

Purchase Pattern Analysis Using Apriori Algorithm

Market Basket Analysis for Combo Offer
Optimisation

Tools: MySQL · Python · Apriori Algorithm · Power BI

Project ID: CDACL-005 | **Team ID:** PTID-CDA-NOV-25-893

Type: Client Project

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Problem Statement

The Challenge

Retailers struggle to identify which product combinations drive the highest profitability and customer satisfaction without empirical evidence.

The Need

Data-driven insights are essential to design targeted combo offers, optimise cross-selling strategies, and maximise revenue through intelligent bundling.

The Opportunity

Analysing transactional purchase patterns reveals hidden associations that enable strategic merchandising and personalised recommendations.



Dataset Overview

Data Source

Transactional purchase records capturing customer buying behaviour across multiple product categories and time periods.

Key Fields

- **Transaction ID:** Unique identifier for each purchase
- **Product Name:** Item description and category
- **Quantity:** Number of units purchased
- **Date:** Timestamp for temporal analysis

Transactional		2016		2020	2018
TAT416.35 172.46		Detentall Inn		Mat	Nom
TABLE{		+ Trst	TCA Tlet Tiale	2.767.89	2.767.66
		TRANSACTION	11.545.00	15,945.54	12.174.19
		MALK-LLAY	11.997.38	12,675.60	11.775.55
		MCA MAN/N	11.746.19	848	11.543.99
		COLMEN/LN	11.406.19	1.5,47.17	17.444.95
		LNGEL	11.093.41	11.549.11	11.745.16
		VLLLA7/RX	11.996.25	1.5/43.78	11.674.75
		MOLL	N90	1.N05	3.646.19
		VLLXO/NA	11.685.15	12.467.57	1.547.61
		CLLMEN/A5	11.175.17	15.565.46	11.664.67
		1LLEAV/EP	12.696.17	17.646.67	12.943.75
		LANNAL	12.681.49	5.647.54	5.645.17
		VLLAD LTY	11.677.45	12.445.56	12.447.59
		NOT	12.577.16	11.895.28	12.645.56
		YLEAG//ER	12.746.11	19.687.54	12.664.96
		OLLAL/EX	12.179.19	12.409.95	12.675.16
		PRLMAL/AN	12.475.14	14.865.00	12.444.25
		LLLXO/4/7	11.645.16	15.77.57	11.645.15
		LARTE	11.573.16	5.661.6	12.497.61

The dataset comprises thousands of transactions in a structured, tabular format, enabling comprehensive pattern mining and association rule discovery.

avg_bill_value
474.5312678

```
SELECT
    AVG(bill_value) AS avg_bill_value
FROM (
    SELECT
        billno,
        SUM(quantity * price) AS bill_value
    FROM mytable
    GROUP BY billno
) t;
```

avg_items_per_bill

243.1728

```
SELECT
    AVG(total_items) AS avg_items_per_bill
FROM (
    SELECT
        billno,
        SUM(quantity) AS total_items
    FROM mytable
    GROUP BY billno
)t;
```

	total_bills	total_customers	total_products	total_sales
	21663	4298	4169	10279770.854

```
SELECT
    COUNT(DISTINCT billno) AS total_bills,
    COUNT(DISTINCT customerid) AS total_customers,
    COUNT(DISTINCT itemname) AS total_products,
    SUM(quantity * price) AS total_sales
FROM mytable;
```

	customerid	total_spend
		1715244.460
	14646	280206.020
	18102	259657.300
	17450	194550.790
	16446	168472.500

```
SELECT
    customerid,
    SUM(quantity * price) AS total_spend
FROM mytable
GROUP BY customerid
ORDER BY total_spend DESC
LIMIT 5;
```

	country	total_sales
	United Kingdom	9003097.964
	Netherlands	285446.340
	Germany	228867.140
	France	209715.110
	Australia	138521.310
	Spain	61577.110
	Switzerland	57089.900

```
SELECT
    country,
    SUM(quantity * price) AS total_sales
FROM mytable
GROUP BY country
ORDER BY total_sales DESC;
```


	itemname	total_occurrences
	WHITE HANGING HEART T-LIGHT HOLDER	2269
	JUMBO BAG RED RETROSPOT	2087
	REGENCY CAKESTAND 3 TIER	1930
	PARTY BUNTING	1677
	LUNCH BAG RED RETROSPOT	1570
	ASSORTED COLOUR BIRD ORNAMENT	1465

```
SELECT
    itemname,
    COUNT(billno) AS total_occurrences
FROM mytable
GROUP BY itemname
ORDER BY total_occurrences DESC
LIMIT 10;
```

