Institute of Computer Technology
B. Tech Computer Science and Engineering
Sub: Data Mining and Warehousing (2CSE60E27)

PRACTICAL 6: APRIORI ALGORITHM

1. Assume a dataset of 10 transactions which has the list of the items that have been bought for each transactions. So the dataset will be having two kind of information in the dataset that is – (1) Transaction ID and (2) List of items.
Find the support value of the each combination of the items.

```
import pandas as pd
import numpy as np
import csv
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules

# QUESTION 1: Find the support value of the each combination of the items.
# creating / assuming a dataset
Cust_id = [1,2,3,4,5,6,7,8,9,10]
#Items =
[['Apples'],['Apples','Bananas'],['Oranges','Bananas'],['Apples','Bananas','Oranges'],['Oranges'],['Apples','Bananas'],['Oranges','Bananas'],['Bananas'],['Apples','Oranges'],['Bananas']]
Items = [['pickles','chocolate','french fries','cake','cookies','soup' ],
        ['tomatoes','muffins','cake','pasta','soup'],
        ['bread','milk','cookies','salt','almond'],
        ['french fries','milk','cookies','almond'],
        ['milk','bread','soup','pasta','cake'],
        ['pickles'],
        ['french fries','cookies'],
        ['bread','pasta'],
        ['chocolate','almond'],
        ['milk','cookies']]
data1 = pd.DataFrame(list(zip(Cust_id,Items)),columns=['Customer_Id','Items_bought'])
data1

l=list(data1['Items_bought'])
l

test =  TransactionEncoder()
test1 = test.fit(l).transform(l)
test1
```

test1.astype('int')

test.columns_

data2=pd.DataFrame(test1,columns=test.columns_)
display(data2)
apriori(data2,min_support = 0.01,use_colnames=True)

In [1]:
```
import pandas as pd
import numpy as np
import csv
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
```

In [14]:
```
# QUESTION 1: Find the support value of the each combination of the items.
# creating / assuming a dataset
Cust_id = [1,2,3,4,5,6,7,8,9,10]
#Items = [['Apples'],['Apples','Bananas'],['Oranges','Bananas'],['Apples','Bananas','Oranges'],['Oranges'],['Apples','Bar
Items = [['pickles','chocolate','french fries','cake','cookies','soup' ],
        ['tomatoes','muffins','cake','pasta','soup'],
        ['bread','milk','cookies','salt','almond'],
        ['french fries','milk','cookies','almond'],
        ['milk','bread','soup','pasta','cake'],
        ['pickles'],
        ['french fries','cookies'],
        ['bread','pasta'],
        ['chocolate','almond'],
        ['milk','cookies']]
data1 = pd.DataFrame(list(zip(Cust_id,Items)),columns=['Customer_Id','Items_bought'])
data1
```

Out[14]:

	Customer_Id	Items_bought
0	1	[pickles, chocolate, french fries, cake, cooki...
1	2	[tomatoes, muffins, cake, pasta, soup]
2	3	[bread, milk, cookies, salt, almond]
3	4	[french fries, milk, cookies, almond]
4	5	[milk, bread, soup, pasta, cake]
5	6	[pickles]
6	7	[french fries, cookies]
7	8	[bread, pasta]
8	9	[chocolate, almond]
9	10	[milk, cookies]

In [15]:
```
l=list(data1['Items_bought'])
l
```

Out[15]:
```
[['pickles', 'chocolate', 'french fries', 'cake', 'cookies', 'soup'],
 ['tomatoes', 'muffins', 'cake', 'pasta', 'soup'],
 ['bread', 'milk', 'cookies', 'salt', 'almond'],
 ['french fries', 'milk', 'cookies', 'almond'],
 ['milk', 'bread', 'soup', 'pasta', 'cake'],
 ['pickles'],
 ['french fries', 'cookies'],
 ['bread', 'pasta'],
 ['chocolate', 'almond'],
 ['milk', 'cookies']]
```

In [16]:
```
test =  TransactionEncoder()
test1 = test.fit(l).transform(l)
test1
```

