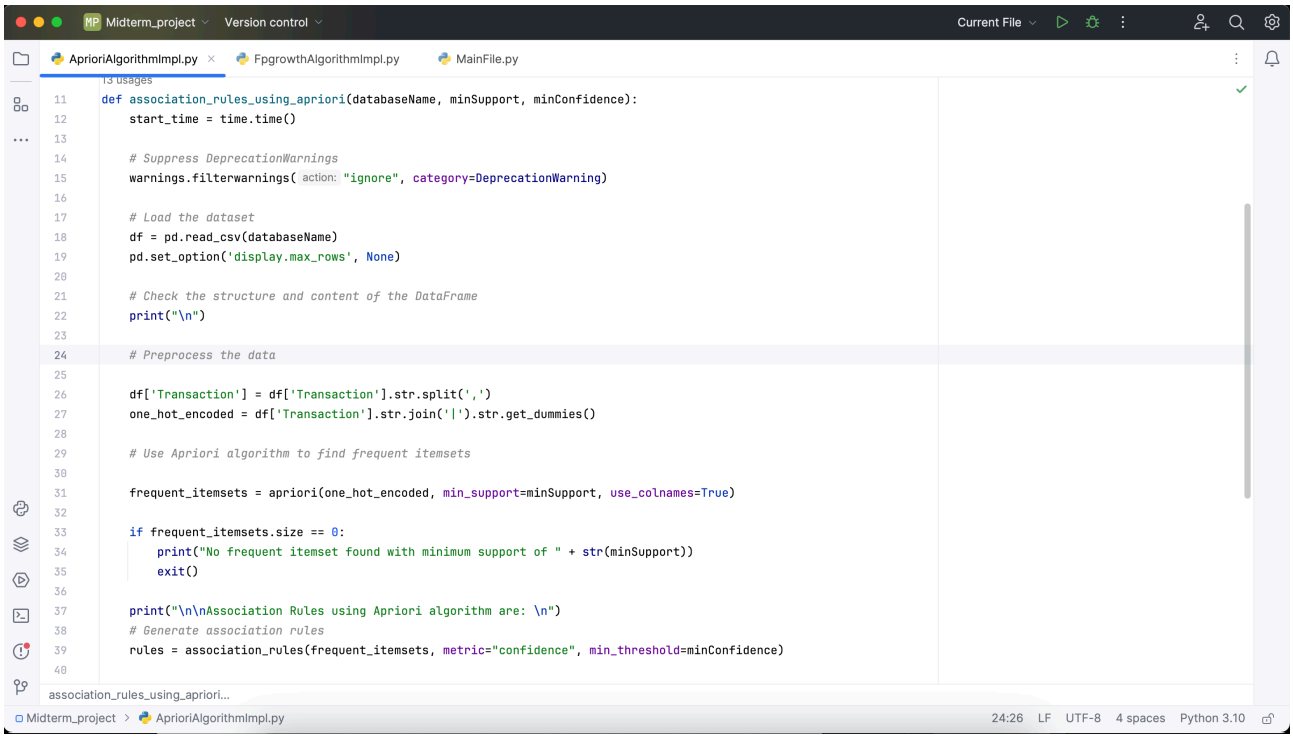
Implementing Brute force algorithm for amazon database:



```
if datasetnumber == "1":
    print("\nYou have selected the Amazon database.\n")
    minSupport = getMinimumSupport()
    minConfidence = getMinimumConfidence()
    amazonDatabase = 'Amazon_Database.csv'
    dataFrame = pd.read_csv(amazonDatabase)

    bruteForceStartTime = time.time()

    transaction = []
    for i in range(0, dataFrame.shape[0]):
        transaction.append([str(dataFrame['Transaction'][i])])

    flattened_list = [sublist[0].split(',') for sublist in transaction]

    frequent_itemsets = generate_frequent_itemsets(flattened_list, float(minSupport/100))

    rules = generate_association_rules(frequent_itemsets, float(minConfidence/100))
    print("\nAssociation Rules:")
    ruleCounter = 1
    for antecedent, consequent, confidence, support in rules:
        print(f"Rule {ruleCounter}: {set(antecedent)} -> {set(consequent)}")
        print("Support: ", support)
        print("Confidence: ", confidence)
        print("-" * 75)
        ruleCounter += 1
    bruteForceEndTime = time.time()
```

