Frequent itemset mining——Apriori algorithm

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实验要求：

基于 Apriori 算法完成 Market Basket 分析实验

数据视图：

Variables	Descriptions
InvoiceNo	发票编号（如果此代码以C 开头，则表示操作已取消）
StockCode	产品代码（每个产品的唯一编号）
Description	产品名称
Quantity	产品数量（发票上的产品数量已售出多少）
InvoiceDate	发票日期
Price	统一价格
CustomerID	唯一的客户编号
Country	国家

第一部分：Import Data & Data Preprocessing

●导入并查看数据信息，统计每个属性缺失值数量，处理缺失值（丢弃）；确定已取消的交易并删除；

●异常值处理；（将异常值定义为位于 1% 和 99% 分位数之外的值，并使用阈值来代替数据中的异常值）

●因为每个 stock code 代表一种产品，所以 Description 和 StockCode 的唯一值应该相等，删除代表多种产品 stock codes；

●stock code 中的 POST 表示邮费，并不代表产品，将其删除；

第二部分：Preparing Invoice-Product Matrix for ARL Data Structure

将原始数据转换为适合进行关联规则分析的格式，例如：其中每一行代表一笔交易，每一列代表一个产品，单元格的值表示该产品在该笔交易中是否存在（1 表示存在，0 表示不存在）。

第三部分：Determination of Association Rules

●使用 Apriori 计算 support values，min_support 设置为 0.01；

●从频繁项集中生成关联规则，评估关联规则的指标为 support，最小支持度阈值为 0.01；

●查看支持度最高的前五个关联规则。

第一部分：Import Data & Data Preprocessing

实验数据 retail.xlsx 有两个 work sheet，分别载入 df_1 和 df_2，所有数据处理操作都分别进行两次，以下代码示例已 df_1 操作为例，df_2 类似。

导入数据

```
# 1. 导入数据
df_1 = pd.read_excel('retail.xlsx', sheet_name='Year 2009-2010')  # 替换为实际的工作表名称
df_2 = pd.read_excel('retail.xlsx', sheet_name='Year 2010-2011')  # 替换为实际的工作表名称
# Print the first few rows of the dataframe
print("Year 2009-2010 dataframe:\n")
print(df_1.head())
print("Number of instances (rows):", df_1.shape[0])
print("Number of attributes (columns):", df_1.shape[1])
print("Column names:", df_1.columns.tolist())
print()
```

数据概况：

```
Year 2009-2010 dataframe:

  Invoice StockCode                          Description  Quantity  \
0  489434     85048  15CM CHRISTMAS GLASS BALL 20 LIGHTS        12
1  489434    79323P                   PINK CHERRY LIGHTS        12
2  489434    79323W                  WHITE CHERRY LIGHTS        12
3  489434     22041         RECORD FRAME 7" SINGLE SIZE         48
4  489434     21232       STRAWBERRY CERAMIC TRINKET BOX        24

          InvoiceDate  Price  Customer ID         Country
0 2009-12-01 07:45:00   6.95      13085.0  United Kingdom
1 2009-12-01 07:45:00   6.75      13085.0  United Kingdom
2 2009-12-01 07:45:00   6.75      13085.0  United Kingdom
3 2009-12-01 07:45:00   2.10      13085.0  United Kingdom
4 2009-12-01 07:45:00   1.25      13085.0  United Kingdom
Number of instances (rows): 525461
Number of attributes (columns): 8
Column names: ['Invoice', 'StockCode', 'Description', 'Quantity', 'InvoiceDate', 'Price', 'Customer ID', 'Country']
```

