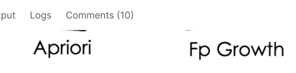
Comparative Analysis Between Apriori and Fp Growth



This kernel is a comprehensive overview focused on the comparative analysis between Apriori and Frequent Pattern Growth algorithms. In the end, we will have a look at the comparative table between additional algorithms such as: **RAMS, ECLAT, ASPMS.** These are all association rule algorithms.
[I wrote this first kernel (https://www.kaggle.com/keitazoumana/a-simple-way-to-understand-association-rule)](https://www.kaggle.com/keitazoumana/a-simple-way-to-understand-association-rule) to give you more information about how an association rule works.
We will be covering the following topics:

Data Preparation for association rules

Association Rules implementation

Comparative Analyzis

Useful Libraries

In [1]:
```python
import time
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from prettytable import PrettyTable
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules, fpgrowth
```

In [2]:
```python
# Load the dataset
groceries = pd.read_csv("../input/groceries-dataset/Groceries_dataset.csv")
```

In [3]:
```python
groceries.shape
```

Out[3]:
```
(38765, 3)
```

In [4]:
```python
groceries.head()
```

Out[4]:

	Member_number	Date	itemDescription
0	1808	21-07-2015	tropical fruit
1	2552	05-01-2015	whole milk
2	2300	19-09-2015	pip fruit
3	1187	12-12-2015	other vegetables
4	3037	01-02-2015	whole milk

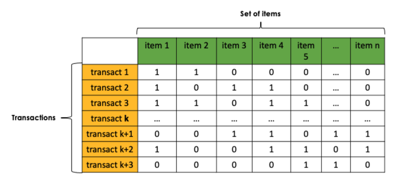
In [5]:
```python
# Get all the transactions as a list of lists
all_transactions = [transaction[1]['itemDescription'].tolist() for transaction in list(groceries.gro
upby(['Member_number', 'Date']))]
```

In [6]:
```python
# First 21st transactions in the transactional dataset
len(all_transactions)
```

Out[6]:
```
14963
```

Data Preparation

We need to transform the data into the following format, which is suitable to perform our association rules.



	item 1	item 2	item 3	item 4	item 5	...	item n
transact 1	1	1	0	0	0	...	0
transact 2	1	0	1	1	0	...	0
transact 3	1	1	0	1	1	...	0
transact k	...	...	...	...	...	...	...
transact k+1	0	0	1	1	0	1	1
transact k+2	1	0	0	1	1	0	1
transact k+3	0	0	0	0	1	1	0

In [7]:
```python
# Look at the 10 first transactions
all_transactions[0:10]
```

Out[7]:
```
[['sausage', 'whole milk', 'semi-finished bread', 'yogurt'],
 ['whole milk', 'pastry', 'salty snack'],
 ['canned beer', 'misc. beverages'],
 ['sausage', 'hygiene articles'],
 ['soda', 'pickled vegetables'],
 ['frankfurter', 'curd'],
 ['sausage', 'whole milk', 'rolls/buns'],
 ['whole milk', 'soda'],
 ['beef', 'white bread'],
 ['frankfurter', 'soda', 'whipped/sour cream']]
```

The Ones and Zeros in the matrix are boolean values, they could also be respectively replaced by True and False, where:

- **True** means that the item exists in the transaction
- **False** means it does not

In [8]:
```python
# The following instructions transform the dataset into the required format
trans_encoder = TransactionEncoder() # Instanciate the encoder
trans_encoder_matrix = trans_encoder.fit(all_transactions).transform(all_transactions)
trans_encoder_matrix = pd.DataFrame(trans_encoder_matrix, columns=trans_encoder.columns_)
```

In [9]:
```python
trans_encoder_matrix.head()
```

Out[9]:

	Instant food products	UHT-milk	abrasive cleaner	artif. sweetener	baby cosmetics	bags	baking powder	bathroom cleaner	beef	berries	...	turkey	vinegar	waffles
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False

5 rows × 167 columns

	Instant food products	UHT-milk	abrasive cleaner	artif. sweetener	baking powder	bathroom cleaner	beef	berries	beverages	bottled beer	...	turkey	vinegar	waffles	whipped/sour cream	whisky	white bread	white wine	whole milk	yogurt	zwieback
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	True	True	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	True	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False

Association Rules Implementation

- **support** tells how popular an item is based on the proportion of all transactions that are included. The popularity is met if it corresponds to the user-specified support thresold. For instance, a support threshold set to 0.2 (20%) means that the user wants all the items that occur together in at least 20% of all transactions.
- A High support thresold does not give much more item combination, so reducing the value might be helpful to see much more item combinations for marketing purpose.