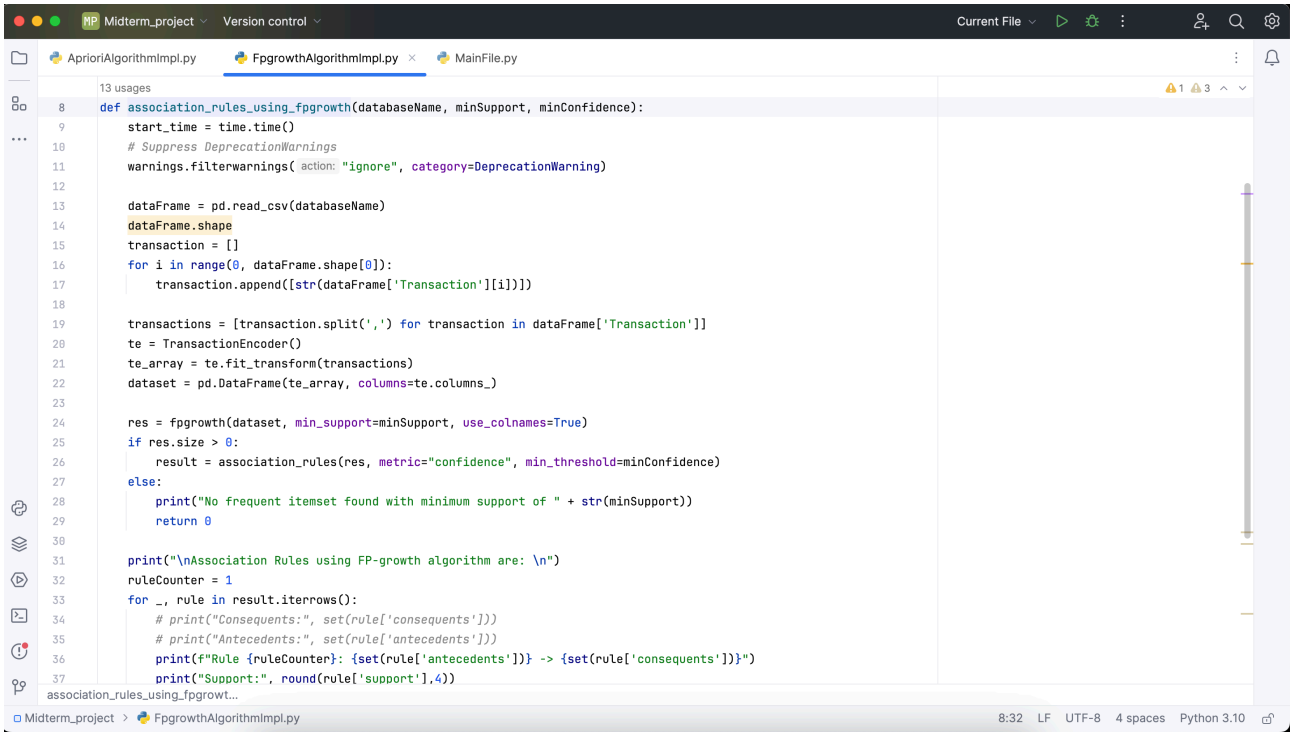
Implementing Apriori algorithm and FP-growth algorithm:

Apriori Algorithm using package:



```
def association_rules_using_apriori(databaseName, minSupport, minConfidence):
    start_time = time.time()

    # Suppress DeprecationWarnings
    warnings.filterwarnings( action: "ignore", category=DeprecationWarning)

    # Load the dataset
    df = pd.read_csv(databaseName)
    pd.set_option('display.max_rows', None)

    # Check the structure and content of the DataFrame
    print("\n")

    # Preprocess the data

    df['Transaction'] = df['Transaction'].str.split(',')
    one_hot_encoded = df['Transaction'].str.join('|').str.get_dummies()

    # Use Apriori algorithm to find frequent itemsets

    frequent_itemsets = apriori(one_hot_encoded, min_support=minSupport, use_colnames=True)

    if frequent_itemsets.size == 0:
        print("No frequent itemset found with minimum support of " + str(minSupport))
        exit()

    print("\n\nAssociation Rules using Apriori algorithm are: \n")
    # Generate association rules
    rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=minConfidence)
```

Implementing FP-growth algorithm using package:



Accepting and validating minimum support and minimum confidence:

```
def getMinimumSupport():
    print("\nPlease enter minimum support in % (value from 1 to 100): \n")
    minimumSupport = input()
    minSupport = int(minimumSupport)
    if 0 < minSupport < 100:
        return minSupport
    else:
        return getMinimumSupport()
```

6 usages

```
def getMinimumConfidence():
    print("\nPlease enter minimum Confidence in % (value from 1 to 100): \n")
    minimumConfidence = input()
    minConfidence = int(minimumConfidence)
    if 0 < minConfidence < 100:
        return minConfidence
    else:
        return getMinimumConfidence()
```