查看每列的缺失值并且丢弃：

```
# 2. 查看数据信息，包括每列的缺失值数量
missing_values_1 = df_1.isnull().sum()
missing_values_2 = df_2.isnull().sum()
print("Missing values in sheet1:\n", missing_values_1)
print()
print("Missing values in sheet2:\n", missing_values_2)
```

```
Missing values in sheet1:
 Invoice             0
StockCode           0
Description      2928
Quantity            0
InvoiceDate         0
Price               0
Customer ID    107927
Country             0
dtype: int64
```

```python
# 3. 删除有缺失值的行
num_rows_before_1 = df_1.shape[0]
num_rows_before_2 = df_2.shape[0]
df_1.dropna(inplace=True)
df_2.dropna(inplace=True)

num_rows_after_1 = df_1.shape[0]
num_rows_after_2 = df_2.shape[0]
print("Year 2009-2010 dataframe:")
print(f"Number of rows before dropping missing values: {num_rows_before_1}")
print(f"Number of rows after dropping missing values: {num_rows_after_1}")

print()
print("Year 2010-2011 dataframe:")
print(f"Number of rows before dropping missing values: {num_rows_before_2}")
print(f"Number of rows after dropping missing values: {num_rows_after_2}")

print()
print("检查一下:")
missing_values_1 = df_1.isnull().sum()
missing_values_2 = df_2.isnull().sum()
print("Missing values in sheet1:\n", missing_values_1)
print()
print("Missing values in sheet2:\n", missing_values_2)
print("目前无缺失值")
```

打印删除前后数据差异并且检查是否完全删除缺失值:

```
Year 2009-2010 dataframe:
Number of rows before dropping missing values: 525461
Number of rows after dropping missing values: 417534

Year 2010-2011 dataframe:
Number of rows before dropping missing values: 541910
Number of rows after dropping missing values: 406830

检查一下:
Missing values in sheet1:
 Invoice        0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
Price          0
Customer ID    0
Country        0
dtype: int64
```

删除已取消的交易（发票编号代码以 C 开头）:

```python
# 4. 确定并删除已取消的交易

print("Year 2009-2010 dataframe:\n")
num_rows_before_1 = df_1.shape[0]
print(f"Number of rows before dropping cancelled transactions: {num_rows_before_1}")
cancelled_transactions_1 = df_1[df_1['Invoice'].astype(str).str.contains('C', na=False)]
print("Year 2009-2010 Cancelled transactions count:", cancelled_transactions_1.shape[0])
df_1 = df_1[~df_1['Invoice'].astype(str).str.contains('C', na=False)]
num_rows_after_1 = df_1.shape[0]
print(f"Number of rows after dropping cancelled transactions: {num_rows_after_1}")
print()
```

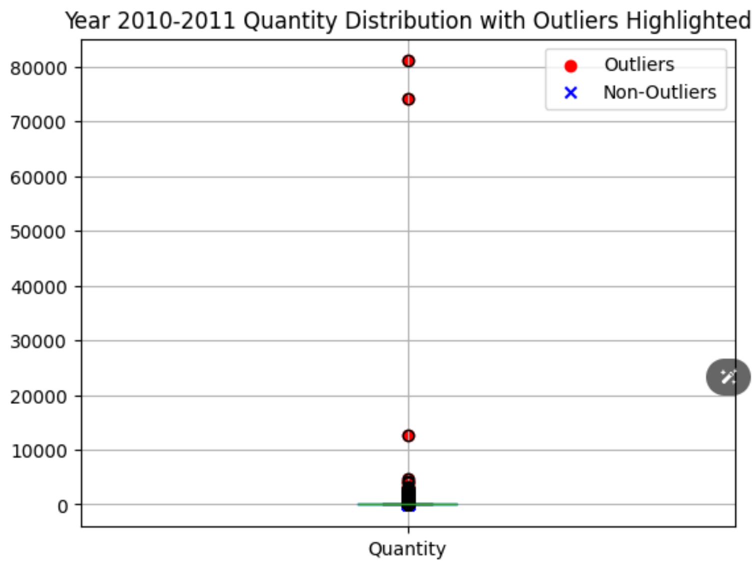
```
Year 2009-2010 dataframe:

Number of rows before dropping cancelled transactions: 417534
Year 2009-2010 Cancelled transactions count: 9839
Number of rows after dropping cancelled transactions: 407695
```

异常值处理:

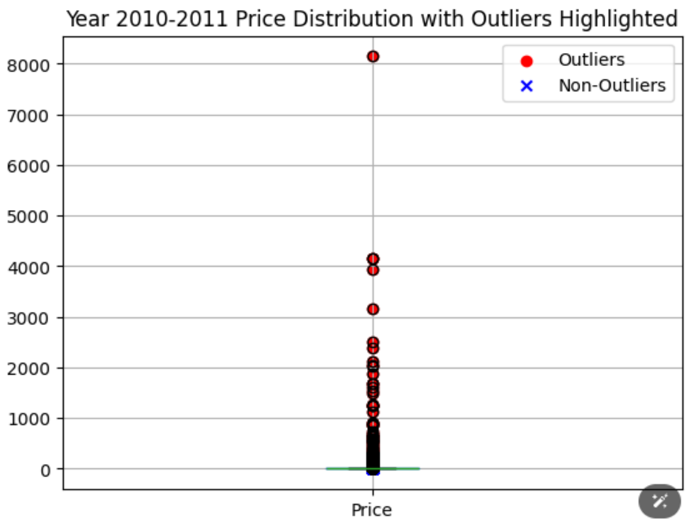
计算分位数: 对每个指定的列（"Quantity"和"Price"），计算 1%和 99%的分位数并打印;
标记非异常值和异常值: 使用 1%和 99%的分位数作为标准，筛选出每列中位于这两个分位数之间的数据，认为它们是正常的数据点。异常值: 选出每列中小于 1%分位数或大于 99%分位数的数据，认为这些是异常值;
打印异常值数量: 统计并打印出每列中被识别为异常值的数据点数量;
绘制箱线图并叠加异常值点: 箱线图能够直观地显示数据的中位数、四分位数及异常值;
绘制箱线图: 用红色圆点标记异常值，用蓝色叉号标记非异常值
裁剪异常值: 对于"Quantity"和"Price"两列中的每个数据点，如果它超出了 1%和 99%分位数的范围，则将其值设置为相应的边界值。这意味着小于 1%分位数的值会被设置为 1%分位数的值，大于 99%分位数的值会被设置为 99%分位数的值;
检查裁剪后的异常值数量: 理论上，由于数据已被裁剪到 1%和 99%的分位数，裁剪操作后的异常值数量应为 0

```
Year 2010-2011 percentiles in Quantity: [  1. 120.]
Number of outliers in Quantity: 3896
```




```
Year 2009-2010 Number of outliers in Quantity after clipping: 0
```

```
Year 2010-2011 percentiles in Price: [ 0.21 14.95]
Number of outliers in Price: 6766
```




```
Year 2009-2010 Number of outliers in Price after clipping: 0
```

