The Apriori Algorithm: Big Data Mining in Market Basket Analysis

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Introduction

The Apriori algorithm is a foundational data mining technique used for extracting frequent itemsets and generating association rules in large transactional datasets. This algorithm plays a crucial role in market basket analysis, enabling businesses to uncover relationships between items purchased together. By leveraging these insights, organizations can optimize inventory management, enhance product recommendations, and design effective marketing strategies.

In this case study, we implement the Apriori algorithm using Hadoop MapReduce to handle the challenges posed by massive datasets. Hadoop's distributed computing framework ensures scalability and efficiency, making it an ideal platform for processing large volumes of data. The study focuses on analyzing transaction data to identify frequent itemsets, calculate support, confidence, and lift metrics, and derive meaningful association rules.

Market Basket Analysis

Market Basket Analysis (MBA) is a data mining technique used to identify patterns or relationships between items frequently purchased together in transactional datasets. This analysis is particularly useful in the retail and e-commerce sectors for understanding customer purchasing behavior and optimizing business strategies.

The goal of MBA is to uncover association rules of the form $A \rightarrow B$, where the presence of item A in a transaction implies a likelihood of item B also being purchased. The strength of these associations is quantified using metrics such as **support**, **confidence**, and **lift**.

Examples of Market Basket Analysis

- **Retail Sector:** In a supermarket, MBA may reveal that customers who purchase bread are likely to buy butter as well. The association rule *bread* $\rightarrow$ *butter* can help managers place these items closer together to increase sales.
- **E-Commerce:** On online platforms, MBA might show that customers who purchase a smartphone frequently buy a phone case or screen protector. This insight can be used to recommend accessories during the checkout process.
- **Healthcare:** In pharmacy data, MBA can identify that customers buying flu medication are more likely to purchase vitamin supplements. Pharmacies can utilize this information to bundle these items for promotions.
- **Food Delivery:** Analysis might reveal that customers ordering pizza often include soft drinks or desserts in their orders. Restaurants can use this knowledge to create combo offers.

By applying Market Basket Analysis, businesses can enhance customer experience through personalized recommendations, improve cross-selling strategies, and optimize inventory management. These advantages make MBA a cornerstone of modern data-driven decision-making.

Importance of the Case Study

The significance of this case study lies in demonstrating the practical application of the Apriori algorithm in a big data environment. With the exponential growth of data, traditional single-machine implementations face limitations in terms of processing speed and scalability. This case study addresses these challenges by utilizing the parallel processing capabilities of Hadoop.

The insights gained from frequent itemset mining have far-reaching implications in various domains such as retail, e-commerce, and healthcare. By identifying frequently co-occurring items, businesses can make data-driven decisions to improve customer experience and increase revenue. Additionally, the study highlights the adaptability of Hadoop MapReduce for real-world data mining tasks, showcasing its potential for future applications in big data analytics.

Use Cases of Market Basket Analysis

Market Basket Analysis has become an essential tool for businesses to understand customer purchasing behavior and optimize their strategies. By analyzing customer purchase history and identifying patterns of frequently purchased items, retailers can gain valuable insights to enhance their product offerings and increase sales. Below are some specific use cases of Market Basket Analysis:

Cross-Selling and Upselling

By identifying complementary products that are frequently purchased together, businesses can use this information to cross-sell or upsell to customers. For example, suggesting a phone case and screen protector to a customer purchasing a smartphone.

Product Bundling

Market Basket Analysis helps businesses identify products that can be bundled together to create attractive packages for customers. This not only increases sales but also assists in clearing out excess inventory.

Inventory Management

Understanding which products are frequently purchased together allows businesses to optimize their inventory management by stocking the right quantities of each product, thereby reducing overstock or understock scenarios.

Pricing Strategy

By analyzing the relationships between different products and their pricing, businesses can determine the optimal price for products, ensuring competitive yet profitable pricing strategies.

Store Layout Optimization

Analyzing customer purchasing patterns enables businesses to optimize their store layout, encouraging customers to purchase complementary products or increasing the sales of slow-moving items by placing them strategically.

These use cases demonstrate the potential of Market Basket Analysis in enhancing business operations and improving customer satisfaction.

01
Increasing Market Share
02
Behavior Analysis
03
Optimization of in-store operations
04
Campaigns & Promotions
05
Recommendations

Figure 1: *Credit: Javapoint.com*

Tools and Technologies Used

In this study, we utilized advanced tools and technologies to implement Market Basket Analysis effectively on large datasets. The tools and technologies used include:

Hadoop MapReduce

Hadoop MapReduce is a powerful framework for processing and analyzing vast amounts of data in a distributed computing environment. It enables parallel processing by dividing tasks into smaller chunks, which are executed across multiple nodes. In this study, MapReduce was employed to implement the Apriori algorithm for mining frequent itemsets and generating association rules.

Apache Pig

Apache Pig is a high-level platform for processing and analyzing large datasets. It provides a scripting language, Pig Latin, which simplifies the development of data analysis programs. In this case study, Pig was used for data preprocessing and transformation, making the data suitable for analysis using MapReduce.

Dataset Used

The Market Basket Analysis dataset, publicly available on Kaggle, has been used for this project. This dataset contains transactional data from a retail store, which is used to perform Market Basket Analysis.

Number of Attributes: 7

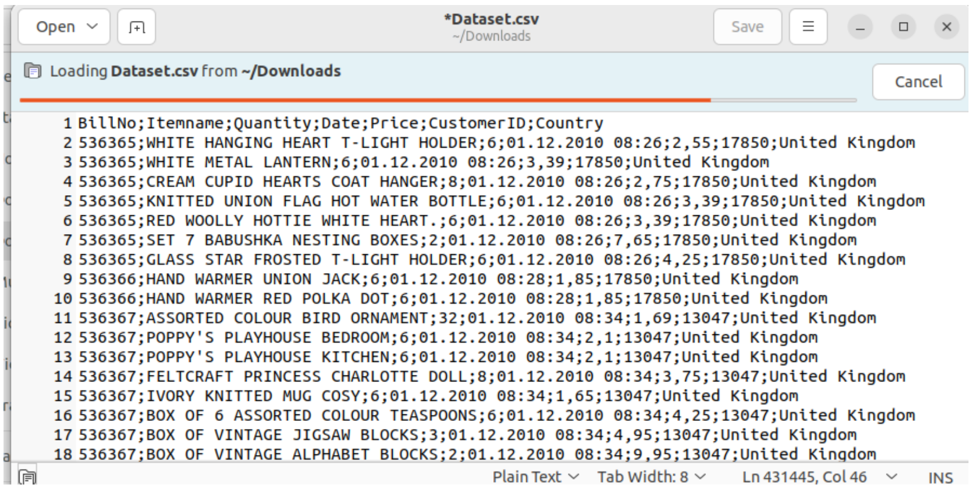
The dataset consists of the following attributes:

- **Itemname**: The product name of the item purchased.
- **Quantity**: The quantity of each product purchased per transaction.
- **Date**: The day and time when each transaction occurred.
- **Price**: The price of each product.
- **CustomerID**: A unique 5-digit number assigned to each customer.
- **Country**: The name of the country where the retail store is located.
- **Bill No.**: The unique identification number for each bill or transaction.

Dataset Preview

A sample record from the dataset is as follows:

- **Bill No.**: 21663
- **Itemname**: 4187
- **Quantity**: 691
- **Date**: 19642
- **Price**: 1268
- **CustomerID**: 2499
- **Country**: 31



```
BillNo;Itemname;Quantity;Date;Price;CustomerID;Country
536365;WHITE HANGING HEART T-LIGHT HOLDER;6;01.12.2010 08:26;2,55;17850;United Kingdom
536365;WHITE METAL LANTERN;6;01.12.2010 08:26;3,39;17850;United Kingdom
536365;CREAM CUPID HEARTS COAT HANGER;8;01.12.2010 08:26;2,75;17850;United Kingdom
536365;KNITTED UNION FLAG HOT WATER BOTTLE;6;01.12.2010 08:26;3,39;17850;United Kingdom
536365;RED WOOLLY HOTTIE WHITE HEART.;6;01.12.2010 08:26;3,39;17850;United Kingdom
536365;SET 7 BABUSHKA NESTING BOXES;2;01.12.2010 08:26;7,65;17850;United Kingdom
536365;GLASS STAR FROSTED T-LIGHT HOLDER;6;01.12.2010 08:26;4,25;17850;United Kingdom
536366;HAND WARMER UNION JACK;6;01.12.2010 08:28;1,85;17850;United Kingdom
536366;HAND WARMER RED POLKA DOT;6;01.12.2010 08:28;1,85;17850;United Kingdom
536367;ASSORTED COLOUR BIRD ORNAMENT;32;01.12.2010 08:34;1,69;13047;United Kingdom
536367;POPPY'S PLAYHOUSE BEDROOM;6;01.12.2010 08:34;2,1;13047;United Kingdom
536367;POPPY'S PLAYHOUSE KITCHEN;6;01.12.2010 08:34;2,1;13047;United Kingdom
536367;FELTCRAFT PRINCESS CHARLOTTE DOLL;8;01.12.2010 08:34;3,75;13047;United Kingdom
536367;IVORY KNITTED MUG COSY;6;01.12.2010 08:34;1,65;13047;United Kingdom
536367;BOX OF 6 ASSORTED COLOUR TEASPOONS;6;01.12.2010 08:34;4,25;13047;United Kingdom
536367;BOX OF VINTAGE JIGSAW BLOCKS;3;01.12.2010 08:34;4,95;13047;United Kingdom
536367;BOX OF VINTAGE ALPHABET BLOCKS;2;01.12.2010 08:34;9,95;13047;United Kingdom
```

Figure 2: Dataset preview

Dataset Statistics

The dataset contains a total of 5,35,260 tuples, each representing a unique transaction or purchase event.