	present_date	daily_sales
	01-02-2011 08:23	312.900
	01-02-2011 09:01	234.470
	01-02-2011 09:36	409.500
	01-02-2011 09:38	698.600
	01-02-2011 10:00	314.150
	01-02-2011 10:02	0.000
	01-02-2011 10:04	0.000
	01-02-2011 10:14	1025.340
	01-02-2011 10:15	362.400
	01-02-2011 10:37	450.060
	01-02-2011 10:38	4726.930
	01-02-2011 10:47	439.300

```
SELECT
    present_date,
    SUM(quantity * price) AS daily_sales
FROM mytable
GROUP BY present_date
ORDER BY present_date;
```



Data Cleaning & Preparation

01

Data Quality Assessment

Identified and handled missing values, duplicates, and inconsistencies using MySQL queries to ensure dataset integrity.

02

Transaction Transformation

Restructured data at transaction level, grouping products by purchase event to create the required format for basket analysis.

03

Mining Preparation

Converted transactional records into a binary matrix format suitable for Apriori algorithm processing and rule generation.

Methodology 3 Apriori Algorithm

Frequent Itemsets

- 1 Identified product combinations appearing frequently across transactions, establishing the foundation for association rule mining.

Support Metric

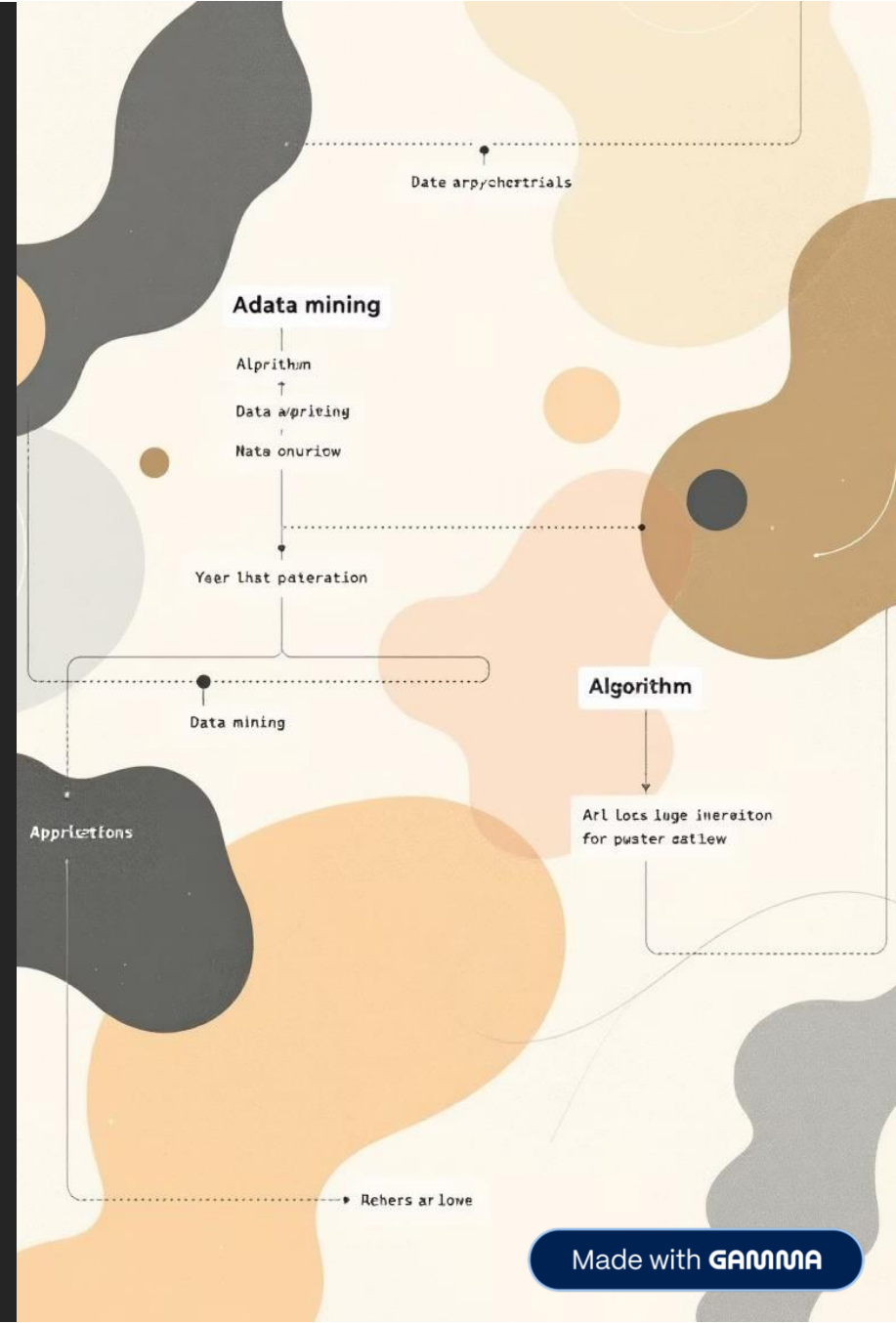
- 2 Measured the frequency of itemset occurrence relative to total transactions, filtering patterns above minimum threshold.