Out[16]:
```
array([[False, False,  True,  True,  True,  True, False, False, False,
         True, False,  True, False],
       [False, False,  True, False, False, False, False,  True,  True,
        False, False,  True,  True],
       [ True,  True, False, False,  True, False,  True, False, False,
        False,  True, False, False],
       [ True, False, False, False,  True,  True,  True, False, False,
        False, False, False, False],
       [False,  True,  True, False, False, False,  True, False,  True,
        False, False,  True, False],
       [False, False, False, False, False, False, False, False, False,
         True, False, False, False],
       [False, False, False, False,  True,  True, False, False, False,
        False, False, False, False],
       [False,  True, False, False, False, False, False, False,  True,
        False, False, False, False],
       [ True, False, False,  True, False, False, False, False, False,
        False, False, False, False],
       [False, False, False, False,  True, False,  True, False, False,
        False, False, False, False]])
```

In [17]:
```
test1.astype('int')
```

Out[17]:
```
array([[0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0],
       [0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1],
       [1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0],
       [1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0],
       [0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0],
       [0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0],
       [1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0]])
```

In [18]:
```
test.columns_
```

Out[18]:
```
['almond',
 'bread',
 'cake',
 'chocolate',
 'cookies',
 'french fries',
 'milk',
 'muffins',
 'pasta',
 'pickles',
 'salt',
 'soup',
 'tomatoes']
```

In [19]:
```
data2=pd.DataFrame(test1,columns=test.columns_)
display(data2)
apriori(data2,min_support = 0.01,use_colnames=True)
```

	almond	bread	cake	chocolate	cookies	french fries	milk	muffins	pasta	pickles	salt	soup	tomatoes
0	False	False	True	True	True	True	False	False	False	True	False	True	False
1	False	False	True	False	False	False	False	True	True	False	False	True	True
2	True	True	False	False	True	False	True	False	False	False	True	False	False
3	True	False	False	False	True	True	True	False	False	False	False	False	False
4	False	True	True	False	False	False	True	False	True	False	False	True	False
5	False	False	False	False	False	False	False	False	False	True	False	False	False
6	False	False	False	False	True	True	False	False	False	False	False	False	False
7	False	True	False	False	False	False	False	False	True	False	False	False	False
8	True	False	False	True	False	False	False	False	False	False	False	False	False
9	False	False	False	False	True	False	True	False	False	False	False	False	False

Out[19]:

	support	itemsets
0	0.3	(almond)
1	0.3	(bread)
2	0.3	(cake)
3	0.2	(chocolate)
4	0.5	(cookies)
...	...	...
144	0.1	(soup, pickles, chocolate, french fries, cake)
145	0.1	(soup, pickles, french fries, cookies, cake)
146	0.1	(soup, tomatoes, pasta, muffins, cake)
147	0.1	(soup, pickles, chocolate, french fries, cookies)
148	0.1	(soup, pickles, chocolate, french fries, cooki...