Pre-processing

Data preprocessing is an important step in the data analysis pipeline that involves transforming raw data into a format that can be used for analysis. This is done in order to improve data quality and model processing.

We performed the following steps to make our dataset suitable for modelling:

1. Removing and filling null values as required
2. Removing unnecessary rows or noise in the data
3. Formatting certain columns in the required format

Frequent Itemset and Association Rule Generation

Association rule learning is a rule-based machine learning method used to discover interesting relationships between variables in large databases. It aims to identify strong rules discovered in databases.

For example, if item A is bought by customer $c1$, then the likelihood of item B being bought by the same customer in the same transaction increases. This can be represented as:

$$A \Rightarrow B, \quad \text{where} \quad A \text{ is the antecedent and } B \text{ is the consequent.}$$

In a large dataset with many transactions, we can have various combinations of itemsets such as:

$$A \Rightarrow B, \quad A\&B \Rightarrow C, \quad A\&B\&C \Rightarrow D, \quad \text{and so on.}$$

To find promising rules, we need to evaluate these itemsets using specific metrics. These metrics are defined as follows:

Metrics for Association Rule Learning

1. Support: Support is the frequency of an item or a combination of items appearing in the dataset.

$$\text{supp}(X) = \frac{\text{Number of transactions in which } X \text{ appears}}{\text{Total number of transactions}}$$

2. Confidence: Confidence measures how often the items in collection B occur, given that the items in collection A occur.

$$\text{conf}(X \Rightarrow Y) = \frac{\text{supp}(X \cup Y)}{\text{supp}(X)}$$

3. Lift: Lift measures the strength of an association rule. It is defined as the ratio of the observed support to the expected support, assuming the items are independent.

$$\text{lift}(X \Rightarrow Y) = \frac{\text{supp}(X \cup Y)}{\text{supp}(X) \times \text{supp}(Y)}$$

Numerical Example

Consider the following transaction data:

Transaction	Items Bought
1	A, B
2	A, C
3	B, C
4	A, B, C

Let's calculate support, confidence, and lift for the rule $A \Rightarrow B$:
- The total number of transactions is 4.
Support:

$$\text{supp}(A \Rightarrow B) = \frac{\text{Transactions with both A and B}}{\text{Total transactions}} = \frac{2}{4} = 0.5$$

Confidence:

$$\text{conf}(A \Rightarrow B) = \frac{\text{supp}(A \cup B)}{\text{supp}(A)} = \frac{2/4}{3/4} = \frac{0.5}{0.75} = 0.67$$

Lift:

$$\text{lift}(A \Rightarrow B) = \frac{\text{supp}(A \cup B)}{\text{supp}(A) \times \text{supp}(B)} = \frac{2/4}{(3/4) \times (2/4)} = \frac{0.5}{0.375} = 1.33$$

This example shows how the support, confidence, and lift metrics can help in determining the strength of the association rule $A \Rightarrow B$. In this case, a lift value greater than 1 indicates that the items A and B are more likely to be bought together than by random chance, making this a promising rule for further analysis.

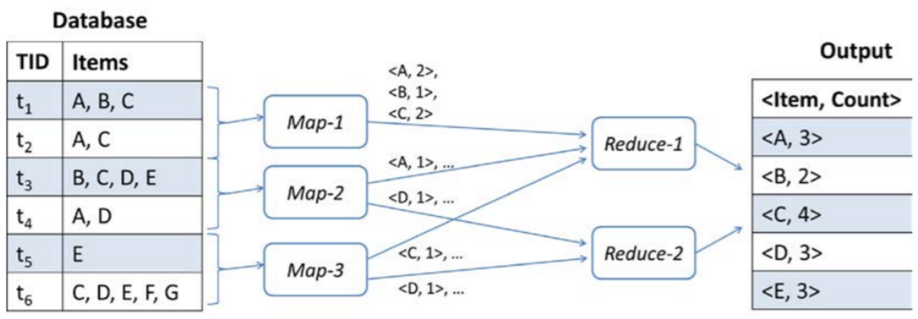
Apriori Algorithm Implementation in Hadoop MapReduce

Part 1 : Just finding frequent item-sets

This section describes the implementation of the Apriori algorithm in Hadoop MapReduce, focusing on the Mapper and Reducer phases for finding frequent itemsets. The implementation consists of two phases: Phase 1 for generating frequent 1-itemsets and Phase 2 for generating frequent k-itemsets.

Phase 1 Mapper

The goal of the Phase 1 Mapper is to process the transaction data and generate frequent 1-itemsets by emitting key-value pairs where the key is a combination of the country and item, and the value is 1. The Mapper then counts the occurrences of each item and computes its support in the reducer phase.



TID	Items
t_1	A, B, C
t_2	A, C
t_3	B, C, D, E
t_4	A, D
t_5	E
t_6	C, D, E, F, G

<Item, Count>
<A, 3>
<B, 2>
<C, 4>
<D, 3>
<E, 3>

Figure 3: Phase 1

```
public static class Phase1Mapper extends Mapper<LongWritable, Text, Text, IntWritable> {
    private final static IntWritable ONE = new IntWritable(1);

    @Override
    protected void map(LongWritable key, Text value, Context context) throws IOException,
    InterruptedException {
        String line = value.toString();
        if (line.startsWith("BillNo")) return;  // Skip header

        String[] fields = line.split(";");
        if (fields.length < 7) return;

        String country = fields[6].trim();
        String[] items = fields[1].trim().split(",");
        for (String item : items) {
            String cleanItem = item.trim();
            if (!cleanItem.isEmpty()) {
                context.write(new Text(country + ":" + cleanItem), ONE);
            }
        }
    }
}
```

Explanation

1. `line.startsWith("BillNo")` ensures the header is skipped. 2. `fields[6].trim()` extracts the country information. 3. `String[] items = fields[1].trim().split(",")` splits the comma-separated items in the transaction. 4. For each item, the Mapper writes a key-value pair where the key is the concatenation of the country and the item, and the value is 1 (indicating the occurrence of that item in the transaction).

Phase 1 Reducer

The Phase 1 Reducer aggregates the counts of the 1-itemsets from the Mapper and filters them based on the minimum support threshold. If the count of an itemset meets or exceeds the minimum support, the itemset is written to the output.

```
public static class Phase1Reducer extends Reducer<Text, IntWritable, Text, IntWritable> {
    private int minSupport;

    @Override
    protected void setup(Context context) {
        minSupport = context.getConfiguration().getInt("minSupport", 2);
    }

    @Override
    protected void reduce(Text key, Iterable<IntWritable> values, Context context)
            throws IOException, InterruptedException {
        int sum = 0;
        for (IntWritable val : values) {
            sum += val.get();  // Count the occurrences of the itemset
        }
        if (sum >= minSupport) {
            context.write(key, new IntWritable(sum));
        }
    }
}
```

Explanation

1. `minSupport = context.getConfiguration().getInt("minSupport", 2)` reads the minimum support from the configuration. 2. The Reducer aggregates the values for each itemset and sums their counts. 3. If the summed count exceeds the minimum support, the itemset is written to the output.

Phase 2 Mapper

The Phase 2 Mapper is responsible for processing the frequent 1-itemsets generated in Phase 1 and generating frequent 2-itemsets. It reads the transaction data, extracts the items, and generates combinations of itemsets of size 2.

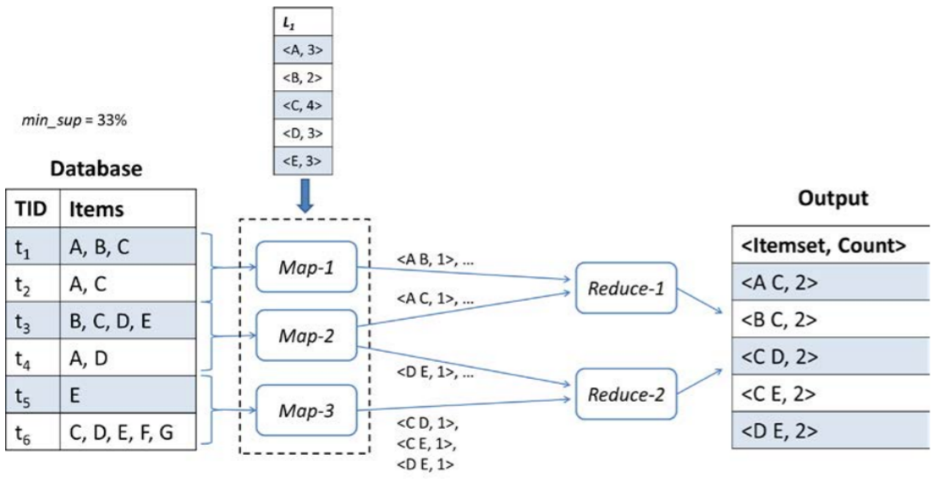
```
public static class Phase2Mapper extends Mapper<LongWritable, Text, Text, IntWritable> {
    private final static IntWritable ONE = new IntWritable(1);

    @Override
    protected void map(LongWritable key, Text value, Context context) throws IOException,
    InterruptedException {
        String line = value.toString();
        if (line.startsWith("BillNo")) return;

        String[] fields = line.split(";");
        if (fields.length < 7) return;

        String country = fields[6].trim();
        String[] items = fields[1].trim().split(",");
        List<String> cleanItems = new ArrayList<>();

        for (String item : items) {
            String cleanItem = item.trim();
            if (!cleanItem.isEmpty()) {
                cleanItems.add(cleanItem);
            }
        }

        if (cleanItems.size() >= 2) {
            Set<Set<String>> combinations = generateCombinations(cleanItems, 2);
            for (Set<String> itemset : combinations) {
                List<String> sortedItems = new ArrayList<>(itemset);
                Collections.sort(sortedItems);  // Sort items for consistent key format
                context.write(new Text(country + ":" + String.join(",", sortedItems)), ONE);
            }
        }
    }

    private Set<Set<String>> generateCombinations(List<String> items, int k) {
        Set<Set<String>> combinations = new HashSet<>();
        generateCombinationsHelper(items, new HashSet<>(), 0, k, combinations);
        return combinations;
    }

    private void generateCombinationsHelper(List<String> items, Set<String> current,
    int start, int k,
            Set<Set<String>> combinations) {
        if (current.size() == k) {
            combinations.add(new HashSet<>(current));  // Add combination to set
            return;
        }
        for (int i = start; i < items.size(); i++) {
            current.add(items.get(i));
            generateCombinationsHelper(items, current, i + 1, k, combinations);
            current.remove(items.get(i));  // Backtrack
        }
    }
}
```