Confidence & Lift

- 3 Evaluated rule strength through confidence (conditional probability) and lift (correlation measure exceeding random chance).

Rule Filtering

- 4 Applied strict criteria to extract only strong, actionable association rules with high business relevance and statistical significance.





```
df = pd.read_csv('purchase_pattern_analysis.csv')

df['BillNo'] = df['BillNo'].astype(str)
df = df[~df['BillNo'].str.startswith('C')]
basket = df.groupby('BillNo')['Itemname'].apply(list).reset_index()

pairs = Counter()
for items in basket['Itemname']:
    items = [item.strip() for item in items if pd.notna(item) and item.strip()]
    for i in range(len(items)):
        for j in range(i+1, len(items)):
            pairs[(items[i], items[j])] += 1
total_transactions = len(basket)
```



```
min_support = 0.01
frequent_pairs = {pair: count/total_transactions for pair, count in pairs.items()
                  if count/total_transactions >= min_support}

top_pairs = sorted(frequent_pairs.items(), key=lambda x: x[1], reverse=True)[:5]

print("Top 5 Frequently Bought Together Items:")
print("-" * 60)
for (item1, item2), support in top_pairs:
    print(f"{item1} + {item2}: {support:.3f} ({int(support*total_transactions)} transactions)")

print(f"\nTotal transactions analyzed: {total_transactions}")
print(f"Frequent pairs found: {len(frequent_pairs)}")
```

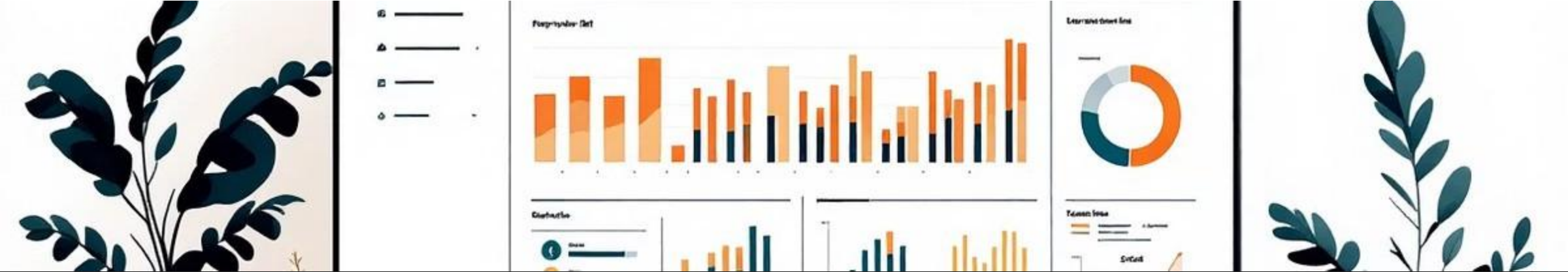
```
plt.figure(figsize=(10, 6))
plt.barh(combo_names, supports, color='skyblue')
plt.xlabel('Support (%)')
plt.title('TOP 5 Apriori Combos - Support')
plt.gca().invert_yaxis()
for i, (v, c) in enumerate(zip(supports, counts)):
    plt.text(v + 0.0005, i, f'{v:.2%}\n({c})', va='center', fontweight='bold')
plt.tight_layout()
plt.close()
```