149 rows × 2 columns

2. Suppose a superstore management wants to analyze buying patterns of the customers and come up with a strategy to increase the profit. The dataset contains details related to transactions.
1) As a data analyst, analyze the data and try to find the correlation between the items.
2) Find the most popular items among the customers.
3) Which items' combinations are bought on most frequent basis?
4) Mention the items and combinations of the items whose sale should be more focused?

```
# QUESTION 2
df = pd.read_excel(r"C:\Users\admin\Desktop\dishwa\dmw\Practical 6\Online Retail.xlsx")
display(df.head(10))

# Removing any unneccesary empty spaces from description
df['Description'] = df['Description'].str.strip()
```

```
# Dropping the rows without any invoice number
df.dropna(axis = 0, subset =['InvoiceNo'], inplace = True)
df['InvoiceNo'] = df['InvoiceNo'].astype('str')

# Dropping all transactions which were done on credit
df = df[~df['InvoiceNo'].str.contains('C')]

#Removing rows with quantity equal to 0
df = df[df['Quantity'] > 0]

# Removing some of the unrelated description rows
df = df[df['Description'] != 'returned']
df = df[df['Description'] != 'taig adjust']
df = df[df['Description'] != 'test']
df = df[df['Description'] != 'to push order througha s stock was']
df = df[df['Description'] != 'website fixed']
df = df[df['Description'] != 'wrongly coded 20713']
df = df[df['Description'] != 'wrongly coded 23343']
df = df[df['Description'] != 'wrongly marked']
df = df[df['Description'] != 'wrongly marked 23343']
df = df[df['Description'] != 'wrongly sold (22719) barcode']
df = df[df['Description'] != 'dotcomstock']
df = df[df['Description'] != 'for online retail orders']
df = df[df['Description'] != 'found']
df = df[df['Description'] != 'found box']
df = df[df['Description'] != 'had been put aside']
df = df[df['Description'] != 'incorrectly credited C550456 see 47']
df = df[df['Description'] != 'mailout']
df = df[df['Description'] != 'michel oops']
df = df[df['Description'] != 'on cargo order']
df = df[df['Description'] != 'rcvd be air temp fix for dotcom sit']

# prints data that will be plotted
# columns shown here are selected by corr() since
# they are ideal for the plot
import seaborn as sb
print(df.corr())

# plotting correlation heatmap
dataplot = sb.heatmap(df.corr(), cmap="YlGnBu", annot=True)

# We can deduce  there is a negative correlation between unit price and quanitity.
# More the quantity lesser the per unit price.

# Converting table to get table for apriori algorithm
basket =
pd.pivot_table(data=df,index='InvoiceNo',columns='Description',values='Quantity',ag
gfunc='sum',fill_value=0)
```

```
display(basket.head())

print(basket['WHITE HANGING HEART T-LIGHT HOLDER'].head(10))

def convert_to_binary(x):
    if x > 0:
        return 1
    else:
        return 0
basket_sets = basket.applymap(convert_to_binary)
print(basket_sets['WHITE HANGING HEART T-LIGHT HOLDER'].head(10))

frequent_itemsets = apriori(basket_sets,min_support = 0.1, use_colnames=True)
print(frequent_itemsets)

frequent_itemsets = apriori(basket_sets,min_support = 0.03, use_colnames=True)
display(frequent_itemsets)

frequent_itemsets['length'] = frequent_itemsets['itemsets'].apply(lambda x:len(x))
frequent_itemsets

display(frequent_itemsets[frequent_itemsets['length'] > 1].head(1))

print(frequent_itemsets[frequent_itemsets['length'] > 1].head(1)['itemsets'])

a=df.groupby('CustomerID').apply(','.join).reset_index()
print(a)
```

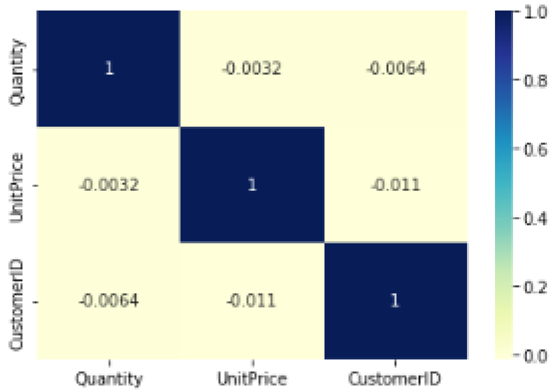
```
In [24]: # QUESTION 2
df = pd.read_excel(r"C:\Users\admin\Desktop\dishwa\dmw\Practical 6\Online Retail.xlsx")
display(df.head(10))
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365.0	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6.0	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365.0	71053.0	WHITE METAL LANTERN	6.0	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365.0	84406B	CREAM CUPID HEARTS COAT HANGER	8.0	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365.0	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6.0	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365.0	84029E	RED WOOLLY HOTTIE WHITE HEART.	6.0	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
5	536365.0	22752.0	SET 7 BABUSHKA NESTING BOXES	2.0	2010-12-01 08:26:00	7.65	17850.0	United Kingdom
6	536365.0	21730.0	GLASS STAR FROSTED T-LIGHT HOLDER	6.0	2010-12-01 08:26:00	4.25	17850.0	United Kingdom
7	536366.0	22633.0	HAND WARMER UNION JACK	6.0	2010-12-01 08:28:00	1.85	17850.0	United Kingdom
8	536366.0	22632.0	HAND WARMER RED POLKA DOT	6.0	2010-12-01 08:28:00	1.85	17850.0	United Kingdom
9	536367.0	84879.0	ASSORTED COLOUR BIRD ORNAMENT	32.0	2010-12-01 08:34:00	1.69	13047.0	United Kingdom

In [26]:
```
# Removing any unneccesary empty spaces from description
df['Description'] = df['Description'].str.strip()