Explanation

1. `generateCombinations(cleanItems, 2)` generates all combinations of size 2 from the list of items in a transaction. 2. `generateCombinationsHelper()` uses backtracking to generate combinations and add them to a set. 3. `String.join(",", sortedItems)` joins the sorted itemset into a string that will be used as the key in the Reducer.

Phase 2 Reducer

The Phase 2 Reducer works similarly to the Phase 1 Reducer, except that it processes 2-itemsets instead of 1-itemsets. It aggregates the counts for the 2-itemsets and filters them based on the minimum support threshold.



L_1
<A, 3>
<B, 2>
<C, 4>
<D, 3>
<E, 3>

Database

TID	Items
t_1	A, B, C
t_2	A, C
t_3	B, C, D, E
t_4	A, D
t_5	E
t_6	C, D, E, F, G

Output

<Itemset, Count>
<A C, 2>
<B C, 2>
<C D, 2>
<C E, 2>
<D E, 2>

Figure 4: Phase 2

```
public static class Phase2Reducer extends Reducer<Text, IntWritable, Text, IntWritable> {
    private int minSupport;

    @Override
    protected void setup(Context context) {
        minSupport = context.getConfiguration().getInt("minSupport", 2);
    }

    @Override
    protected void reduce(Text key, Iterable<IntWritable> values, Context context)
            throws IOException, InterruptedException {
        int sum = 0;
        for (IntWritable val : values) {
            sum += val.get();  // Count occurrences of the itemset
        }
        if (sum >= minSupport) {
            context.write(key, new IntWritable(sum));
        }
    }
}
```

Explanation

1. The Reducer aggregates the counts for each 2-itemset. 2. It checks if the itemset meets the minimum support threshold and writes the itemset to the output if it does.

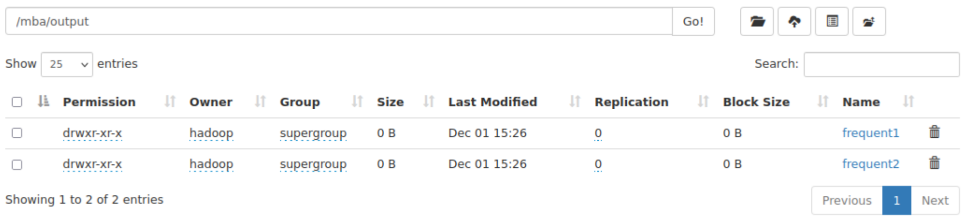
Main Driver

The main driver configures and initiates two MapReduce jobs: one for finding frequent 1-itemsets and another for finding frequent 2-itemsets.

```
public static void main(String[] args) throws Exception {
    if (args.length < 2) {
        System.err.println("Usage: AprioriDriver <input path> <output path>");
        System.exit(-1);
    }

    Configuration conf = new Configuration();
    conf.setInt("minSupport", 8);  // Set minimum support

    // Job 1: Frequent 1-itemsets
    Job job1 = Job.getInstance(conf, "Frequent 1-itemsets");
    job1.setJarByClass(AprioriDriver.class);
    job1.setMapperClass(Phase1Mapper.class);
    job1.setReducerClass(Phase1Reducer.class);
    job1.setOutputKeyClass(Text.class);
    job1.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job1, new Path(args[0]));
    Path phase1Output = new Path(args[1] + "/frequent1");
    FileOutputFormat.setOutputPath(job1, phase1Output);

    if (!job1.waitForCompletion(true)) {
        System.exit(1);
    }

    // Job 2: Frequent k-itemsets
    conf.setInt("k", 2);  // Set k for frequent 2-itemsets
    Job job2 = Job.getInstance(conf, "Frequent k-itemsets");
    job2.setJarByClass(AprioriDriver.class);
    job2.setMapperClass(Phase2Mapper.class);
    job2.setReducerClass(Phase2Reducer.class);
    job2.setOutputKeyClass(Text.class);
    job2.setOutputValueClass(IntWritable.class);
    FileInputFormat.addInputPath(job2, phase1Output);
    FileOutputFormat.setOutputPath(job2, new Path(args[1] + "/frequent2"));

    System.exit(job2.waitForCompletion(true) ? 0 : 1);
}
```

This implementation demonstrates how to execute Apriori on Hadoop using MapReduce to find frequent itemsets for a given dataset.

Output



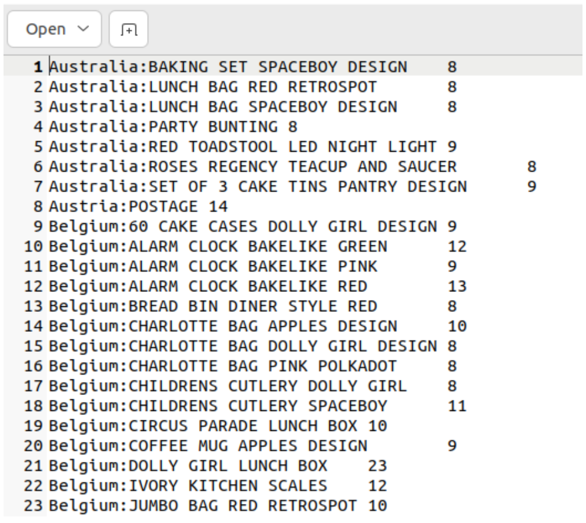
/mba/output Go!

Show 25 entries Search:

	Permission	Owner	Group	Size	Last Modified	Replication	Block Size	Name
	drwxr-xr-x	hadoop	supergroup	0 B	Dec 01 15:26	0	0 B	frequent1
	drwxr-xr-x	hadoop	supergroup	0 B	Dec 01 15:26	0	0 B	frequent2

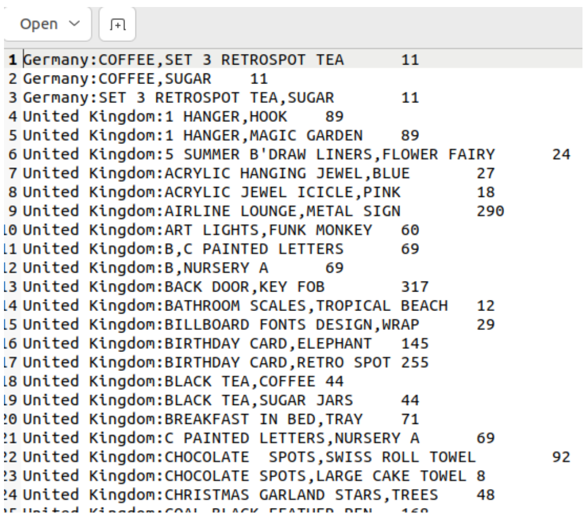
Showing 1 to 2 of 2 entries

Figure 5: The output directory after running the code will have 2 folders as shown above.



```
Australia:BAKING SET SPACEBOY DESIGN    8
Australia:LUNCH BAG RED RETROSPOT       8
Australia:LUNCH BAG SPACEBOY DESIGN     8
Australia:PARTY BUNTING 8
Australia:RED TOADSTOOL LED NIGHT LIGHT 9
Australia:ROSES REGENCY TEACUP AND SAUCER       8
Australia:SET OF 3 CAKE TINS PANTRY DESIGN      9
Austria:POSTAGE 14
Belgium:60 CAKE CASES DOLLY GIRL DESIGN 9
Belgium:ALARM CLOCK BAKELIKE GREEN      12
Belgium:ALARM CLOCK BAKELIKE PINK       9
Belgium:ALARM CLOCK BAKELIKE RED        13
Belgium:BREAD BIN DINER STYLE RED       8
Belgium:CHARLOTTE BAG APPLES DESIGN     10
Belgium:CHARLOTTE BAG DOLLY GIRL DESIGN 8
Belgium:CHARLOTTE BAG PINK POLKADOT     8
Belgium:CHILDRENS CUTLERY DOLLY GIRL    8
Belgium:CHILDRENS CUTLERY SPACEBOY      11
Belgium:CIRCUS PARADE LUNCH BOX 10
Belgium:COFFEE MUG APPLES DESIGN        9
Belgium:DOLLY GIRL LUNCH BOX    23
Belgium:IVORY KITCHEN SCALES    12
Belgium:JUMBO BAG RED RETROSPOT 10
```