Generating frequent itemsets:

Calculating association rules:

```
def generate_association_rules(frequent_itemsets, min_confidence):
    rules = []
    for itemset, support in frequent_itemsets:
        if len(itemset) >= 1:
            for i in range(1, len(itemset)):
                antecedent = itemset[:i]
                consequent = itemset[i:]
                antecedent_support = calculate_support(antecedent, frequent_itemsets)
                if antecedent_support > 0:
                    confidence = support / antecedent_support
                    if confidence >= min_confidence:
                        rules.append((antecedent, consequent, confidence,antecedent_support))
    return rules
```

Result:

Brute force algorithm output:

```
def generate_frequent_itemsets(transactions, min_support):
    items = {}
    for transaction in transactions:
        for item in transaction:
            if item in items:
                items[item] += 1
            else:
                items[item] = 1

    frequent_itemsets = []
    n = len(transactions)
    for item, count in items.items():
        support = count / n
        if support >= min_support:
            frequent_itemsets.append(([item], support))

    k = 2
    while True:
        candidates = generate_candidates([itemset[0] for itemset in frequent_itemsets], k)
        if not candidates:
            break

        frequent_candidates = []
        for candidate in candidates:
            count = 0
            for transaction in transactions:
                if set(candidate).issubset(set(transaction)):
```

Apriori Algorithm Output:

```
Please enter minimum Confidence in % (value from 1 to 100):

40

Association Rules:
Rule 1: {'Notebook'} -> {'Pen'}
Support:  0.55
Confidence:  0.8181818181818181
--------------------------------------------------------------------------------
Rule 2: {'Notebook'} -> {'Pencil'}
Support:  0.55
Confidence:  0.8181818181818181
--------------------------------------------------------------------------------
Rule 3: {'Pen'} -> {'Pencil'}
Support:  0.5
Confidence:  1.0
--------------------------------------------------------------------------------
Rule 4: {'Eraser'} -> {'Pencil'}
Support:  0.65
Confidence:  0.6923076923076923
--------------------------------------------------------------------------------
Rule 5: {'Notebook'} -> {'Pencil', 'Pen'}
Support:  0.55
Confidence:  0.8181818181818181
--------------------------------------------------------------------------------
Rule 6: {'Notebook', 'Pen'} -> {'Pencil'}
```

```
Association Rules using Apriori algorithm are:

Rule 1: {'Pencil'} -> {'Eraser'}
Support: 0.45
Confidence: 0.6923076923076923
--------------------------------------------------------------------------------
Rule 2: {'Eraser'} -> {'Pencil'}
Support: 0.45
Confidence: 0.6923076923076923
--------------------------------------------------------------------------------
Rule 3: {'Notebook'} -> {'Pen'}
Support: 0.45
Confidence: 0.8181818181818181
--------------------------------------------------------------------------------
Rule 4: {'Pen'} -> {'Notebook'}
Support: 0.45
Confidence: 0.9
--------------------------------------------------------------------------------
Rule 5: {'Notebook'} -> {'Pencil'}
Support: 0.45
Confidence: 0.8181818181818181
--------------------------------------------------------------------------------
Rule 6: {'Pencil'} -> {'Notebook'}
Support: 0.45
Confidence: 0.6923076923076923
--------------------------------------------------------------------------------
```

Execution of all 3 algorithms:

```
 Total execution time of Brute Force algorithm is 0.002 seconds.

 Total execution time of Apriori algorithm is 0.0097 seconds.

 Total execution time of FP-growth algorithm is 0.0035 seconds.

(base) zeal@zeals-Air Midterm_project %
```

```
Association Rules using FP-growth algorithm are:

Rule 1: {'Pencil'} -> {'Eraser'}
Support: 0.45
Confidence: 0.6923
--------------------------------------------------------------------------------
Rule 2: {'Eraser'} -> {'Pencil'}
Support: 0.45
Confidence: 0.6923
--------------------------------------------------------------------------------
Rule 3: {'Notebook'} -> {'Pencil'}
Support: 0.45
Confidence: 0.8182
--------------------------------------------------------------------------------
Rule 4: {'Pencil'} -> {'Notebook'}
Support: 0.45
Confidence: 0.6923
--------------------------------------------------------------------------------
Rule 5: {'Pencil'} -> {'Pen'}
Support: 0.5
Confidence: 0.7692
--------------------------------------------------------------------------------
Rule 6: {'Pen'} -> {'Pencil'}
Support: 0.5
Confidence: 1.0
--------------------------------------------------------------------------------
```