МИНОБРНАУКИ РОССИИ

САНКТ-ПЕТЕРБУРГСКИЙ ГОСУДАРСТВЕННЫЙ

ЭЛЕКТРОТЕХНИЧЕСКИЙ УНИВЕРСИТЕТ

«ЛЭТИ» ИМ. В.И. УЛЬЯНОВА (ЛЕНИНА)

Кафедра МОЭВМ

ОТЧЕТ

по лабораторной работе №4

по дисциплине «Машинное обучение»

Тема: Ассоциативный анализ

Студент гр. 6307 _____ Новиков Б.М.

Преподаватель _____ Жангиров Т.Р.

2020

lb4

3 декабря 2020 г.

1 LB4

[169]:
```
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import fpgrowth
from mlxtend.frequent_patterns import fpmax
```

1.1 Часть 1 Загрузка данных

2. Загрузить данные в датафрейм

[170]:
```
all_data = pd.read_csv("data/groceries - groceries.csv")
all_data.head()
```

[170]:

	Item(s)	Item 1	Item 2	Item 3	\
0	4	citrus fruit	semi-finished bread	margarine	
1	3	tropical fruit	yogurt	coffee	
2	1	whole milk	NaN	NaN	
3	4	pip fruit	yogurt	cream cheese	
4	4	other vegetables	whole milk	condensed milk	

	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	...	Item 23	\
0	ready soups	NaN	NaN	NaN	NaN	NaN	...	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	
2	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	
3	meat spreads	NaN	NaN	NaN	NaN	NaN	...	NaN	
4	long life bakery product	NaN	NaN	NaN	NaN	NaN	...	NaN	

	Item 24	Item 25	Item 26	Item 27	Item 28	Item 29	Item 30	Item 31	Item 32
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

[5 rows x 33 columns]

3. Переформировать данные, удалив все значения NaN

[171]:
```
np_data = all_data.to_numpy()
np_data = [[elem for elem in row[1:] if isinstance(elem,str)] for row in np_data]
```

4. Получить список всех уникальных товаров

[172]:
```
unique_items = set()
for row in np_data:
    for elem in row:
        unique_items.add(elem)
```

5. Вывести список товаров и их количество

[173]:
```
print(unique_items)
print(len(unique_items))
```

```
{'canned beer', 'soft cheese', 'hard cheese', 'sound storage medium', 'cling
film/bags', 'soap', 'salad dressing', 'dish cleaner', 'kitchen utensil',
'flour', 'processed cheese', 'cereals', 'sausage', 'female sanitary products',
'specialty bar', 'frozen fish', 'potato products', 'mustard', 'shopping bags',
'sauces', 'organic sausage', 'margarine', 'instant coffee', 'whipped/sour
cream', 'spread cheese', 'hygiene articles', 'liquor', 'beef', 'frozen meals',
'bottled beer', 'cookware', 'baby food', 'potted plants', 'canned vegetables',
'jam', 'cream', 'dog food', 'butter', 'prosecco', 'rubbing alcohol', 'specialty
chocolate', 'honey', 'sliced cheese', 'abrasive cleaner', 'domestic eggs', 'meat
spreads', 'pasta', 'red/blush wine', 'sparkling wine', 'yogurt', 'napkins',
'misc. beverages', 'canned fruit', 'tea', 'tropical fruit', 'waffles', 'cream
cheese', 'photo/film', 'white wine', 'whisky', 'other vegetables', 'beverages',
'newspapers', 'pickled vegetables', 'make up remover', 'turkey', 'cocoa drinks',
'ice cream', 'citrus fruit', 'finished products', 'butter milk', 'ready soups',
'condensed milk', 'cleaner', 'hamburger meat', 'salt', 'house keeping products',
'mayonnaise', 'baking powder', 'pudding powder', 'fruit/vegetable juice',
'preservation products', 'popcorn', 'long life bakery product', 'canned fish',
'zwieback', 'frozen fruits', 'specialty cheese', 'kitchen towels', 'frozen
vegetables', 'dishes', 'toilet cleaner', 'bags', 'chicken', 'chocolate
marshmallow', 'rice', 'ham', 'chocolate', 'rolls/buns', 'pet care', 'liquor
(appetizer)', 'coffee', 'packaged fruit/vegetables', 'dessert', 'cooking
chocolate', 'bottled water', 'meat', 'syrup', 'rum', 'skin care', 'UHT-milk',
'frozen dessert', 'light bulbs', 'tidbits', 'liver loaf', 'brandy', 'seasonal
products', 'curd', 'herbs', 'candy', 'ketchup', 'sugar', 'specialty vegetables',
'chewing gum', 'flower (seeds)', 'male cosmetics', 'baby cosmetics', 'bathroom
cleaner', 'pip fruit', 'frankfurter', 'frozen potato products', 'liqueur', 'cat
food', 'specialty fat', 'curd cheese', 'salty snack', 'snack products',
'spices', 'pork', 'sweet spreads', 'flower soil/fertilizer', 'roll products',
'frozen chicken', 'grapes', 'fish', 'white bread', 'soups', 'nuts/prunes',
'vinegar', 'candles', 'root vegetables', 'onions', 'softener', 'organic
products', 'artif. sweetener', 'soda', 'cake bar', 'whole milk', 'detergent',
'hair spray', 'dental care', 'nut snack', 'Instant food products',
'decalcifier', 'berries', 'semi-finished bread', 'brown bread', 'oil', 'pastry'}
```

```
169
```