删除 StockCode 和 Description 没有一一对应的数据行:

```
# 6. 确保StockCode和Description的一一对应性，并删除不符合条件的数据
print("Year 2009-2010 dataframe:\n")
unique_desc_1 = df_1.groupby('StockCode').Description.nunique()
non_unique_stock_codes_1 = unique_desc_1[unique_desc_1 > 1].index.tolist()
non_unique_descriptions_1 = df_1[df_1['StockCode'].isin(non_unique_stock_codes_1)]
num_rows_before_1 = df_1.shape[0]
print("Number of rows before removing non-unique StockCode entries:", num_rows_before_1)
print("Year 2009-2010 Number of rows with non-unique StockCodes:", non_unique_descriptions_1.shape[0])
print("Year 2009-2010 Non-unique StockCodes and their Descriptions:\n", non_unique_descriptions_1)
df_1 = df_1[~df_1['StockCode'].isin(non_unique_stock_codes_1)]
# 打印删除后的数据行数
num_rows_after_1 = df_1.shape[0]
print("Number of rows after removing non-unique StockCode entries:\n", num_rows_after_1)
```

```
Year 2009-2010 dataframe:

Number of rows before removing non-unique StockCode entries: 407695
Year 2009-2010 Number of rows with non-unique StockCodes: 87045
Year 2009-2010 Non-unique StockCodes and their Descriptions:
       Invoice StockCode                        Description  Quantity  \
2       489434    79323W                 WHITE CHERRY LIGHTS        12
7       489434     21523  FANCY FONT HOME SWEET HOME DOORMAT        10
8       489435     22350                            CAT BOWL        12
9       489435     22349      DOG BOWL , CHASING BALL DESIGN        12
10      489435     22195        HEART MEASURING SPOONS LARGE        24
...        ...       ...                                 ...       ...
525434  538171     21156             RETROSPOT CHILDRENS APRON         1
525435  538171    47591D        PINK FAIRY CAKE CHILDRENS APRON         1
525436  538171    47591B            SCOTTIES CHILDRENS APRON         2
525437  538171     22899          CHILDREN'S APRON DOLLY GIRL          1
525441  538171     22837           HOT WATER BOTTLE BABUSHKA          2

               InvoiceDate  Price  Customer ID         Country
2      2009-12-01 07:45:00   6.75      13085.0  United Kingdom
7      2009-12-01 07:45:00   5.95      13085.0  United Kingdom
8      2009-12-01 07:46:00   2.55      13085.0  United Kingdom
9      2009-12-01 07:46:00   3.75      13085.0  United Kingdom
10     2009-12-01 07:46:00   1.65      13085.0  United Kingdom
...                    ...    ...          ...             ...
525434 2010-12-09 20:01:00   1.95      17530.0  United Kingdom
525435 2010-12-09 20:01:00   1.95      17530.0  United Kingdom
525436 2010-12-09 20:01:00   1.65      17530.0  United Kingdom
525437 2010-12-09 20:01:00   2.10      17530.0  United Kingdom
525441 2010-12-09 20:01:00   4.65      17530.0  United Kingdom

[87045 rows x 8 columns]
Number of rows after removing non-unique StockCode entries:
 320650
```

stock code 中的 POST 表示邮费，并不代表产品，将其删除

```
# 7. 删除StockCode为'POST'的行
print("Year 2009-2010 dataframe:\n")
num_rows_before_removal_1 = df_1.shape[0]
print(f"Number of rows before removing 'POST' entries: {num_rows_before_removal_1}")
num_post_entries_1 = df_1[df_1['StockCode'] == 'POST'].shape[0]
print(f"Number of rows with 'StockCode' as 'POST' in Year 2009-2010: {num_post_entries_1}")
df_1 = df_1[df_1['StockCode'] != 'POST']
num_rows_after_removal_1 = df_1.shape[0]
print(f"Number of rows after removing 'POST' entries: {num_rows_after_removal_1}")
print()
```

```
Year 2009-2010 dataframe:

Number of rows before removing 'POST' entries: 320650
Number of rows with 'StockCode' as 'POST' in Year 2009-2010: 738
Number of rows after removing 'POST' entries: 319912
```

第二部分：Preparing Invoice-Product Matrix for ARL Data Structure

将原始数据转换为适合进行关联规则分析的格式，其中每一行代表一笔交易，每一列代表一个产品，由于 StockCode 和 Description 是一一对应的关系且都表示唯一的产品，所以我选择了看起来更直观的 Description。单元格的值表示该产品在该笔交易中是否存在（1 表示存在，0 表示不存在）。

由于数据量巨大，所以只需要选择一个国家，本次实验中我选择的是 **Korea**，该字段只在 Year 2009-2010 出现，所以只需要加载 df_1。由于内存限制，我无法把 48 个产品全都纳入计算，因此我将产品数量限制在"销量最高的前 13 个"中。

```python
import pandas as pd
from mlxtend.frequent_patterns import apriori, association_rules

# 假设df_1已经加载并进行了必要的预处理，筛选'Korea'的数据
df_1_Korea = df_1[df_1['Country'] == 'Korea']
print(f"Number of entries in df_1 for Korea: {df_1_Korea.shape[0]}")

# 计算每个产品的总销量并选择销量排名前13的产品
top_products = df_1_Korea.groupby('Description')['Quantity'].sum().sort_values(ascending=False).head(13).index

# 根据销量排名前13的产品创建一个发票-产品矩阵
basket = (df_1_Korea[df_1_Korea['Description'].isin(top_products)]
          .groupby(['Invoice', 'Description'])['Quantity']
          .sum().unstack().reset_index().fillna(0)
          .set_index('Invoice'))

# 将数量转换为1或0的函数
def encode_units(x):
    if x <= 0:
        return 0
    if x >= 1:
        return 1

# 应用encode_units函数到basket
basket_sets = basket.applymap(encode_units)

# 打印basket_sets的实例和属性数量
print(f"Number of instances (rows) in basket_sets: {basket_sets.shape[0]}")
print(f"Number of attributes (columns) in basket_sets: {basket_sets.shape[1]}")

# 打印basket_sets的前几行以验证结果
basket_sets.head()
```