(a) 1-frequent items



```
Germany:COFFEE,SET 3 RETROSPOT TEA      11
Germany:COFFEE,SUGAR    11
Germany:SET 3 RETROSPOT TEA,SUGAR       11
United Kingdom:1 HANGER,HOOK    89
United Kingdom:1 HANGER,MAGIC GARDEN    89
United Kingdom:5 SUMMER B'DRAW LINERS,FLOWER FAIRY      24
United Kingdom:ACRYLIC HANGING JEWEL,BLUE       27
United Kingdom:ACRYLIC JEWEL ICICLE,PINK        18
United Kingdom:AIRLINE LOUNGE,METAL SIGN        290
United Kingdom:ART LIGHTS,FUNK MONKEY   60
United Kingdom:B,C PAINTED LETTERS      69
United Kingdom:B,NURSERY A      69
United Kingdom:BACK DOOR,KEY FOB        317
United Kingdom:BATHROOM SCALES,TROPICAL BEACH   12
United Kingdom:BILLBOARD FONTS DESIGN,WRAP      29
United Kingdom:BIRTHDAY CARD,ELEPHANT   145
United Kingdom:BIRTHDAY CARD,RETRO SPOT 255
United Kingdom:BLACK TEA,COFFEE 44
United Kingdom:BLACK TEA,SUGAR JARS     44
United Kingdom:BREAKFAST IN BED,TRAY    71
United Kingdom:C PAINTED LETTERS,NURSERY A      69
United Kingdom:CHOCOLATE  SPOTS,SWISS ROLL TOWEL        92
United Kingdom:CHOCOLATE SPOTS,LARGE CAKE TOWEL 8
United Kingdom:CHRISTMAS GARLAND STARS,TREES    48
```

(b) 2-frequent items

Figure 6: Part 1 : Output

Part 2 : Partitioning the results based on the location of the retail stores.

Phase 1: Mapper for Frequent 1-itemsets

In Phase 1, we focus on identifying frequent 1-itemsets. The ‘Phase1Mapper‘ class processes each transaction, extracts the country and items, and emits key-value pairs with the format `country:item` as the key and 1 as the value.

```
public static class Phase1Mapper extends Mapper<LongWritable, Text, Text, IntWritable> {
    private final static IntWritable ONE = new IntWritable(1);

    @Override
    protected void map(LongWritable key, Text value, Context context) throws IOException,
    InterruptedException {
        String line = value.toString();
        if (line.startsWith("BillNo")) return;

        String[] fields = line.split(";");
        if (fields.length < 7) return;

        String country = fields[6].trim();
        String[] items = fields[1].trim().split(",");
        for (String item : items) {
            String cleanItem = item.trim();
            if (!cleanItem.isEmpty()) {
                // Key format: country:item
                context.write(new Text(country + ":" + cleanItem), ONE);
            }
        }
    }
}
```

This mapper:

- Skips any lines that start with "BillNo".
- Splits the input line to extract the country and items.
- Emits the country-item pairs as keys and 1 as the value.

Phase 1: Reducer for Frequent 1-itemsets

The 'Phase1Reducer' class receives the country-item key-value pairs from the mapper and aggregates them by summing the occurrences. It then filters the results to keep only those itemsets with a frequency greater than or equal to the minimum support threshold.

```
public static class Phase1Reducer extends Reducer<Text, IntWritable, Text, IntWritable> {
    private int minSupport;

    @Override
    protected void setup(Context context) {
        minSupport = context.getConfiguration().getInt("minSupport", 2);
    }

    @Override
    protected void reduce(Text key, Iterable<IntWritable> values, Context context)
    throws IOException,
    InterruptedException {
        int sum = 0;
        for (IntWritable val : values) {
            sum += val.get();
        }
        if (sum >= minSupport) {
            context.write(key, new IntWritable(sum));
        }
    }
}
```

The reducer:

- Sums the occurrences of each country-item pair.
- Filters out any itemsets whose frequency is below the minimum support.
- Outputs the frequent 1-itemsets (country:item and their counts).

Phase 2: Mapper for Frequent k-itemsets

In Phase 2, the mapper processes transactions to generate combinations of items. The 'Phase2Mapper' class extracts the items from the transaction, generates 2-item combinations (for simplicity, the value of `k` is set to 2), and emits them as key-value pairs, where the key is the sorted itemset and the value is 1.

```
public static class Phase2Mapper extends Mapper<LongWritable, Text, Text, IntWritable> {
    private final static IntWritable ONE = new IntWritable(1);

    @Override
    protected void map(LongWritable key, Text value, Context context) throws IOException,
    InterruptedException {
        String line = value.toString();
        if (line.startsWith("BillNo")) return;

        String[] fields = line.split(";");
        if (fields.length < 7) return;

        String country = fields[6].trim();
        String[] items = fields[1].trim().split(",");
        List<String> cleanItems = new ArrayList<>();

        for (String item : items) {
            String cleanItem = item.trim();
            if (!cleanItem.isEmpty()) {
                cleanItems.add(cleanItem);
            }
        }

        if (cleanItems.size() >= 2) {
            Set<Set<String>> combinations = generateCombinations(cleanItems, 2);
            for (Set<String> itemset : combinations) {
                List<String> sortedItems = new ArrayList<>(itemset);
                Collections.sort(sortedItems);
                context.write(new Text(country + ":" + String.join(",", sortedItems)), ONE);
            }
        }
    }

    private Set<Set<String>> generateCombinations(List<String> items, int k) {
        Set<Set<String>> combinations = new HashSet<>();
        generateCombinationsHelper(items, new HashSet<>(), 0, k, combinations);
        return combinations;
    }

    private void generateCombinationsHelper
    (List<String> items, Set<String> current, int start, int k,
            Set<Set<String>> combinations) {
        if (current.size() == k) {
            combinations.add(new HashSet<>(current));
            return;
        }
        for (int i = start; i < items.size(); i++) {
            current.add(items.get(i));
            generateCombinationsHelper(items, current, i + 1, k, combinations);
            current.remove(items.get(i));
        }
    }
}
```

This mapper:

- Extracts the items from each transaction and generates 2-item combinations.
- Emits these combinations as keys and 1 as the value.

Phase 2: Reducer for Frequent k-itemsets

The ‘Phase2Reducer‘ class processes the 2-item combinations, sums their occurrences, and filters out those that do not meet the minimum support threshold.

```
public static class Phase2Reducer extends Reducer<Text, IntWritable, Text, IntWritable> {
    private int minSupport;

    @Override
    protected void setup(Context context) {
        minSupport = context.getConfiguration().getInt("minSupport", 2);
    }

    @Override
    protected void reduce(Text key, Iterable<IntWritable> values, Context context)
            throws IOException, InterruptedException {
        int sum = 0;
        for (IntWritable val : values) {
            sum += val.get();
        }
        if (sum >= minSupport) {
            context.write(key, new IntWritable(sum));
        }
    }
}
```

The reducer:

- Sums the occurrences of each itemset.
- Filters out itemsets whose frequency is below the minimum support.
- Outputs the frequent k-itemsets (country:itemset and their counts).

Location Partitioner

The 'LocationPartitioner' class assigns each key to a partition based on the country, ensuring that itemsets from the same country are processed by the same reducer.

```
public static class LocationPartitioner extends Partitioner<Text, IntWritable> {
    @Override
    public int getPartition(Text key, IntWritable value, int numPartitions) {
        String[] parts = key.toString().split(":");
        String country = parts[0];

        // Assign partitions based on country
        return Math.abs(country.hashCode()) % numPartitions;
    }
}
```

The partitioner:

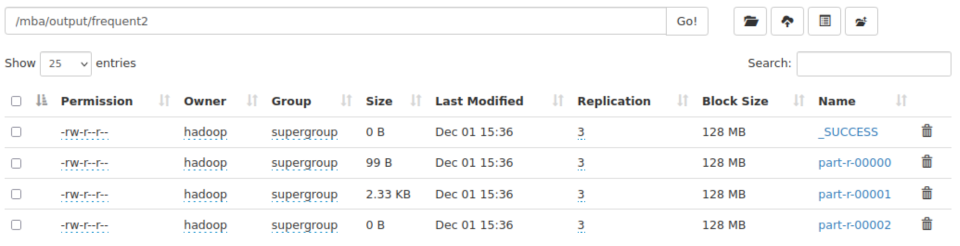
- Uses the country (extracted from the key) to determine which partition the data should go to.
- Ensures data is grouped by country for more efficient processing.