1.2 Часть 2 FPGrowth и FPMax

1. Преобразуем данные к виду, удобному для анализа

[174]:
```
te = TransactionEncoder()
te_ary = te.fit(np_data).transform(np_data)
data = pd.DataFrame(te_ary, columns=te.columns_)
data.head()
```

[174]:

	Instant food products	UHT-milk	abrasive cleaner	artif. sweetener	baby cosmetics	baby food	bags	baking powder	bathroom cleaner	beef	...	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	False	False	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	True	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	True	False	False
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	True	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	True	False	False

[5 rows x 169 columns]

2. Проведем ассоциативный анализ, используя FPGrowth с поддержкой 0.03

[175]:
```
result = fpgrowth(data, min_support=0.03, use_colnames = True)
result['length'] = result['itemsets'].apply(lambda x: len(x))
result
```

[175]:

	support	itemsets	length
0	0.082766	(citrus fruit)	1
1	0.058566	(margarine)	1
2	0.139502	(yogurt)	1
3	0.104931	(tropical fruit)	1
4	0.058058	(coffee)	1
..	...	...	...
58	0.033249	(whole milk, pastry)	2
59	0.047382	(root vegetables, other vegetables)	2
60	0.048907	(root vegetables, whole milk)	2
61	0.030605	(sausage, rolls/buns)	2
62	0.032232	(whipped/sour cream, whole milk)	2

[63 rows x 3 columns]

3. Определите минимальное и максимальное значение для уровня поддержки для набора из 1, 2 и тд объектов

[176]:
```
for l in range(1, result['length'].max() +  1):
    print(f"leng {l}: ",'[', result[result['length'] == l]['support'].min(), ';',
      result[result['length'] == l]['support'].max(), ']')
```

```
leng 1:  [ 0.03040162684290798 ; 0.25551601423487547 ]
leng 2:  [ 0.030096593797661414 ; 0.07483477376715811 ]
```

4. Проведем анализ, используя FPMax

[177]:
```
result = fpmax(data, min_support=0.03, use_colnames = True)
result['length'] = result['itemsets'].apply(lambda x: len(x))
result
```

[177]:

	support	itemsets	length
0	0.030402	(specialty chocolate)	1
1	0.031012	(onions)	1
2	0.032944	(hygiene articles)	1
3	0.033249	(berries)	1
4	0.033249	(hamburger meat)	1
5	0.033452	(UHT-milk)	1
6	0.033859	(sugar)	1
7	0.037112	(dessert)	1
8	0.037417	(long life bakery product)	1
9	0.037824	(salty snack)	1
10	0.038434	(waffles)	1
11	0.039654	(cream cheese)	1
12	0.042095	(white bread)	1
13	0.042908	(chicken)	1
14	0.048094	(frozen vegetables)	1
15	0.049619	(chocolate)	1