Helper Functions

In [10]:
```python
def perform_rule_calculation(transact_items_matrix, rule_type="fpgrowth", min_support=0.001):
    """
    desc: this function performs the association rule calculation
    @params:
        - transact_items_matrix: the transaction X Items matrix
        - rule_type:
                    - apriori or Growth algorithms (default="fpgrowth")

        - min_support: minimum support threshold value (default = 0.001)

    @returns:
        - the matrix containing 3 columns:
            - support: support values for each combination of items
            - itemsets: the combination of items
            - number_of_items: the number of items in each combination of items

        - the excution time for the corresponding algorithm

    """
    start_time = 0
    total_execution = 0

    if(not rule_type=="fpgrowth"):
        start_time = time.time()
        rule_items = apriori(transact_items_matrix,
                       min_support=min_support,
                       use_colnames=True)
        total_execution = time.time() - start_time
        print("Computed Apriori!")

    else:
        start_time = time.time()
        rule_items = fpgrowth(transact_items_matrix,
                       min_support=min_support,
                       use_colnames=True)
        total_execution = time.time() - start_time
        print("Computed Fp Growth!")

    rule_items['number_of_items'] = rule_items['itemsets'].apply(lambda x: len(x))

    return rule_items, total_execution
```

In [11]:
```python
def compute_association_rule(rule_matrix, metric="lift", min_thresh=1):
    """
    @desc: Compute the final association rule
    @params:
        - rule_matrix: the corresponding algorithms matrix
        - metric: the metric to be used (default is lift)
        - min_thresh: the minimum threshold (default is 1)

    @returns:
        - rules: all the information for each transaction satisfying the given metric & threshold
    """
    rules = association_rules(rule_matrix,
                              metric=metric,
                              min_threshold=min_thresh)

    return rules
```

In [ ]:

In [12]:
```python
# Plot Lift Vs Coverage(confidence)
def plot_metrics_relationship(rule_matrix, col1, col2):
    """
    desc: shows the relationship between the two input columns
    @params:
        - rule_matrix: the matrix containing the result of a rule (apriori or Fp Growth)
        - col1: first column
        - col2: second column
    """
    fit = np.polyfit(rule_matrix[col1], rule_matrix[col2], 1)
    fit_funt = np.poly1d(fit)
    plt.plot(rule_matrix[col1], rule_matrix[col2], 'yo', rule_matrix[col1],
    fit_funt(rule_matrix[col1]))
    plt.xlabel(col1)
    plt.ylabel(col2)
    plt.title('{} vs {}'.format(col1, col2))
```

In [13]:
```python
def compare_time_exec(algo1=list, alg2=list):
    """
    @desc: shows the execution time between two algorithms
    @params:
        - algo1: list containing the description of first algorithm, where

        - algo2: list containing the description of second algorithm, where
    """

    execution_times = [algo1[1], algo2[1]]
    algo_names = (algo1[0], algo2[0])
    y=np.arange(len(algo_names))

    plt.bar(y,execution_times,color=['orange', 'blue'])
    plt.xticks(y,algo_names)
    plt.xlabel('Algorithms')
    plt.ylabel('Time')
    plt.title("Execution Time (seconds) Comparison")
    plt.show()
```

In [14]:
```python
val = {'name':12}
value = list(val.items())[0]
```

In [15]:
```python
value
```

Out[15]:
```
('name', 12)
```

Case n°1: Using Fp Growph Algorithm

In [16]:
```python
fpgrowth_matrix, fp_growth_exec_time = perform_rule_calculation(trans_encoder_matrix) # Run the algo
rithm
print("Fp Growth execution took: {} seconds".format(fp_growth_exec_time))
```

```
Computed Fp Growth!
Fp Growth execution took: 0.15892648696899414 seconds
```

In [17]:
```python
fpgrowth_matrix.head()
```

Out[17]:

	support	itemsets	number_of_items
0	0.157923	(whole milk)	1
1	0.085879	(yogurt)	1
2	0.060349	(sausage)	1
3	0.009490	(semi-finished bread)	1
4	0.051728	(pastry)	1

In [18]:
```python
fpgrowth_matrix.tail()
```

Out[18]:

	support	itemsets	number_of_items
745	0.001403	(chewing gum, yogurt)	2
746	0.001069	(other vegetables, chewing gum)	2
747	0.001002	(chewing gum, soda)	2
748	0.001069	(pasta, whole milk)	2
749	0.001002	(seasonal products, rolls/buns)	2

Lift

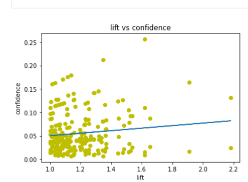
In [19]:
```python
fp_growth_rule_lift = compute_association_rule(fpgrowth_matrix)
```

In [20]:
```python
fp_growth_rule_lift.head()
```

Out[20]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(whole milk, yogurt)	(rolls/buns)	0.011161	0.110005	0.001337	0.119760	1.088685	0.000109	1.011083
1	(whole milk, rolls/buns)	(yogurt)	0.013968	0.085879	0.001337	0.095694	1.114293	0.000137	1.010854
2	(yogurt, rolls/buns)	(whole milk)	0.007819	0.157923	0.001337	0.170940	1.082428	0.000102	1.015701
3	(whole milk)	(yogurt, rolls/buns)	0.157923	0.007819	0.001337	0.008464	1.082428	0.000102	1.000650
4	(yogurt)	(whole milk, rolls/buns)	0.085879	0.013968	0.001337	0.015564	1.114293	0.000137	1.001622

In [21]:
```python
plot_metrics_relationship(fp_growth_rule_lift, col1='lift', col2='confidence')
```



Confidence