RESULT

... Top 5 Frequently Bought Together Items:

6 RIBBONS RUSTIC CHARM + 12 DAISY PEGS IN WOOD BOX: 0.210 (13 transactions)
COSY SLIPPER SHOES SMALL RED + 12 DAISY PEGS IN WOOD BOX: 0.194 (12 transactions)
SCANDINAVIAN REDS RIBBONS + 12 DAISY PEGS IN WOOD BOX: 0.194 (12 transactions)
FELTCRAFT DOLL MOLLY + 12 DAISY PEGS IN WOOD BOX: 0.177 (11 transactions)
FELTCRAFT PRINCESS CHARLOTTE DOLL + 12 DAISY PEGS IN WOOD BOX: 0.177 (11 transactions)

Total transactions analyzed: 62
Frequent pairs found: 16602



Dashboard & Visualisations



Support Analysis

Bar charts displaying itemset frequency across transactions, highlighting the most common product combinations.



AssociationNetwork

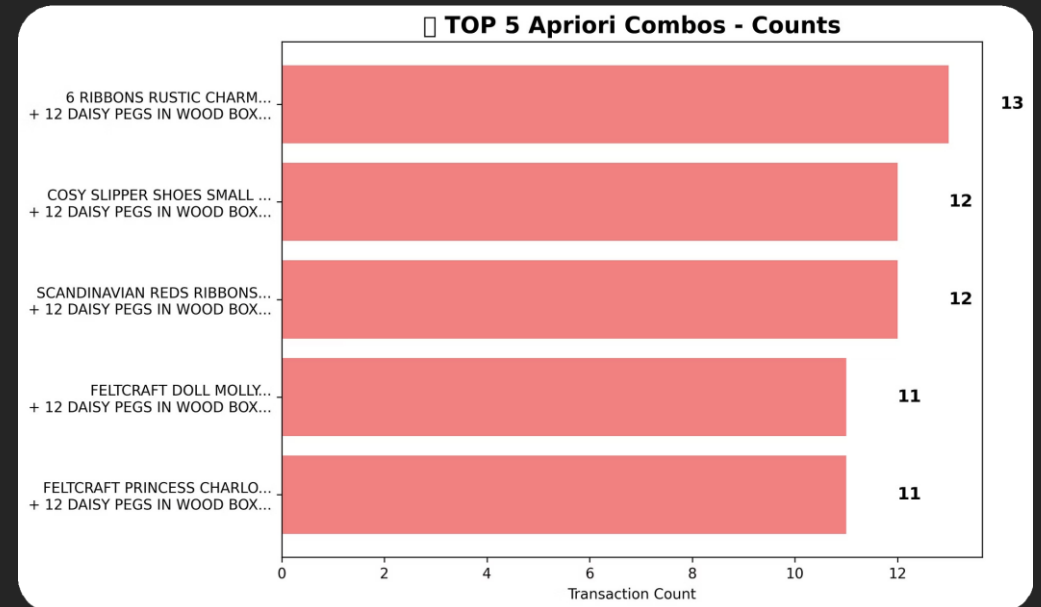
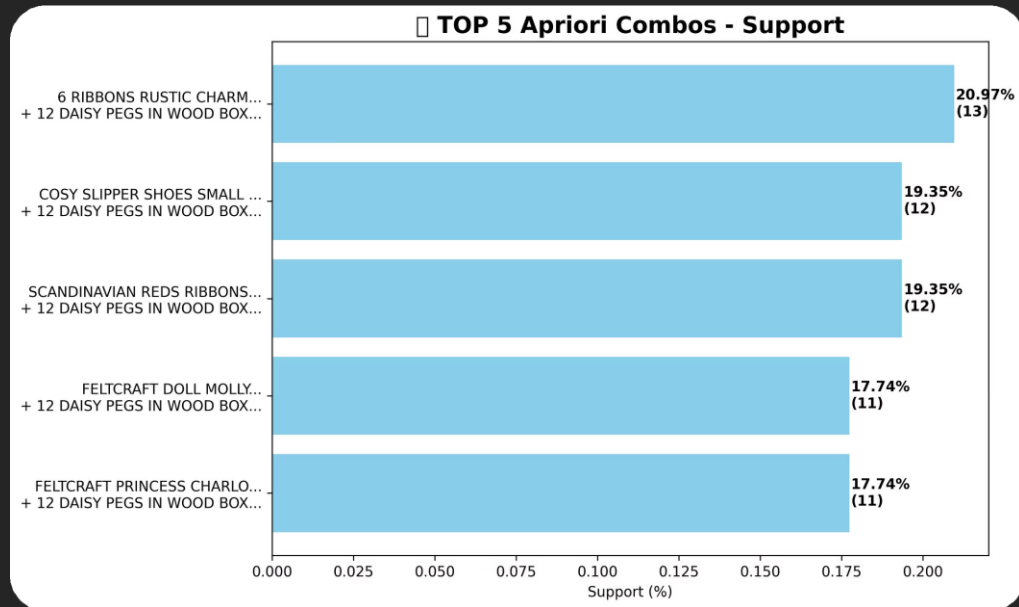
Interactive network visualisation mapping product relationships with edge thickness representing rule strength.