16	0.052364	(napkins)	1
17	0.052466	(beef)	1
18	0.053279	(curd)	1
19	0.055414	(butter)	1
20	0.057651	(pork)	1
21	0.058058	(coffee)	1
22	0.058566	(margarine)	1
23	0.058973	(frankfurter)	1
24	0.063447	(domestic eggs)	1
25	0.064870	(brown bread)	1
26	0.032232	(whipped/sour cream, whole milk)	2
27	0.072293	(fruit/vegetable juice)	1
28	0.030097	(pip fruit, whole milk)	2
29	0.077682	(canned beer)	1
30	0.079817	(newspapers)	1
31	0.080529	(bottled beer)	1
32	0.030503	(citrus fruit, whole milk)	2
33	0.033249	(whole milk, pastry)	2
34	0.030605	(sausage, rolls/buns)	2
35	0.098526	(shopping bags)	1
36	0.035892	(tropical fruit, other vegetables)	2
37	0.042298	(whole milk, tropical fruit)	2
38	0.047382	(root vegetables, other vegetables)	2
39	0.048907	(root vegetables, whole milk)	2
40	0.034367	(whole milk, bottled water)	2
41	0.034367	(rolls/buns, yogurt)	2
42	0.043416	(yogurt, other vegetables)	2
43	0.056024	(whole milk, yogurt)	2
44	0.032740	(other vegetables, soda)	2
45	0.038332	(rolls/buns, soda)	2
46	0.040061	(whole milk, soda)	2
47	0.042603	(rolls/buns, other vegetables)	2
48	0.056634	(whole milk, rolls/buns)	2
49	0.074835	(whole milk, other vegetables)	2

[178]:
```
for l in range(1, result['length'].max() +  1):
    print('[', result[result['length'] == l]['support'].min(), ';',
      result[result['length'] == l]['support'].max(), ']')
```

```
[ 0.03040162684290798 ; 0.09852567361464158 ]
[ 0.030096593797661414 ; 0.07483477376715811 ]
```

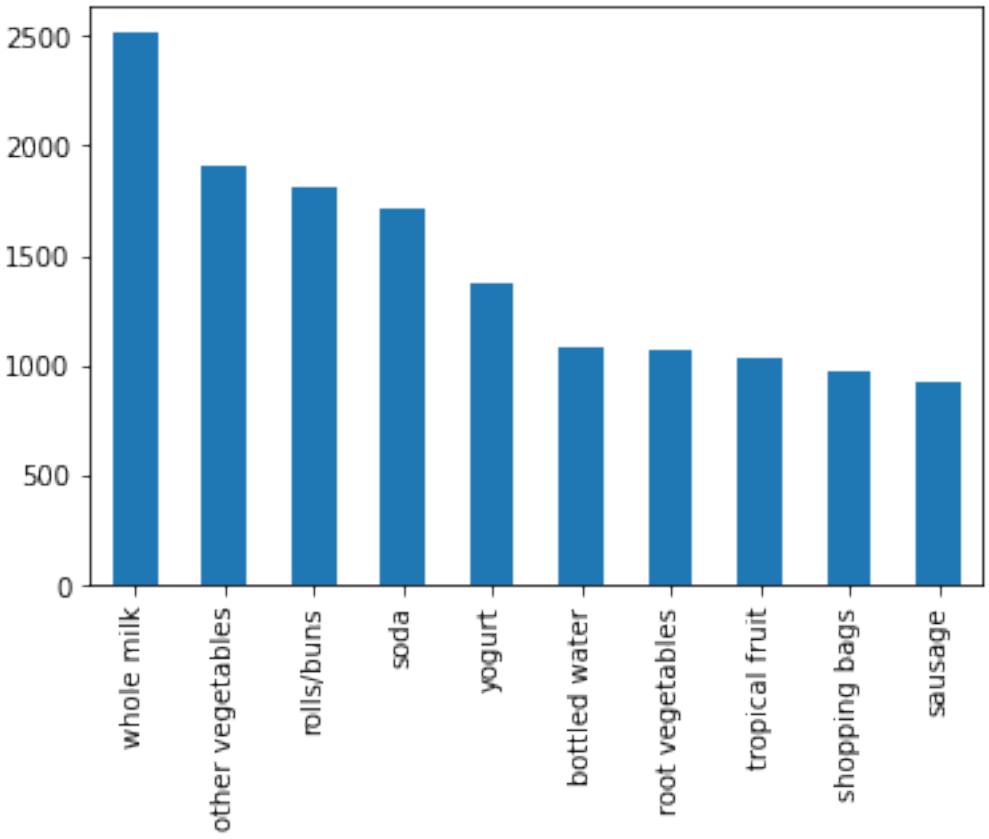
5. Сравнить результаты работы алгоритмов

FPMax в результате работы возвращает максимальные множества. Под максимальными подразумеваются такие, которые являются частыми и не существует таких множеств, в которые они входит и они также являются частыми.