# Dropping the rows without any invoice number
df.dropna(axis = 0, subset =['InvoiceNo'], inplace = True)
df['InvoiceNo'] = df['InvoiceNo'].astype('str')

# Dropping all transactions which were done on credit
df = df[~df['InvoiceNo'].str.contains('C')]

#Removing rows with quantity equal to 0
df = df[df['Quantity'] > 0]

# Removing some of the unrelated description rows
df = df[df['Description'] != 'returned']
df = df[df['Description'] != 'taig adjust']
df = df[df['Description'] != 'test']
df = df[df['Description'] != 'to push order througha s stock was']
df = df[df['Description'] != 'website fixed']
df = df[df['Description'] != 'wrongly coded 20713']
df = df[df['Description'] != 'wrongly coded 23343']
df = df[df['Description'] != 'wrongly marked']
df = df[df['Description'] != 'wrongly marked 23343']
df = df[df['Description'] != 'wrongly sold (22719) barcode']
df = df[df['Description'] != 'dotcomstock']
df = df[df['Description'] != 'for online retail orders']
df = df[df['Description'] != 'found']
df = df[df['Description'] != 'found box']
df = df[df['Description'] != 'had been put aside']
df = df[df['Description'] != 'incorrectly credited C550456 see 47']
df = df[df['Description'] != 'mailout']
df = df[df['Description'] != 'michel oops']
df = df[df['Description'] != 'on cargo order']
df = df[df['Description'] != 'rcvd be air temp fix for dotcom sit']
```

In [29]:
```
# prints data that will be plotted
# columns shown here are selected by corr() since
# they are ideal for the plot
import seaborn as sb
print(df.corr())

# plotting correlation heatmap
dataplot = sb.heatmap(df.corr(), cmap="YlGnBu", annot=True)

# We can deduce  there is a negative correlation between unit price and quanitity.
# More the quantity lesser the per unit price.
```

```
            Quantity  UnitPrice  CustomerID
Quantity    1.000000  -0.003206   -0.006411
UnitPrice  -0.003206   1.000000   -0.010863
CustomerID -0.006411  -0.010863    1.000000
```



```
# Converting table to get table for apriori algorithm
basket = pd.pivot_table(data=df,index='InvoiceNo',columns='Description',values='Quantity',aggfunc='sum',fill_value=0)
display(basket.head())
```

Description	*Boombox Ipod Classic	*USB Office Mirror Ball	10 COLOUR SPACEBOY PEN	12 COLOURED PARTY BALLOONS	12 DAISY PEGS IN WOOD BOX	12 EGG HOUSE PAINTED WOOD	12 HANGING EGGS HAND PAINTED	12 IVORY ROSE PEG PLACE SETTINGS	12 MESSAGE CARDS WITH ENVELOPES	12 PENCIL SMALL TUBE WOODLAND	...	amazon	amazon adjust	amazon sales
InvoiceNo														
536365	0	0	0	0	0	0	0	0	0	0	...	0	0	0
536366	0	0	0	0	0	0	0	0	0	0	...	0	0	0
536367	0	0	0	0	0	0	0	0	0	0	...	0	0	0
536368	0	0	0	0	0	0	0	0	0	0	...	0	0	0
536369	0	0	0	0	0	0	0	0	0	0	...	0	0	0

5 rows × 4045 columns

In [ ]:
```
print(basket['WHITE HANGING HEART T-LIGHT HOLDER'].head(10))
```

```
InvoiceNo
536365    6
536366    0
536367    0
536368    0
536369    0
536370    0
536371    0
536372    0
536373    6
536374    0
Name: WHITE HANGING HEART T-LIGHT HOLDER, dtype: int64
```

In [ ]:
```
def convert_to_binary(x):
    if x > 0:
        return 1
    else:
        return 0
basket_sets = basket.applymap(convert_to_binary)
print(basket_sets['WHITE HANGING HEART T-LIGHT HOLDER'].head(10))
```

