Step 1: Importing the required libraries

```
import numpy as np
```

import pandas as pd

from mlxtend.frequent patterns import apriori, association rules

Step 2: Loading and exploring the data

data = pd.read excel('Online Retail.xlsx')

data.head()

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

data.columns

```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate']
       'UnitPrice', 'CustomerID', 'Country'],
     dtype='object')
data.Country.unique()
'Channel Islands', 'Denmark', 'Cyprus', 'Sweden', 'Austria',
      'Israel', 'Finland', 'Bahrain', 'Greece', 'Hong Kong', 'Singapore',
      'Lebanon', 'United Arab Emirates', 'Saudi Arabia',
      'Czech Republic', 'Canada', 'Unspecified', 'Brazil', 'USA',
      'European Community', 'Malta', 'RSA'], dtype=object)
```

Step 3: Cleaning the Data

```
data['Description'] = data['Description'].str.strip()
```

data.dropna(axis = 0, subset =['InvoiceNo'], inplace = True)

data['InvoiceNo'] = data['InvoiceNo'].astype('str')

data = data[~data['InvoiceNo'].str.contains('C')]

Step 4: Splitting the data according to the region of transaction

Transactions done in France

```
basket France = (data[data['Country'] =="France"]
      .groupby(['InvoiceNo', 'Description'])['Quantity']
     .sum().unstack().reset index().fillna(0)
     .set index('InvoiceNo'))
```

Transactions done in the United Kingdom

```
basket UK = (data[data['Country'] =="United Kingdom"]
      .groupby(['InvoiceNo', 'Description'])['Quantity']
     .sum().unstack().reset_index().fillna(0)
     .set index('InvoiceNo'))
```

Step 5: Hot encoding the Data

```
def hot encode(x):
  if(x \le 0):
    return 0
 if(x>=1):
    return 1
# Encoding the datasets
basket_encoded = basket_France.applymap(hot_encode)
basket France = basket encoded
```

```
basket_encoded = basket_UK.applymap(hot_encode)
basket_UK = basket_encoded
```

Step 6: Building the models and analyzing the results

a) France:

Building the model

frq_items = apriori(basket_France, min_support = 0.05, use_colnames = True)

Collecting the inferred rules in a dataframe

rules = association_rules(frq_items, metric ="lift", min_threshold = 1)

rules = rules.sort_values(['confidence', 'lift'], ascending =[False, False])

print(rules.head())

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
44	(JUMBO BAG WOODLAND ANIMALS)	(POSTAGE)	0.076531	0.765306	0.076531	1.000	1.306667	0.017961	inf
258	(PLASTERS IN TIN CIRCUS PARADE, RED TOADSTOOL	(POSTAGE)	0.051020	0.765306	0.051020	1.000	1.306667	0.011974	inf
270	(PLASTERS IN TIN WOODLAND ANIMALS, RED TOADSTO	(POSTAGE)	0.053571	0.765306	0.053571	1.000	1.306667	0.012573	inf
301	(SET/6 RED SPOTTY PAPER CUPS, SET/20 RED RETRO	(SET/6 RED SPOTTY PAPER PLATES)	0.102041	0.127551	0.099490	0.975	7.644000	0.086474	34.897959
302	(SET/6 RED SPOTTY PAPER PLATES, SET/20 RED RET	(SET/6 RED SPOTTY PAPER CUPS)	0.102041	0.137755	0.099490	0.975	7.077778	0.085433	34.489796

b) United Kingdom:

frq_items = apriori(basket_UK, min_support = 0.01, use_colnames = True)
rules = association_rules(frq_items, metric ="lift", min_threshold = 1)
rules = rules.sort_values(['confidence', 'lift'], ascending =[False, False])
print(rules.head())

,	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
116	(BEADED CRYSTAL HEART PINK ON STICK)	(DOTCOM POSTAGE)	0.011036	0.037928	0.010768	0.975728	25.725872	0.010349	39.637371
2019	(SUKI SHOULDER BAG, JAM MAKING SET PRINTED)	(DOTCOM POSTAGE)	0.011625	0.037928	0.011196	0.963134	25.393807	0.010755	26.096206
2296	(HERB MARKER THYME, HERB MARKER MINT)	(HERB MARKER ROSEMARY)	0.010714	0.012375	0.010232	0.955000	77.173095	0.010099	21.947227
2302	(HERB MARKER PARSLEY, HERB MARKER ROSEMARY)	(HERB MARKER THYME)	0.011089	0.012321	0.010553	0.951691	77.240055	0.010417	20.444951
2300	(HERB MARKER THYME, HERB MARKER PARSLEY)	(HERB MARKER ROSEMARY)	0.011089	0.012375	0.010553	0.951691	76.905682	0.010416	20.443842