6. Получим гистограмму для каждого товара (самые часто встречающиеся)

[179]:
```
data.sum().nlargest(10).plot.bar()
```

[179]: <AxesSubplot:>



7. Преобразуем набор данных, чтобы он содержал ограниченный набор товаров

[180]:
```
items = ['whole milk', 'yogurt', 'soda', 'tropical fruit', 'shopping bags',␣
 ↪'sausage',
        'whipped/sour cream', 'rolls/buns', 'other vegetables', 'root␣
 ↪vegetables',
        'pork', 'bottled water', 'pastry', 'citrus fruit', 'canned beer',␣
 ↪'bottled beer']
np_data = all_data.to_numpy()
np_data = [[elem for elem in row[1:] if isinstance(elem,str) and elem in items]␣
 ↪for row in np_data]
```

8. Проведем анализ обоих алгоритмов на этом наборе

[181]:
```
te = TransactionEncoder()
te_ary = te.fit(np_data).transform(np_data)
data = pd.DataFrame(te_ary, columns=te.columns_)
```

```
data.head()
```

[181]:

	bottled beer	bottled water	canned beer	citrus fruit	other vegetables	pastry	pork	rolls/buns	root vegetables	sausage	shopping bags	soda	tropical fruit	whipped/sour cream	whole milk	yogurt
0	False	False	False	True	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	True	False	False	True
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False	True	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	True
4	False	False	False	False	True	False	False	False	False	False	False	False	False	False	True	False

```
result = fpgrowth(data, min_support=0.03, use_colnames=True)
result['length'] = result['itemsets'].apply(lambda x: len(x))
result
```

[182]:

	support	itemsets	length
0	0.082766	(citrus fruit)	1
1	0.139502	(yogurt)	1
2	0.104931	(tropical fruit)	1
3	0.255516	(whole milk)	1
4	0.193493	(other vegetables)	1
5	0.183935	(rolls/buns)	1
6	0.080529	(bottled beer)	1
7	0.110524	(bottled water)	1
8	0.174377	(soda)	1
9	0.088968	(pastry)	1
10	0.108998	(root vegetables)	1
11	0.077682	(canned beer)	1
12	0.093950	(sausage)	1
13	0.098526	(shopping bags)	1
14	0.071683	(whipped/sour cream)	1
15	0.057651	(pork)	1
16	0.030503	(citrus fruit, whole milk)	2
17	0.056024	(whole milk, yogurt)	2
18	0.034367	(rolls/buns, yogurt)	2

```
19  0.043416          (yogurt, other vegetables)       2
20  0.035892   (tropical fruit, other vegetables)       2
21  0.042298         (whole milk, tropical fruit)       2
22  0.074835       (whole milk, other vegetables)       2
23  0.042603       (rolls/buns, other vegetables)       2
24  0.056634             (whole milk, rolls/buns)       2
25  0.034367          (whole milk, bottled water)       2
26  0.038332                    (rolls/buns, soda)       2
27  0.040061                    (whole milk, soda)       2
28  0.032740             (other vegetables, soda)       2
29  0.033249                 (whole milk, pastry)       2
30  0.047382  (root vegetables, other vegetables)       2
31  0.048907        (root vegetables, whole milk)       2
32  0.030605                (sausage, rolls/buns)       2
33  0.032232     (whipped/sour cream, whole milk)       2
```

[183]:
```
result = fpmax(data, min_support=0.03, use_colnames=True)
result['length'] = result['itemsets'].apply(lambda x: len(x))
result
```

[183]:
```
     support                           itemsets  length
0   0.057651                             (pork)       1
1   0.032232     (whipped/sour cream, whole milk)       2
2   0.077682                       (canned beer)       1
3   0.080529                      (bottled beer)       1
4   0.030503           (citrus fruit, whole milk)       2
5   0.033249                 (whole milk, pastry)       2
6   0.030605                (sausage, rolls/buns)       2
7   0.098526                      (shopping bags)       1
8   0.035892   (tropical fruit, other vegetables)       2
9   0.042298         (whole milk, tropical fruit)       2
10  0.047382  (root vegetables, other vegetables)       2
11  0.048907        (root vegetables, whole milk)       2
12  0.034367          (whole milk, bottled water)       2
13  0.034367                (rolls/buns, yogurt)       2
14  0.043416          (yogurt, other vegetables)       2
15  0.056024                (whole milk, yogurt)       2
16  0.032740             (other vegetables, soda)       2
17  0.038332                    (rolls/buns, soda)       2
18  0.040061                    (whole milk, soda)       2
19  0.042603       (rolls/buns, other vegetables)       2
20  0.056634             (whole milk, rolls/buns)       2
21  0.074835       (whole milk, other vegetables)       2
```