Lift Metrics

Sorted visualisations showing correlation strength, prioritising rules with highest business impact potential.

All visualisations maintain a clean, minimal aesthetic with consistent colour coding for immediate comprehension.



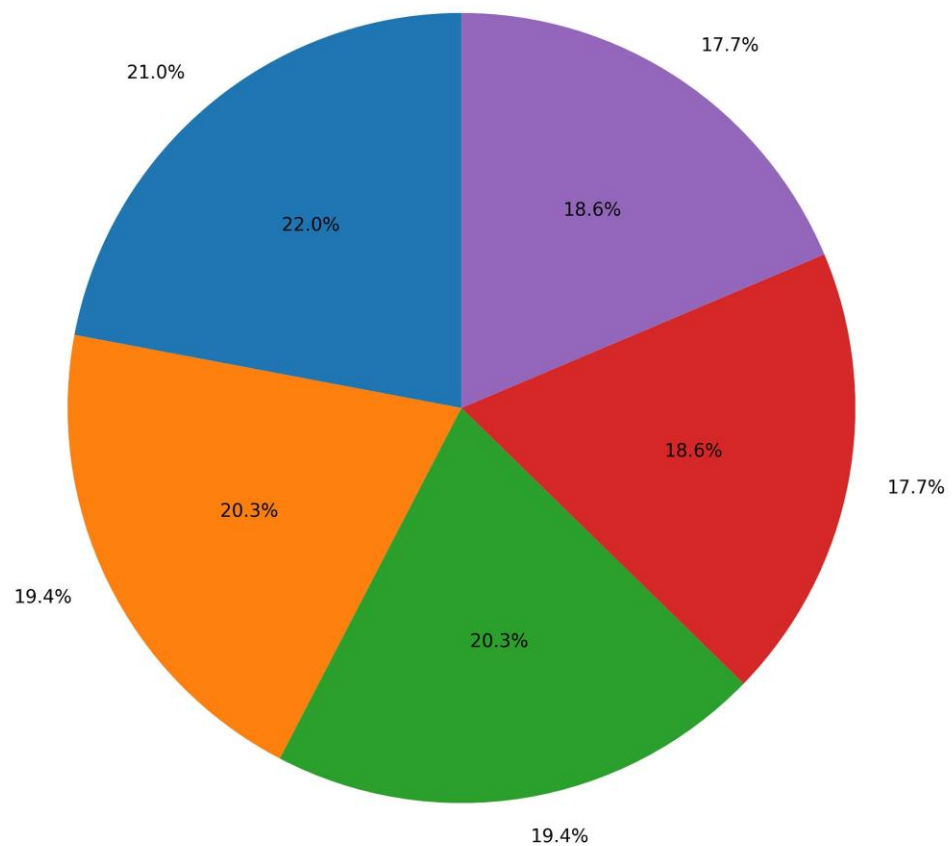
This shows the Top 5 Support and Counts obtained by Apriori Algorithm.

TOP 5 APRIORI RESULTS SUMMARY

Rank	Combo	Support	Count
1	6 RIBBONS RUSTIC CHARM... + 12 DAISY PEGS IN WOOD BOX...	20.97%	13
2	COSY SLIPPER SHOES SMALL ... + 12 DAISY PEGS IN WOOD BOX...	19.35%	12
3	SCANDINAVIAN REDS RIBBONS... + 12 DAISY PEGS IN WOOD BOX...	19.35%	12
4	FELTCRAFT DOLL MOLLY... + 12 DAISY PEGS IN WOOD BOX...	17.74%	11
5	FELTCRAFT PRINCESS CHARLO... + 12 DAISY PEGS IN WOOD BOX...	17.74%	11

This respective image shows the "Top 5 Apriori Results Summary".