得出的数据大小如下:

```
Number of entries in df_1 for Korea: 49
Number of instances (rows) in basket_sets: 2
Number of attributes (columns) in basket_sets: 13
```

Description Invoice	CACTI T-LIGHT CANDLES	CITRONELLA CANDLE GARDEN POT	DISCO BALL CHRISTMAS DECORATION	FROG CANDLE	HEART T-LIGHT HOLDER	MIRRORED WALL ART POPPIES	MIRRORED WALL ART SKULLS	MIRRORED WALL ART SNOWFLAKES	MIRRORED WALL ART SPLODGES	PACK 3 BOXES CHRISTMAS PANNETONE	ROTATING SILVER ANGELS T-LIGHT HLDR	SET OF 20 VINTAGE CHRISTMAS NAPKINS	TROPICAL HONEYCOMB PAPER GARLAND
522570	0	0	0	1	1	0	0	0	0	0	0	0	0
535831	1	1	1	0	0	1	1	1	1	1	1	1	1

第三部分：Determination of Association Rules

●利用 apriori 函数从购物篮数据中计算出频繁项集，即找出那些经常一起出现在交易中的商品组合。通过设置 min_support=0.01，只有那些至少在 1%的交易中出现的项集才被认为是频繁的。

●基于上一步得到的频繁项集，使用 association_rules 函数生成关联规则。这里使用的指标是支持度（metric="support"），且只考虑支持度至少为 1%的规则。

```
from mlxtend.frequent_patterns import apriori, association_rules
# 使用Apriori算法计算支持度，min_support设置为0.01
frequent_itemsets = apriori(basket_sets, min_support=0.01, use_colnames=True)
# 从频繁项集中生成关联规则
rules = association_rules(frequent_itemsets, metric="support", min_threshold=0.01)
# 排序并查看支持度最高的前五个关联规则
top_rules = rules.sort_values(by="support", ascending=False).head(5)
print(top_rules)
```

●将生成的关联规则按支持度从高到低排序，并提取支持度最高的前五条规则。

```
                                   antecedents  \
173053  (TROPICAL  HONEYCOMB PAPER GARLAND )
0                      (CACTI T-LIGHT CANDLES)
1               (CITRONELLA CANDLE GARDEN POT)
2            (DISCO BALL CHRISTMAS DECORATION)
3                      (CACTI T-LIGHT CANDLES)

                                               consequents  antecedent support  \
173053  (MIRRORED WALL ART SPLODGES, SET OF 20 VINTAGE...                  0.5
0                            (CITRONELLA CANDLE GARDEN POT)                  0.5
1                                   (CACTI T-LIGHT CANDLES)                  0.5
2                                   (CACTI T-LIGHT CANDLES)                  0.5
3                         (DISCO BALL CHRISTMAS DECORATION)                  0.5

        consequent support  support  confidence  lift  leverage  conviction  \
173053                 0.5      0.5         1.0   2.0      0.25         inf
0                      0.5      0.5         1.0   2.0      0.25         inf
1                      0.5      0.5         1.0   2.0      0.25         inf
2                      0.5      0.5         1.0   2.0      0.25         inf
3                      0.5      0.5         1.0   2.0      0.25         inf

        zhangs_metric
173053            1.0
0                 1.0
1                 1.0
2                 1.0
3                 1.0
```