9. Построим графики изменения количества получаемых правил от уровня поддержки

[184]:
```
np_data = all_data.to_numpy()
np_data = [[elem for elem in row[1:] if isinstance(elem,str)] for row in np_data]

te = TransactionEncoder()
te_ary = te.fit(np_data).transform(np_data)
data = pd.DataFrame(te_ary, columns=te.columns_)
```

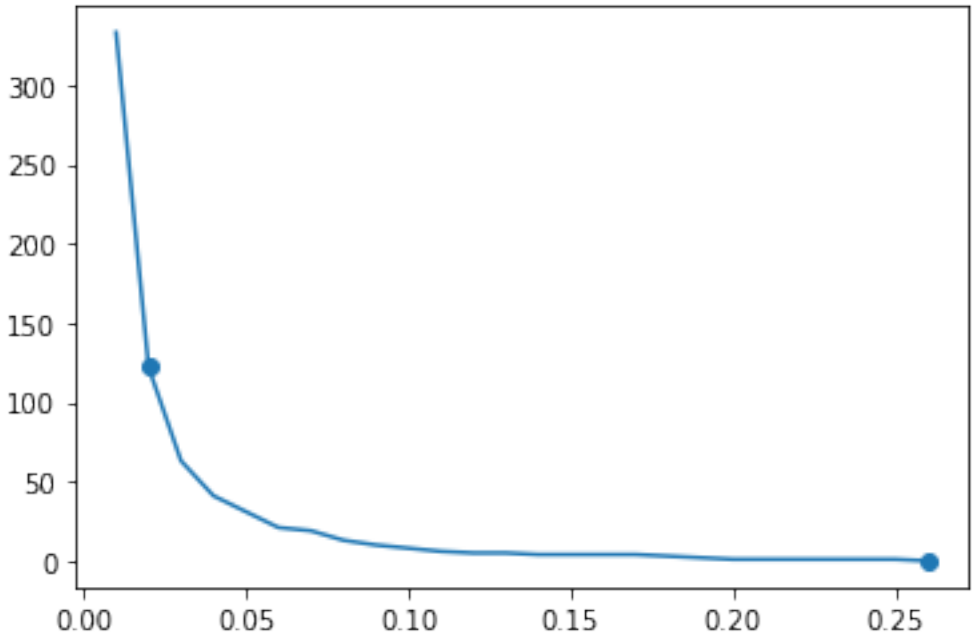
[185]:
```
import numpy as np
import matplotlib.pyplot as plt

support_range = np.arange(0.01, 1, 0.01)
count = pd.Series(dtype='float64')
border = pd.Series(dtype='float64')
k = None
for support in support_range:
    result = fpgrowth(data, min_support=support, use_colnames=True)
    count[support] = len(result)

    length = result['itemsets'].apply(lambda x: len(x))
    if k is None:
        k = length.max()
    else:
        while k > 0 and len(length[length == k] == 0):
            border[support] = len(result)
            k -= 1

    if count[support] == 0:
        border[support] = len(result)
        break

plt.scatter(border.index, border)
plt.plot(count.index, count)
plt.show()
```