```
InvoiceNo
536365    1
536366    0
536367    0
536368    0
536369    0
536370    0
536371    0
536372    0
536373    1
536374    0
Name: WHITE HANGING HEART T-LIGHT HOLDER, dtype: int64
```

In [ ]:
```
frequent_itemsets = apriori(basket_sets,min_support = 0.1, use_colnames=True)
print(frequent_itemsets)
```

```
    support                              itemsets
0  0.104173             (JUMBO BAG RED RETROSPOT)
1  0.112539  (WHITE HANGING HEART T-LIGHT HOLDER)
```

```
In [ ]: frequent_itemsets = apriori(basket_sets,min_support = 0.03, use_colnames=True)
        display(frequent_itemsets)
```

	support	itemsets
0	0.047555	(6 RIBBONS RUSTIC CHARM)
1	0.030774	(60 CAKE CASES VINTAGE CHRISTMAS)
2	0.041231	(60 TEATIME FAIRY CAKE CASES)
3	0.030624	(72 SWEETHEART FAIRY CAKE CASES)
4	0.048800	(ALARM CLOCK BAKELIKE GREEN)
...	...	...
133	0.041082	(JUMBO BAG PINK POLKADOT, JUMBO BAG RED RETROS...
134	0.033861	(JUMBO SHOPPER VINTAGE RED PAISLEY, JUMBO BAG ...
135	0.036052	(JUMBO STORAGE BAG SUKI, JUMBO BAG RED RETROSPOT)
136	0.031919	(LUNCH BAG BLACK SKULL., LUNCH BAG RED RETROS...
137	0.030176	(LUNCH BAG PINK POLKADOT, LUNCH BAG RED RETROS...

138 rows × 2 columns

```
In [ ]: frequent_itemsets['length'] = frequent_itemsets['itemsets'].apply(lambda x:len(x))
        frequent_itemsets
```

Out[20]:

	support	itemsets	length
0	0.047555	(6 RIBBONS RUSTIC CHARM)	1
1	0.030774	(60 CAKE CASES VINTAGE CHRISTMAS)	1
2	0.041231	(60 TEATIME FAIRY CAKE CASES)	1
3	0.030624	(72 SWEETHEART FAIRY CAKE CASES)	1
4	0.048800	(ALARM CLOCK BAKELIKE GREEN)	1
...	...	...	...
133	0.041082	(JUMBO BAG PINK POLKADOT, JUMBO BAG RED RETROS...	2
134	0.033861	(JUMBO SHOPPER VINTAGE RED PAISLEY, JUMBO BAG ...	2
135	0.036052	(JUMBO STORAGE BAG SUKI, JUMBO BAG RED RETROSPOT)	2
136	0.031919	(LUNCH BAG BLACK SKULL., LUNCH BAG RED RETROS...	2
137	0.030176	(LUNCH BAG PINK POLKADOT, LUNCH BAG RED RETROS...	2

138 rows × 3 columns

```
In [ ]: display(frequent_itemsets[frequent_itemsets['length'] > 1].head(1))
```

	support	itemsets	length
130	0.031869	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...	2

```
In [ ]: print(frequent_itemsets[frequent_itemsets['length'] > 1].head(1)['itemsets'])

130    (ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...
Name: itemsets, dtype: object
```

In [31]:
```python
a=data.groupby('CustomerID').apply(','.join).reset_index()
print(a)
```

```
      CustomerID                                                  0
0        12346.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
1        12347.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
2        12348.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
3        12349.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
4        12350.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
...          ...                                                ...
4334     18280.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
4335     18281.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
4336     18282.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
4337     18283.0  InvoiceNo,StockCode,Description,Quantity,Invoi...
4338     18287.0  InvoiceNo,StockCode,Description,Quantity,Invoi...

[4339 rows x 2 columns]
```

3. Using the same dataset, Get the most frequent item-sets using WEKA. Provide justification of the parameters you have set to extract the rules.