Driver for Job Configuration

The 'AprioriDriver' class configures and runs the two MapReduce jobs for frequent itemset mining.

```
public static void main(String[] args) throws Exception {
    if (args.length < 2) {
        System.err.println("Usage: AprioriDriver <input path> <output path>");
        System.exit(-1);
    }

    Configuration conf = new Configuration();
    conf.setInt("minSupport", 8);

    // Job 1: Frequent 1-itemsets
    Job job1 = Job.getInstance(conf, "Frequent 1-itemsets with Partitioning");
    job1.setJarByClass(AprioriDriver.class);

    job1.setMapperClass(Phase1Mapper.class);
    job1.setPartitionerClass(LocationPartitioner.class);
    job1.setReducerClass(Phase1Reducer.class);

    job1.setOutputKeyClass(Text.class);
    job1.setOutputValueClass(IntWritable.class);

    FileInputFormat.addInputPath(job1, new Path(args[0]));
    Path phase1Output = new Path(args[1] + "/frequent1");
    FileOutputFormat.setOutputPath(job1, phase1Output);

    job1.setNumReduceTasks(3);

    if (!job1.waitForCompletion(true)) {
        System.exit(1);
    }

    // Job 2: Frequent k-itemsets
    conf.setInt("k", 3);
    Job job2 = Job.getInstance(conf, "Frequent k-itemsets with Partitioning");
    job2.setJarByClass(AprioriDriver.class);

    job2.setMapperClass(Phase2Mapper.class);
    job2.setPartitionerClass(LocationPartitioner.class);
    job2.setReducerClass(Phase2Reducer.class);

    job2.setOutputKeyClass(Text.class);
    job2.setOutputValueClass(IntWritable.class);

    FileInputFormat.addInputPath(job2, phase1Output);
    Path phase2Output = new Path(args[1] + "/frequentk");
    FileOutputFormat.setOutputPath(job2, phase2Output);

    job2.setNumReduceTasks(3);
    System.exit(job2.waitForCompletion(true) ? 0 : 1);
}
```

Output

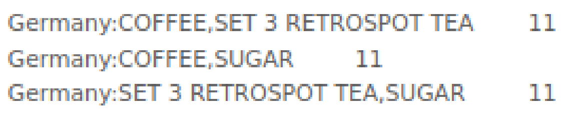


/mba/output/frequent2

Show 25 entries Search:

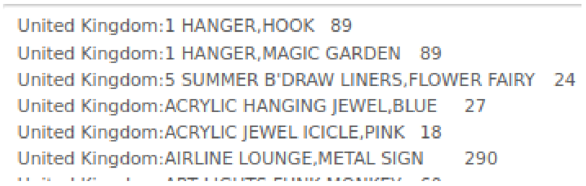
Permission	Owner	Group	Size	Last Modified	Replication	Block Size	Name
-rw-r--r--	hadoop	supergroup	0 B	Dec 01 15:36	3	128 MB	_SUCCESS
-rw-r--r--	hadoop	supergroup	99 B	Dec 01 15:36	3	128 MB	part-r-00000
-rw-r--r--	hadoop	supergroup	2.33 KB	Dec 01 15:36	3	128 MB	part-r-00001
-rw-r--r--	hadoop	supergroup	0 B	Dec 01 15:36	3	128 MB	part-r-00002

Figure 7: The output directory after running the code will have 2 folders as shown above. The second folder will have 3 output files based on the location wise results.



```
Germany:COFFEE,SET 3 RETROSPOT TEA        11
Germany:COFFEE,SUGAR        11
Germany:SET 3 RETROSPOT TEA,SUGAR        11
```

(a) part-r-00000



```
United Kingdom:1 HANGER,HOOK   89
United Kingdom:1 HANGER,MAGIC GARDEN   89
United Kingdom:5 SUMMER B'DRAW LINERS,FLOWER FAIRY   24
United Kingdom:ACRYLIC HANGING JEWEL,BLUE    27
United Kingdom:ACRYLIC JEWEL ICICLE,PINK   18
United Kingdom:AIRLINE LOUNGE,METAL SIGN      290
```

(b) part-r-00001

Figure 8: Part 2 : Output. Here we get 2 files since only 2 locations have exceeded the minimum support of 8 in the frequent item set mining algorithm.

Part 3 : Finding frequent itemsets as well as generating rules based on confidence level and support value.

Only the Phase 2 reducer logic changes here.

Phase 2 Reducer: Distributed Cache and Confidence Calculation

Purpose of Distributed Cache

In Hadoop, the distributed cache is used to share files across all nodes participating in a job. In the case of Phase 2, the item support values from the first phase (frequent 1-itemsets) are loaded into a distributed cache for quick access by the Phase 2 Reducer. This cache allows the reducer to efficiently access the support values for individual items when calculating the confidence and lift of itemsets.

The Phase 2 Reducer uses the distributed cache to store the output of Phase 1 (frequent 1-itemsets). This approach allows the reducer to efficiently access the support count of individual items, which is essential for calculating confidence and lift for frequent 2-itemsets. By loading this data into memory, the computation avoids repeated and expensive I/O operations during the reducer's execution, thus improving performance.

Implementation of Distributed Cache

The distributed cache is implemented by reading the frequent 1-itemsets from HDFS during the reducer's setup phase. This data is stored in a 'HashMap' for quick lookups. Each line in the Phase 1 output file is parsed to extract the item and its support count, which are then added to the map. Below is the verbatim code for the distributed cache setup:

```
@Override
protected void setup(Context context) {
    minSupport = context.getConfiguration().getInt("minSupport", 2);
    totalTransactions = context.getConfiguration().getInt("totalTransactions", 43328);

    // Load item support from Phase 1 output into the map
    try {
        Path phase1OutputPath = new Path("hdfs://localhost:9000/mba/output_assoc/frequent1");
        FileSystem fs = FileSystem.get(context.getConfiguration());
        FileStatus[] statuses = fs.listStatus(phase1OutputPath);
        for (FileStatus status : statuses) {
            if (status.isFile()) {
                BufferedReader br = new BufferedReader(new InputStreamReader
                (fs.open(status.getPath())));
                String line;
                while ((line = br.readLine()) != null) {
                    String[] parts = line.split("\t");
                    if (parts.length >= 2) {
                        String item = parts[0].trim();
                        int support = Integer.parseInt(parts[1]);
                        itemSupportMap.put(item, support);
                    }
                }
                br.close();
            }
        }
    } catch (IOException e) {
        e.printStackTrace();
    }
}
```

Support, Confidence, and Lift Calculation

In the context of the Apriori algorithm, support, confidence, and lift are used to evaluate the strength of the relationships between itemsets.

Support

Support represents the frequency of occurrence of an itemset in the dataset. For each itemset S, the support is calculated as:

$$\text{Support}(S) = \frac{\text{Count of transactions containing } S}{\text{Total number of transactions}}$$

In the Phase 2 Reducer, the support for a k-itemset is simply the count of occurrences of the itemset in the input data. This count is compared to the minimum support threshold specified in the configuration. If the support meets or exceeds this threshold, the itemset is considered frequent and passed to the output.

Confidence

Confidence measures the likelihood that an item A will be bought given that item B is bought, i.e., $P(A|B)$. It is computed as the ratio of the support of the itemset $A \cup B$ to the support of the item B:

$$\text{Confidence}(A \rightarrow B) = \frac{\text{Support}(A \cup B)}{\text{Support}(B)}$$

In the reducer, confidence is calculated for item pairs (or larger itemsets) using the item support values from Phase 1 stored in the distributed cache. The confidence of a rule is only calculated if the itemset's support meets the minimum support threshold.

Lift

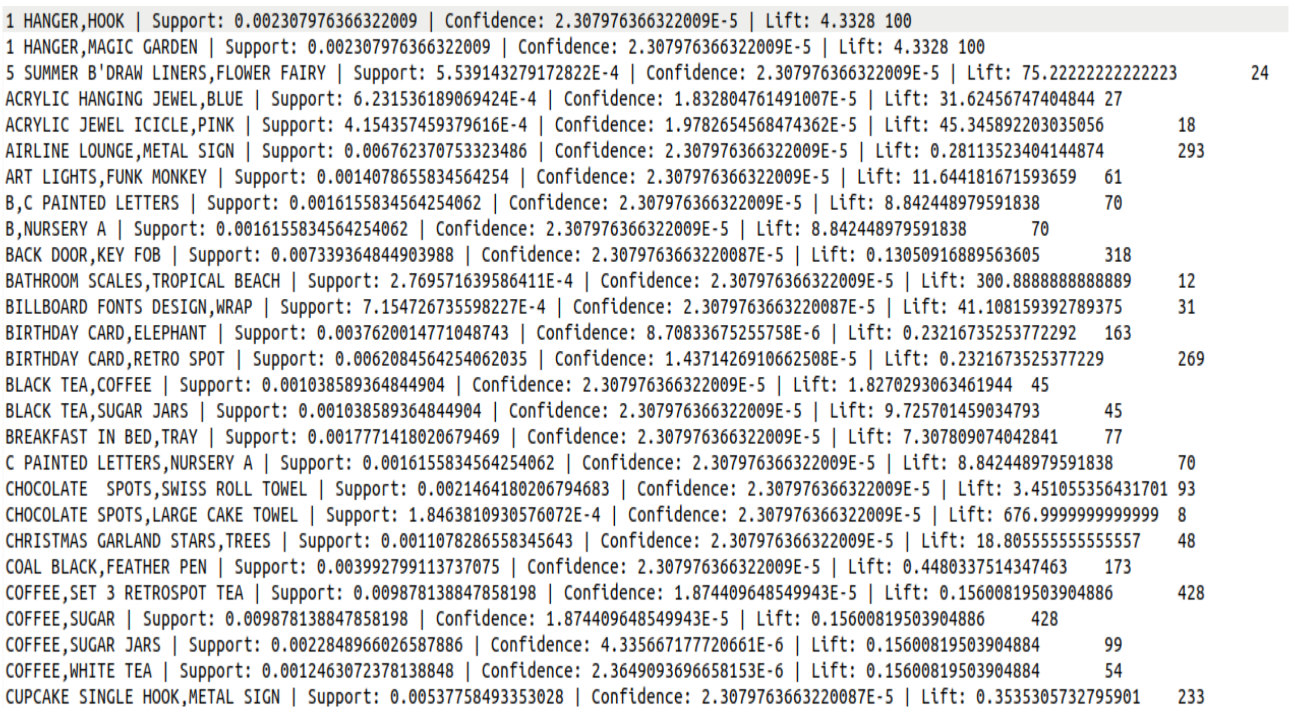
Lift quantifies the strength of a rule over the baseline of independence. It is defined as the ratio of the observed support of the itemset to the expected support if the items were independent:

$$\text{Lift}(A \rightarrow B) = \frac{\text{Confidence}(A \rightarrow B)}{\text{Support}(A) \times \text{Support}(B)}$$

Lift is a measure of how much more likely A and B are to appear together than by random chance. A lift value greater than 1 indicates a positive association between the items, while a value less than 1 suggests a negative association.