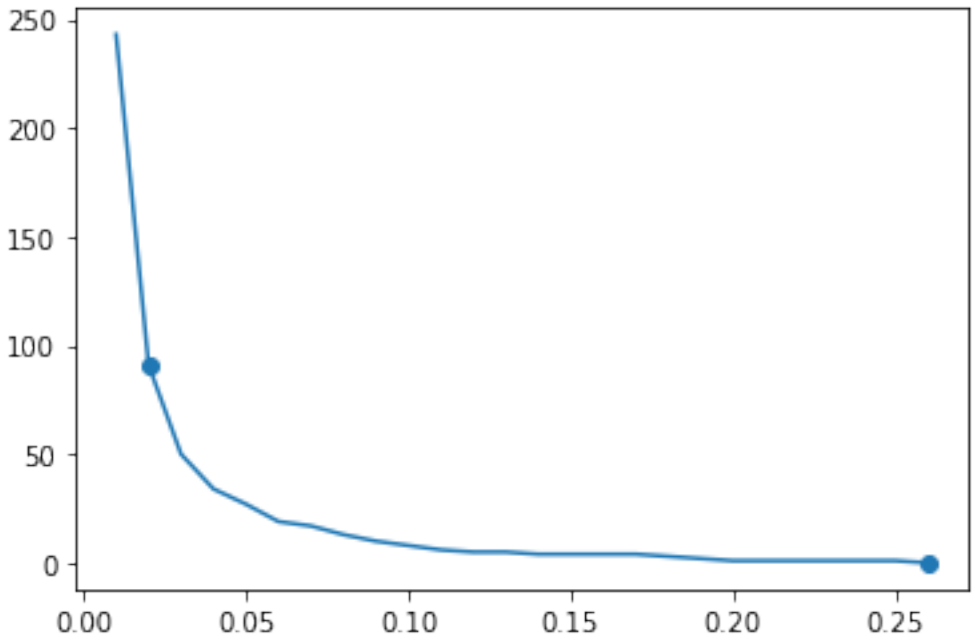


[186]:
```
support_range = np.arange(0.01, 1, 0.01)
count = pd.Series(dtype='float64')
border = pd.Series(dtype='float64')
k = None
for support in support_range:
    result = fpmax(data, min_support=support, use_colnames=True)
    count[support] = len(result)

    length = result['itemsets'].apply(lambda x: len(x))
    if k is None:
        k = length.max()
    else:
        while k > 0 and len(length[length == k] == 0):
            border[support] = len(result)
            k -= 1

    if count[support] == 0:
        border[support] = len(result)
        break

plt.scatter(border.index, border)
plt.plot(count.index, count)
plt.show()
```



1.3 Часть 3 Ассоциативные правила

1. Сформируем набор данных из определенных товаров так, чтобы размер транзакций был 2 и более

[187]:
```
np_data = all_data.to_numpy()
np_data = [[elem for elem in row[1:] if isinstance(elem, str) and elem in items]␣
 ↪for row in np_data]
np_data = [row for row in np_data if len(row) > 1]

te = TransactionEncoder()
te_ary = te.fit(np_data).transform(np_data)
data = pd.DataFrame(te_ary, columns=te.columns_)
```

2. Получим частоты наборов, используя алгоритм FPGrowth

[188]:
```
result = fpgrowth(data, min_support=0.05, use_colnames=True)
result
```

[188]:

	support	itemsets
0	0.241240	(yogurt)
1	0.185864	(tropical fruit)
2	0.421869	(whole milk)
3	0.335079	(other vegetables)
4	0.296214	(rolls/buns)
5	0.113371	(bottled beer)

```
6   0.185461                        (bottled water)
7   0.146395                         (citrus fruit)
8   0.267217                                (soda)
9   0.196335                      (root vegetables)
10  0.082763                          (canned beer)
11  0.167539                              (sausage)
12  0.166935                       (shopping bags)
13  0.124245                  (whipped/sour cream)
14  0.099476                                (pork)
15  0.150624                              (pastry)
16  0.110954                  (whole milk, yogurt)
17  0.054168                        (yogurt, soda)
18  0.068063                  (rolls/buns, yogurt)
19  0.085985            (yogurt, other vegetables)
20  0.057994              (tropical fruit, yogurt)
21  0.071083    (tropical fruit, other vegetables)
22  0.083770          (whole milk, tropical fruit)
23  0.148208        (whole milk, other vegetables)
24  0.084374        (rolls/buns, other vegetables)
25  0.112163             (whole milk, rolls/buns)
26  0.068063           (whole milk, bottled water)
27  0.057390                 (soda, bottled water)
28  0.060411            (citrus fruit, whole milk)
29  0.057189      (citrus fruit, other vegetables)
30  0.075916                  (rolls/buns, soda)
31  0.079340                  (whole milk, soda)
32  0.064841              (other vegetables, soda)
33  0.093838   (root vegetables, other vegetables)
34  0.096859         (root vegetables, whole milk)
35  0.051148             (root vegetables, yogurt)
36  0.060612                 (sausage, rolls/buns)
37  0.059203                 (sausage, whole milk)
38  0.053363           (sausage, other vegetables)
39  0.063834      (whipped/sour cream, whole milk)
40  0.057189  (whipped/sour cream, other vegetables)
41  0.065848                  (whole milk, pastry)
```

3. Проведем ассоциативный анализ

[189]:
```
from mlxtend.frequent_patterns import association_rules

rules = association_rules(result, min_threshold=0.3)
rules
```

[189]:
```
             antecedents         consequents  antecedent support  \
0               (yogurt)        (whole milk)            0.241240
1               (yogurt)  (other vegetables)            0.241240
```