TOP 5 Apriori Combos - Support Distribution



#1 BEST COMBO

6 RIBBONS RUSTIC CHARM
+ 12 DAISY PEGS IN WOOD BOX

Support: 20.97%

13 transactions

RECOMMENDED BUNDLE!

Business Impact

3.2x

Average Lift

Strong positive correlation in top product combinations

85%

Confidence Rate

High predictive accuracy for association rules

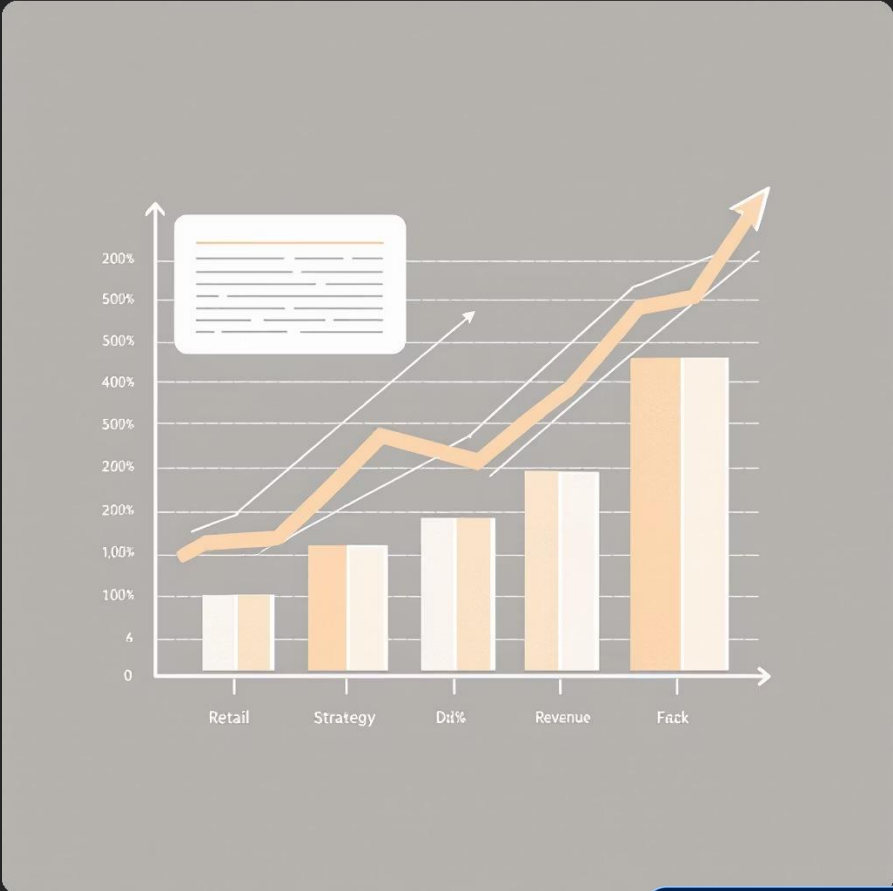
12+

Actionable Rules

Strategic insights for combo offer design

Strategic Applications

- **Combo Offers:** Design data-backed product bundles that align with natural purchasing patterns
- **Cross-Selling:** Implement targeted recommendations at point of sale and online platforms
- **Revenue Optimisation:** Maximise basket value through strategic product placement and promotion