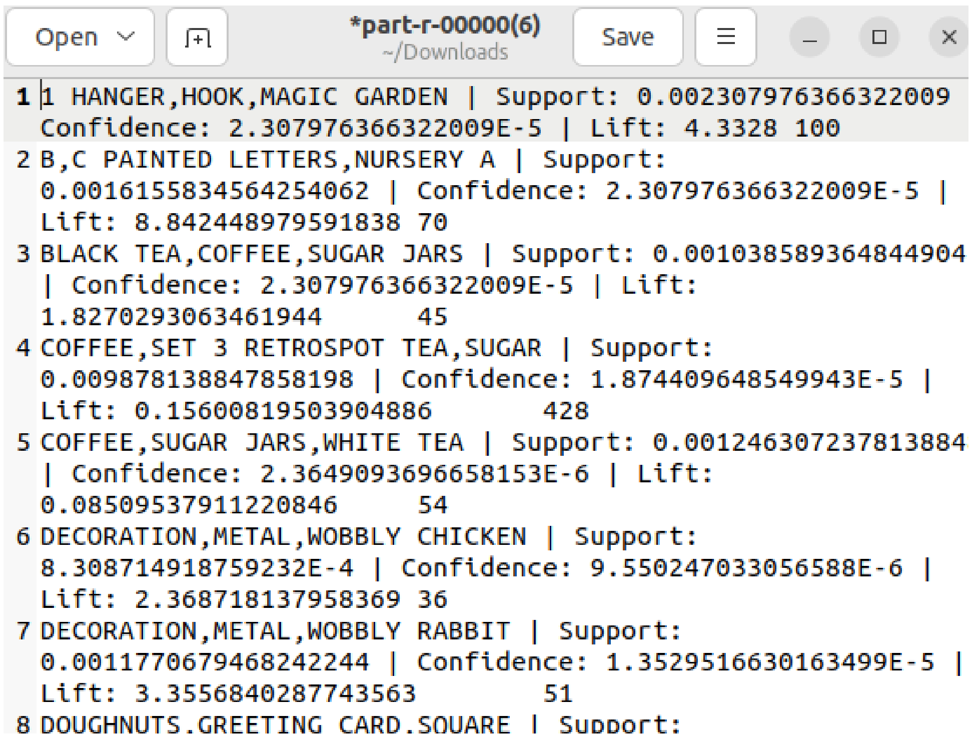
```
@Override
protected void reduce(Text key, Iterable<IntWritable> values, Context context)
throws IOException, InterruptedException {
    int sum = 0;
    for (IntWritable val : values) {
        sum += val.get();
    }

    if (sum >= minSupport) {
        // Support calculation
        double support = (double) sum / totalTransactions;

        // Confidence and Lift calculation
        String[] items = key.toString().split(",");
        if (items.length > 1) {
            String itemset = String.join(",", items);
            double confidence = getConfidence(items[0], support);
            double lift = getLift(items[0], items[1], confidence);

            // Avoid Infinity by checking for zero values in support
            if (Double.isInfinite(confidence) || Double.isInfinite(lift)) {
                confidence = 0.0; // or handle as per your requirement
                lift = 0.0; // or handle as per your requirement
            }

            context.write(new Text(itemset + " | Support: " + support + "
            | Confidence: " + confidence + " | Lift: " + lift), new IntWritable(sum));
        }
    }
}

private double getConfidence(String item, double itemsetSupport) {
    Integer itemSupport = itemSupportMap.get(item);
    if (itemSupport != null && itemSupport > 0) {
        return itemsetSupport / (double) itemSupport;
    }
    return 0.0; // If item support is zero or not found, return zero to avoid division by zero
}

private double getLift(String item1, String item2, double confidence) {
    Integer item1Support = itemSupportMap.get(item1);
    Integer item2Support = itemSupportMap.get(item2);

    if (item1Support != null && item2Support != null && item1Support > 0 && item2Support > 0) {
        double lift = confidence / ((double) item1Support / totalTransactions * (double)
        item2Support / totalTransactions);
        return lift;
    }

    return 0.0; // If support for either item is zero, return zero
}
```

Output



```
1 HANGER,HOOK | Support: 0.002307976366322009 | Confidence: 2.307976366322009E-5 | Lift: 4.3328 100
1 HANGER,MAGIC GARDEN | Support: 0.002307976366322009 | Confidence: 2.307976366322009E-5 | Lift: 4.3328 100
5 SUMMER B'DRAW LINERS,FLOWER FAIRY | Support: 5.539143279172822E-4 | Confidence: 2.307976366322009E-5 | Lift: 75.22222222222223       24
ACRYLIC HANGING JEWEL,BLUE | Support: 6.231536189069424E-4 | Confidence: 1.832804761491007E-5 | Lift: 31.62456747404844 27
ACRYLIC JEWEL ICICLE,PINK | Support: 4.154357459379616E-4 | Confidence: 1.9782654568474362E-5 | Lift: 45.345892203035056       18
AIRLINE LOUNGE,METAL SIGN | Support: 0.006762370753323486 | Confidence: 2.307976366322009E-5 | Lift: 0.28113523404144874       293
ART LIGHTS,FUNK MONKEY | Support: 0.0014078655834564254 | Confidence: 2.307976366322009E-5 | Lift: 11.644181671593659   61
B,C PAINTED LETTERS | Support: 0.0016155834564254062 | Confidence: 2.307976366322009E-5 | Lift: 8.842448979591838       70
B,NURSERY A | Support: 0.0016155834564254062 | Confidence: 2.307976366322009E-5 | Lift: 8.842448979591838       70
BACK DOOR,KEY FOB | Support: 0.007339364844903988 | Confidence: 2.3079763663220087E-5 | Lift: 0.13050916889563605       318
BATHROOM SCALES,TROPICAL BEACH | Support: 2.769571639586411E-4 | Confidence: 2.307976366322009E-5 | Lift: 300.8888888888889      12
BILLBOARD FONTS DESIGN,WRAP | Support: 7.154726735598227E-4 | Confidence: 2.3079763663220087E-5 | Lift: 41.108159392789375      31
BIRTHDAY CARD,ELEPHANT | Support: 0.0037620014771048743 | Confidence: 8.70833675255758E-6 | Lift: 0.23216735253772292   163
BIRTHDAY CARD,RETRO SPOT | Support: 0.0062084564254062035 | Confidence: 1.4371426910662508E-5 | Lift: 0.2321673525377229       269
BLACK TEA,COFFEE | Support: 0.001038589364844904 | Confidence: 2.307976366322009E-5 | Lift: 1.8270293063461944  45
BLACK TEA,SUGAR JARS | Support: 0.001038589364844904 | Confidence: 2.307976366322009E-5 | Lift: 9.725701459034793       45
BREAKFAST IN BED,TRAY | Support: 0.0017771418020679469 | Confidence: 2.307976366322009E-5 | Lift: 7.307809074042841      77
C PAINTED LETTERS,NURSERY A | Support: 0.0016155834564254062 | Confidence: 2.307976366322009E-5 | Lift: 8.842448979591838       70
CHOCOLATE  SPOTS,SWISS ROLL TOWEL | Support: 0.0021464180206794683 | Confidence: 2.307976366322009E-5 | Lift: 3.451055356431701 93
CHOCOLATE SPOTS,LARGE CAKE TOWEL | Support: 1.8463810930576072E-4 | Confidence: 2.307976366322009E-5 | Lift: 676.9999999999999  8
CHRISTMAS GARLAND STARS,TREES | Support: 0.0011078286558345643 | Confidence: 2.307976366322009E-5 | Lift: 18.805555555555557      48
COAL BLACK,FEATHER PEN | Support: 0.003992799113737075 | Confidence: 2.307976366322009E-5 | Lift: 0.4480337514347463     173
COFFEE,SET 3 RETROSPOT TEA | Support: 0.009878138847858198 | Confidence: 1.874409648549943E-5 | Lift: 0.15600819503904886       428
COFFEE,SUGAR | Support: 0.009878138847858198 | Confidence: 1.874409648549943E-5 | Lift: 0.15600819503904886     428
COFFEE,SUGAR JARS | Support: 0.0022848966026587886 | Confidence: 4.335667177720661E-6 | Lift: 0.15600819503904884       99
COFFEE,WHITE TEA | Support: 0.0012463072378138848 | Confidence: 2.3649093696658153E-6 | Lift: 0.15600819503904884       54
CUPCAKE SINGLE HOOK,METAL SIGN | Support: 0.00537758493353028 | Confidence: 2.3079763663220087E-5 | Lift: 0.3535305732795901    233
```