2	(tropical fruit)	(yogurt)	0.185864
3	(tropical fruit)	(other vegetables)	0.185864
4	(tropical fruit)	(whole milk)	0.185864
5	(whole milk)	(other vegetables)	0.421869
6	(other vegetables)	(whole milk)	0.335079
7	(rolls/buns)	(whole milk)	0.296214
8	(bottled water)	(whole milk)	0.185461
9	(bottled water)	(soda)	0.185461
10	(citrus fruit)	(whole milk)	0.146395
11	(citrus fruit)	(other vegetables)	0.146395
12	(root vegetables)	(other vegetables)	0.196335
13	(root vegetables)	(whole milk)	0.196335
14	(sausage)	(rolls/buns)	0.167539
15	(sausage)	(whole milk)	0.167539
16	(sausage)	(other vegetables)	0.167539
17	(whipped/sour cream)	(whole milk)	0.124245
18	(whipped/sour cream)	(other vegetables)	0.124245
19	(pastry)	(whole milk)	0.150624

	consequent support	support	confidence	lift	leverage	conviction
0	0.421869	0.110954	0.459933	1.090228	0.009183	1.070481
1	0.335079	0.085985	0.356427	1.063713	0.005150	1.033172
2	0.241240	0.057994	0.312026	1.293423	0.013156	1.102890
3	0.335079	0.071083	0.382449	1.141370	0.008804	1.076706
4	0.421869	0.083770	0.450704	1.068352	0.005359	1.052495
5	0.335079	0.148208	0.351313	1.048449	0.006849	1.025026
6	0.421869	0.148208	0.442308	1.048449	0.006849	1.036649
7	0.421869	0.112163	0.378654	0.897564	-0.012801	0.930450
8	0.421869	0.068063	0.366992	0.869921	-0.010177	0.913309
9	0.267217	0.057390	0.309446	1.158033	0.007832	1.061153
10	0.421869	0.060411	0.412655	0.978159	-0.001349	0.984313
11	0.335079	0.057189	0.390646	1.165836	0.008135	1.091192
12	0.335079	0.093838	0.477949	1.426378	0.028050	1.273671
13	0.421869	0.096859	0.493333	1.169400	0.014031	1.141049
14	0.296214	0.060612	0.361779	1.221342	0.010985	1.102730
15	0.421869	0.059203	0.353365	0.837619	-0.011477	0.894062
16	0.335079	0.053363	0.318510	0.950552	-0.002776	0.975687
17	0.421869	0.063834	0.513776	1.217858	0.011419	1.189023
18	0.335079	0.057189	0.460292	1.373683	0.015557	1.232002
19	0.421869	0.065848	0.437166	1.036260	0.002304	1.027179

Что означает каждая колонка? - antecedents - первый член отношения - consequents - второй член отношения - antecedent support - поддержка первого члена отношения - consequent support - поддержка второго члена отношения - support - поддержка отношения - confidence - отношение поддержки отношения и поддержки первого члена - lift - отношение поддержки отношения и поддержки второго члена - leverage - разность поддержки отношения и поддержки членов, если бы они существовали раздельно - conviction - отношение обратной поддержки

второго члена и обратной поддержки отношения

4. На основании какой метрики проводился расчет? confidence
5. Провести анализ для различных метрик

[190]:
```
rules = association_rules(result, metric='lift', min_threshold = 1.1)
rules
```

[190]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(tropical fruit)	(yogurt)	0.185864	0.241240	0.057994	0.312026	1.293423	0.013156	1.102890
1	(yogurt)	(tropical fruit)	0.241240	0.185864	0.057994	0.240401	1.293423	0.013156	1.071797
2	(tropical fruit)	(other vegetables)	0.185864	0.335079	0.071083	0.382449	1.141370	0.008804	1.076706
3	(other vegetables)	(tropical fruit)	0.335079	0.185864	0.071083	0.212139	1.141370	0.008804	1.033351
4	(soda)	(bottled water)	0.267217	0.185461	0.057390	0.214770	1.158033	0.007832	1.037325
5	(bottled water)	(soda)	0.185461	0.267217	0.057390	0.309446	1.158033	0.007832	1.061153
6	(citrus fruit)	(other vegetables)	0.146395	0.335079	0.057189	0.390646	1.165836	0.008135	1.091192
7	(other vegetables)	(citrus fruit)	0.335079	0.146395	0.057189	0.170673	1.165836	0.008135	1.029274
8	(root vegetables)	(other vegetables)	0.196335	0.335079	0.093838	0.477949	1.426378	0.028050	1.273671
9	(other vegetables)	(root vegetables)	0.335079	0.196335	0.093838	0.280048	1.426378	0.028050	1.116276
10	(root vegetables)	(whole milk)	0.196335	0.421869	0.096859	0.493333	1.169400	0.014031	1.141049
11	(whole milk)	(root vegetables)	0.421869	0.196335	0.096859	0.229594	1.169400	0.014031	1.043171
12	(sausage)	(rolls/buns)	0.167539	0.296214	0.060612	0.361779	1.221342	0.010985	1.102730
13	(rolls/buns)	(sausage)	0.296214	0.167539	0.060612	0.204623	1.221342	0.010985	1.046624
14	(whipped/sour cream)	(whole milk)	0.124245	0.421869	0.063834	0.513776	1.217858	0.011419	1.189023
15	(whole milk)	(whipped/sour cream)	0.421869	0.124245	0.063834	0.151313	1.217858	0.011419	1.031894
16	(whipped/sour cream)	(other vegetables)	0.124245	0.335079	0.057189	0.460292	1.373683	0.015557	1.232002
17	(other vegetables)	(whipped/sour cream)	0.335079	0.124245	0.057189	0.170673	1.373683	0.015557	1.055983