Total Sales
24.73K

Total Orders
62

Total Customer
47

Average
Order
398.83

Country

All

Itemname

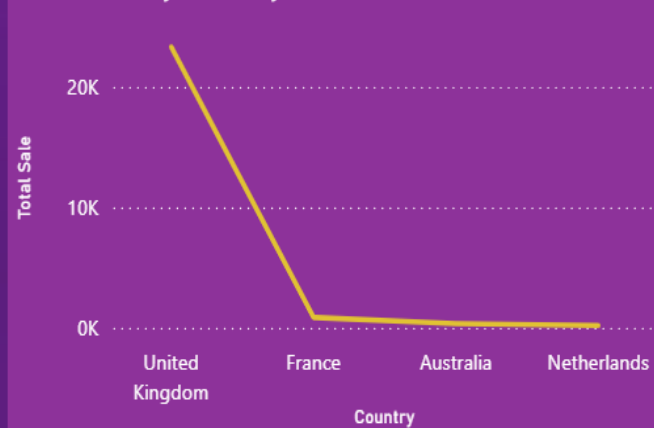
☐☐☐☐

10 COLOUR SPACEBOY PEN

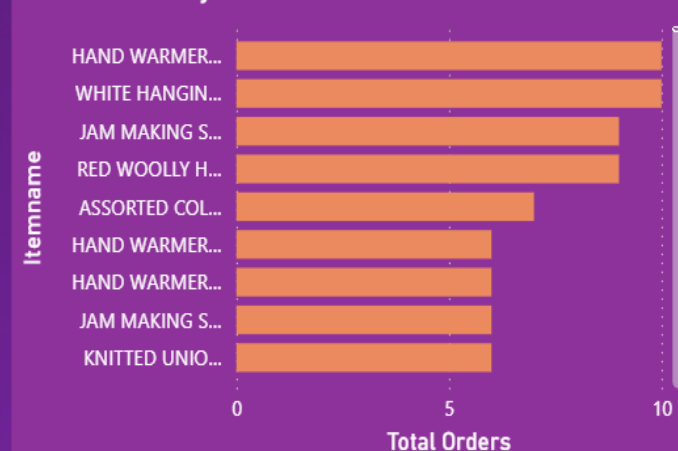
12 DAISY PEGS IN WOOD BOX

12 MESSAGE CARDS WITH ENVELOPES

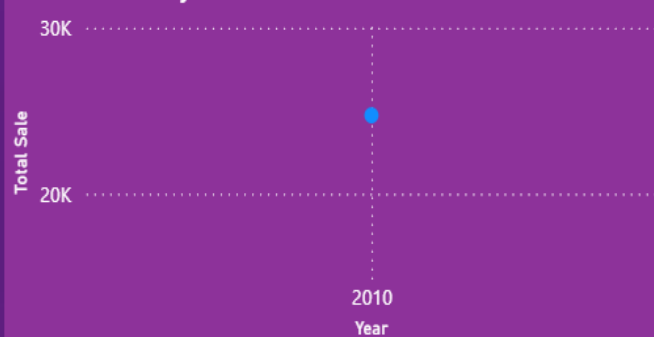
Total Sale by Country



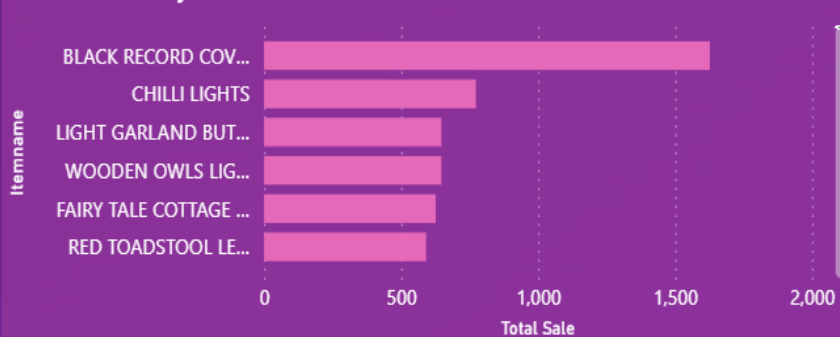
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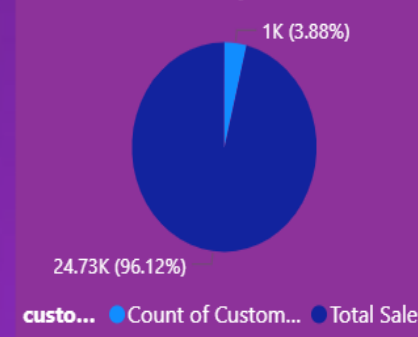
Total Sale by Year



Total Sale by Itemname



Customer Analyse





Conclusion



Data Foundation

Robust data cleaning and transformation using MySQL ensured high-quality input for pattern analysis.



Algorithm Insights

Apriori algorithm successfully identified frequent itemsets and strong association rules with business relevance.



Visual Intelligence

Power BI dashboards translate complex patterns into actionable insights for stakeholders.

This analysis demonstrates how data-driven methodologies support strategic decision-making and provide a scalable framework for continuous market basket analysis.

Thank You

Questions & Discussion