Figure 9: Association Rules for k=2 i.e. 2 items bought together



```
1 HANGER,HOOK,MAGIC GARDEN | Support: 0.002307976366322009 | Confidence: 2.307976366322009E-5 | Lift: 4.3328 100
B,C PAINTED LETTERS,NURSERY A | Support: 0.0016155834564254062 | Confidence: 2.307976366322009E-5 | Lift: 8.842448979591838 70
BLACK TEA,COFFEE,SUGAR JARS | Support: 0.001038589364844904 | Confidence: 2.307976366322009E-5 | Lift: 1.8270293063461944      45
COFFEE,SET 3 RETROSPOT TEA,SUGAR | Support: 0.009878138847858198 | Confidence: 1.874409648549943E-5 | Lift: 0.15600819503904886       428
COFFEE,SUGAR JARS,WHITE TEA | Support: 0.0012463072378138848 | Confidence: 2.3649093696658153E-6 | Lift: 0.08509537911220846      54
DECORATION,METAL,WOBBLY CHICKEN | Support: 8.308714918759232E-4 | Confidence: 9.550247033056588E-6 | Lift: 2.368718137958369 36
DECORATION,METAL,WOBBLY RABBIT | Support: 0.0011770679468242244 | Confidence: 1.3529516630163499E-5 | Lift: 3.3556840287743563       51
DOUGHNUTS,GREETING CARD,SQUARE | Support:
```

Figure 10: Generalizing. Here we have set the value of k to be 3. So how 3 items bought together what are their confidence values and lift values can be noted. P.S : the maximum limit of k depends on the type of dataset and transactions made for items to be present together.

Interpretation of Part 3: Association Rule Mining in part 3

In Figure 9 we have the first row as

```
1 HANGER_HOOK | Support: 0.002307976336223209
| Confidence: 2.307976336223209E-5 | Lift: 4.3328 100
```

The first row contains the following information:

- **Itemset**: HANGER_HOOK
  This represents an itemset in the dataset.
- **Support**: 0.002307976336223209
  Support is the fraction of transactions that contain this itemset. Here, it means that HANGER_HOOK appears in approximately 0.23% of all transactions.
- **Confidence**: $2.307976336223209 \times 10^{-5}$
  Confidence is the probability that if a customer buys this item (HANGER_HOOK), they will also buy another item in the rule. The value $2.307976336223209 \times 10^{-5}$ is very small, indicating low confidence for this rule.
- **Lift**: 4.3328
  Lift is a measure of how much more likely the items in the rule are to appear together than by random chance. **A lift value of 4.3328 suggests that the occurrence of HANGER_HOOK is more than four times as likely as it would be if the items were independent.**

Improving Business Using Association Rule Mining

Association Rule Mining provides valuable insights into customer purchasing behavior by identifying itemsets frequently bought together. From the analysis results presented, businesses can implement the following strategies to improve sales and customer satisfaction:

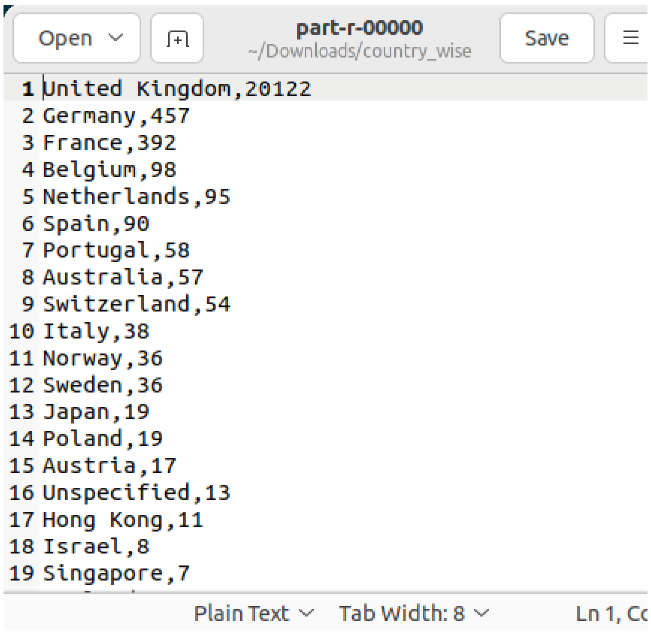
- **Cross-Selling Opportunities:** The rule with itemset HANGER_HOOK demonstrates a lift value of 4.3328. This indicates that customers are over four times more likely to purchase HOOK alongside HANGER than by random chance. Businesses can leverage this by promoting these items together, for example, through bundle offers or targeted advertising.
- **Improving Product Placement:** The high lift values for various itemsets, such as DECORATION, METAL, WOBBLY CHICKEN, suggest strong co-purchase likelihoods. Placing these products in close proximity within the store or online platform can increase visibility and sales of related items.
- **Targeted Marketing Campaigns:** Although the confidence value for some rules (e.g., HANGER_HOOK) is low, businesses can use insights about frequent itemsets to design specific promotions. For instance, discounts or loyalty points can be offered to customers who purchase items like HANGER to encourage further purchases.
- **Inventory Management: Itemsets with significant support values, such as COFFEE, SUGAR JARS, WHITE TEA, indicate popular combinations**. Retailers can ensure adequate stock of these items to prevent shortages and maintain customer satisfaction.
- **Personalized Recommendations:** By analyzing rules with high confidence and lift values, businesses can enhance recommendation systems. **For instance, suggesting COFFEE when customers purchase SUGAR JARS can lead to higher conversion rates in online stores.**
- **Product Bundling:** For itemsets like DECORATION, METAL, WOBBLY RABBIT (Lift: 3.3556), creating pre-packaged bundles or themed kits can encourage customers to purchase more items together, thus increasing average order value.

Additional Business Analysis in the Retail Store using Apache Pig

Country-wise Transaction Count

The purpose of this analysis is to calculate the number of unique transactions for each country. This is useful to understand how many transactions have been conducted in each country.

```
raw_data = LOAD '/home/hadoop/Downloads/Dataset(1).csv' USING PigStorage(';') AS (
    BillNo:chararray,
    Items:chararray,
    Date:chararray,
    Price:float,
    Quantity:int,
    CustomerID:chararray,
    Country:chararray
);

filtered_data = FILTER raw_data BY BillNo != 'BillNo';

country_bills = GROUP filtered_data BY (Country, BillNo);

country_unique_trans = FOREACH country_bills GENERATE group.Country as Country;

country_counts = GROUP country_unique_trans BY Country;

final_count = FOREACH country_counts GENERATE
    group as Country,
    COUNT(country_unique_trans) as TransactionCount;

ordered_result = ORDER final_count BY TransactionCount DESC;

STORE ordered_result INTO '/home/hadoop/Downloads/country_wise' USING PigStorage(',');
```



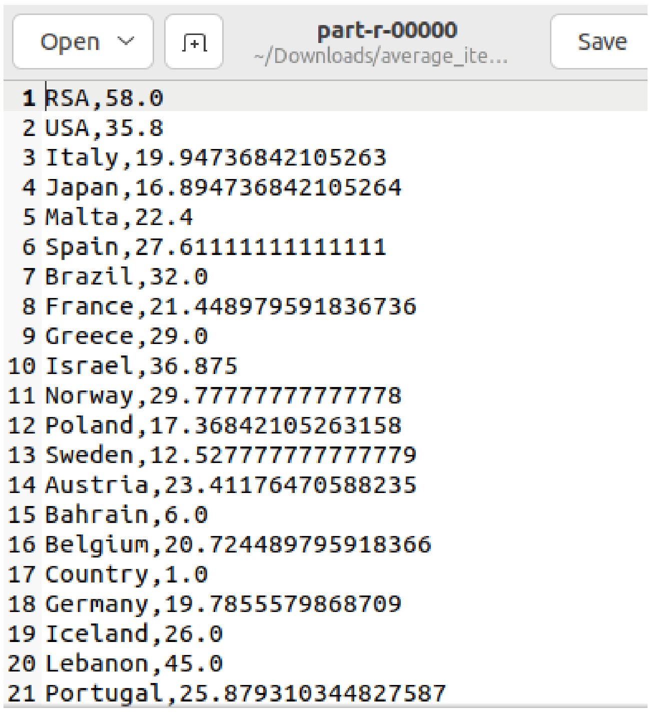
```
United Kingdom,20122
Germany,457
France,392
Belgium,98
Netherlands,95
Spain,90
Portugal,58
Australia,57
Switzerland,54
Italy,38
Norway,36
Sweden,36
Japan,19
Poland,19
Austria,17
Unspecified,13
Hong Kong,11
Israel,8
Singapore,7
```

Figure 11: Country Wise in-store transactions

Average Basket Size per Country

This analysis calculates the average number of items purchased in each transaction for every country, which helps identify the typical basket size in different countries.

```
retail_data = LOAD '/home/hadoop/Downloads/Dataset.csv' USING PigStorage('\t') AS (
    BillNo:chararray,
    ItemName:chararray,
    Quantity:int,
    Date:chararray,
    Price:float,
    CustomerID:chararray,
    Country:chararray
);

grouped_by_transaction = GROUP retail_data BY (BillNo, Country);

count_items_per_transaction = FOREACH grouped_by_transaction GENERATE
    FLATTEN(group) AS (BillNo, Country),
    COUNT(retail_data.ItemName) AS CountOfItemName;

grouped_by_country = GROUP count_items_per_transaction BY Country;

average_item_count_per_country = FOREACH grouped_by_country GENERATE
    group AS Country,
    AVG(count_items_per_transaction.CountOfItemName) AS AverageBasketSize;

STORE average_item_count_per_country
INTO '/home/hadoop/Downloads/average_item_count_by_country' USING PigStorage(',');
```



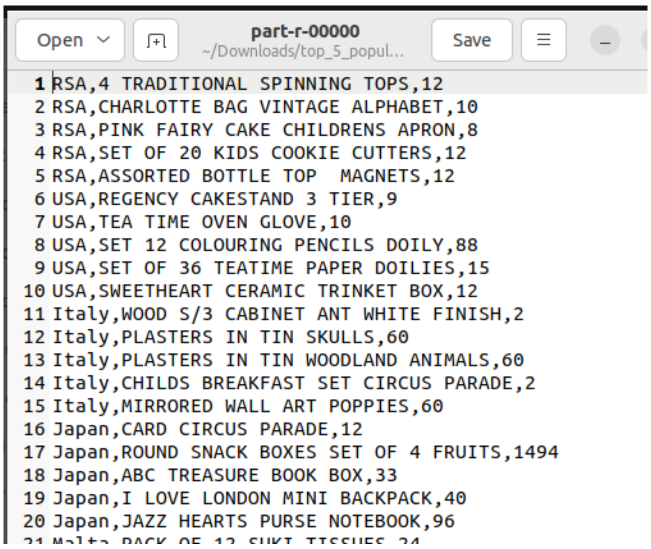
```
RSA,58.0
USA,35.8
Italy,19.94736842105263
Japan,16.894736842105264
Malta,22.4
Spain,27.61111111111111
Brazil,32.0
France,21.448979591836736
Greece,29.0
Israel,36.875
Norway,29.77777777777778
Poland,17.36842105263158
Sweden,12.527777777777779
Austria,23.41176470588235
Bahrain,6.0
Belgium,20.724489795918366
Country,1.0
Germany,19.7855579868709
Iceland,26.0
Lebanon,45.0
Portugal,25.879310344827587
```

Figure 12: Average Basket size

Most Popular Items per Country

This script identifies the most popular items sold in each country by calculating the total quantity of each item sold in each country and selecting the top 5 items.

```
retail_data = LOAD '/home/hadoop/Downloads/Dataset.csv' USING PigStorage('\t') AS (
    BillNo:chararray,
    ItemName:chararray,
    Quantity:int,
    Date:chararray,
    Price:float,
    CustomerID:chararray,
    Country:chararray
);

grouped_by_country_item = GROUP retail_data BY (Country, ItemName);

count_items_by_country = FOREACH grouped_by_country_item GENERATE
    group.Country AS Country,
    group.ItemName AS ItemName,
    SUM(retail_data.Quantity) AS TotalQuantity;

sorted_by_popularity = ORDER count_items_by_country BY TotalQuantity DESC;

grouped_by_country = GROUP sorted_by_popularity BY Country;

top_5_items_by_country = FOREACH grouped_by_country {
    sorted_data = LIMIT sorted_by_popularity 5;
    GENERATE FLATTEN(sorted_data);
}

STORE top_5_items_by_country INTO
'/home/hadoop/Downloads/top_5_popular_items_by_country' USING PigStorage(',');
```



```
RSA,4 TRADITIONAL SPINNING TOPS,12
RSA,CHARLOTTE BAG VINTAGE ALPHABET,10
RSA,PINK FAIRY CAKE CHILDRENS APRON,8
RSA,SET OF 20 KIDS COOKIE CUTTERS,12
RSA,ASSORTED BOTTLE TOP  MAGNETS,12
USA,REGENCY CAKESTAND 3 TIER,9
USA,TEA TIME OVEN GLOVE,10
USA,SET 12 COLOURING PENCILS DOILY,88
USA,SET OF 36 TEATIME PAPER DOILIES,15
USA,SWEETHEART CERAMIC TRINKET BOX,12
Italy,WOOD S/3 CABINET ANT WHITE FINISH,2
Italy,PLASTERS IN TIN SKULLS,60
Italy,PLASTERS IN TIN WOODLAND ANIMALS,60
Italy,CHILDS BREAKFAST SET CIRCUS PARADE,2
Italy,MIRRORED WALL ART POPPIES,60
Japan,CARD CIRCUS PARADE,12
Japan,ROUND SNACK BOXES SET OF 4 FRUITS,1494
Japan,ABC TREASURE BOOK BOX,33
Japan,I LOVE LONDON MINI BACKPACK,40
Japan,JAZZ HEARTS PURSE NOTEBOOK,96
Malta,PACK OF 12 SUKI TISSUES,24
```

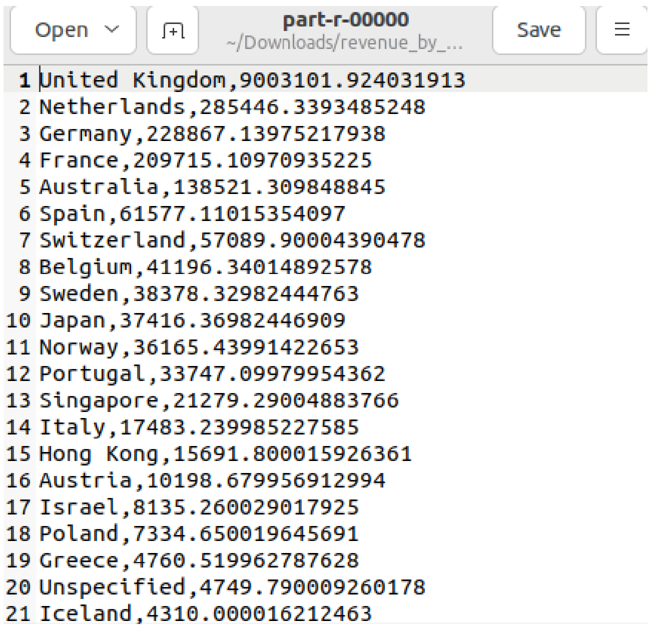
Figure 13: Popular items sold

Revenue by Country

This analysis calculates the total revenue generated by each country by multiplying the quantity and price of each item sold, and then summing the revenue per country.

```
retail_data = LOAD '/home/hadoop/Downloads/Dataset.csv' USING PigStorage('\t') AS (
    BillNo:chararray,
    ItemName:chararray,
    Quantity:int,
    Date:chararray,
    Price:float,
    CustomerID:chararray,
    Country:chararray
);
```

```
revenue_data = FOREACH retail_data GENERATE
    Country,
    (Quantity * Price) as revenue;

grouped_by_country = GROUP revenue_data BY Country;

country_revenue = FOREACH grouped_by_country GENERATE
    group as Country,
    SUM(revenue_data.revenue) as TotalRevenue;

ordered_results = ORDER country_revenue BY TotalRevenue DESC;

STORE ordered_results INTO '/home/hadoop/Downloads/revenue_by_country' USING PigStorage(',');
```



```
United Kingdom,9003101.924031913
Netherlands,285446.3393485248
Germany,228867.13975217938
France,209715.10970935225
Australia,138521.309848845
Spain,61577.11015354097
Switzerland,57089.90004390478
Belgium,41196.34014892578
Sweden,38378.32982444763
Japan,37416.36982446909
Norway,36165.43991422653
Portugal,33747.09979954362
Singapore,21279.29004883766
Italy,17483.239985227585
Hong Kong,15691.800015926361
Austria,10198.679956912994
Israel,8135.260029017925
Poland,7334.650019645691
Greece,4760.519962787628
Unspecified,4749.790009260178
Iceland,4310.000016212463
```

Figure 14: Revenue generated in store location wise

Summary of the analyses done in Apache Pig

The analysis conducted using Apache Pig on the retail store data has provided notable points into customer purchasing behavior and sales performance across different regions. Key findings from the analysis include:

- **Revenue Analysis:** The United Kingdom (UK) generated the highest revenue among all countries, indicating strong market performance and a high volume of sales in the region.
- **Popular Items per Country:** Popular items were analyzed by country, revealing the most frequently purchased products in each region.
- **Average Basket Size:** An average basket size was found that, in South Africa (RSA), was the highest in contrast with the United States of America. This implies that lot of opportunities are then generated toward targeted promotions and upselling in these branches.
- **Transaction Volume:** The UK, also had the highest number of transactions, followed by Germany, which suggests a high level of customer engagement and frequent purchases in these countries, providing an insight into regional customer behavior and potential areas for business expansion.

Conclusion

The analysis performed with the Hadoop framework proves that big data tools can draw meaningful insights from large datasets. By using MapReduce, we efficiently processed and analyzed transaction data to discover patterns like frequent itemsets, support, confidence, and lift values. These insights will guide business decisions such as optimizing inventory, targeted marketing, and customer segmentation, which enhances overall business performance. The study emphasizes the importance of association rule mining in product relationship identification and improving sales strategies.

Limitations

While the results of this analysis are insightful, there are certain limitations to be considered:

- The calculated confidence and lift values suggest some item associations but do not guarantee causality, limiting their predictive capabilities.
- Data preprocessing was simplified, and errors or inconsistencies in the original data might have affected the results.
- External factors such as seasonality, promotions, and market trends were not considered, which could have impacted itemset relationships.

Future research and implementation are expected to overcome these limitations by incorporating additional contextual data and using advanced algorithms for better scalability and accuracy.

Appendix

Github Link :
Click Here

References

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