[191]:
```
rules = association_rules(result, metric='support', min_threshold = 0.08)
rules
```

[191]:

	antecedents	consequents	antecedent support	\
0	(whole milk)	(yogurt)	0.421869	
1	(yogurt)	(whole milk)	0.241240	
2	(yogurt)	(other vegetables)	0.241240	
3	(other vegetables)	(yogurt)	0.335079	
4	(whole milk)	(tropical fruit)	0.421869	
5	(tropical fruit)	(whole milk)	0.185864	
6	(whole milk)	(other vegetables)	0.421869	
7	(other vegetables)	(whole milk)	0.335079	
8	(rolls/buns)	(other vegetables)	0.296214	
9	(other vegetables)	(rolls/buns)	0.335079	
10	(whole milk)	(rolls/buns)	0.421869	
11	(rolls/buns)	(whole milk)	0.296214	
12	(root vegetables)	(other vegetables)	0.196335	
13	(other vegetables)	(root vegetables)	0.335079	
14	(root vegetables)	(whole milk)	0.196335	
15	(whole milk)	(root vegetables)	0.421869	

	consequent support	support	confidence	lift	leverage	conviction
0	0.241240	0.110954	0.263007	1.090228	0.009183	1.029535
1	0.421869	0.110954	0.459933	1.090228	0.009183	1.070481
2	0.335079	0.085985	0.356427	1.063713	0.005150	1.033172
3	0.241240	0.085985	0.256611	1.063713	0.005150	1.020676
4	0.185864	0.083770	0.198568	1.068352	0.005359	1.015852
5	0.421869	0.083770	0.450704	1.068352	0.005359	1.052495
6	0.335079	0.148208	0.351313	1.048449	0.006849	1.025026
7	0.421869	0.148208	0.442308	1.048449	0.006849	1.036649
8	0.335079	0.084374	0.284840	0.850070	-0.014881	0.929752
9	0.296214	0.084374	0.251803	0.850070	-0.014881	0.940642
10	0.296214	0.112163	0.265871	0.897564	-0.012801	0.958668
11	0.421869	0.112163	0.378654	0.897564	-0.012801	0.930450
12	0.335079	0.093838	0.477949	1.426378	0.028050	1.273671
13	0.196335	0.093838	0.280048	1.426378	0.028050	1.116276
14	0.421869	0.096859	0.493333	1.169400	0.014031	1.141049
15	0.196335	0.096859	0.229594	1.169400	0.014031	1.043171

[192]:
```
rules = association_rules(result, metric='confidence', min_threshold = 0.3)
rules
```

[192]:

	antecedents	consequents	antecedent support	\
0	(yogurt)	(whole milk)	0.241240	
1	(yogurt)	(other vegetables)	0.241240	
2	(tropical fruit)	(yogurt)	0.185864	
3	(tropical fruit)	(other vegetables)	0.185864	

4	(tropical fruit)	(whole milk)	0.185864
5	(whole milk)	(other vegetables)	0.421869
6	(other vegetables)	(whole milk)	0.335079
7	(rolls/buns)	(whole milk)	0.296214
8	(bottled water)	(whole milk)	0.185461
9	(bottled water)	(soda)	0.185461
10	(citrus fruit)	(whole milk)	0.146395
11	(citrus fruit)	(other vegetables)	0.146395
12	(root vegetables)	(other vegetables)	0.196335
13	(root vegetables)	(whole milk)	0.196335
14	(sausage)	(rolls/buns)	0.167539
15	(sausage)	(whole milk)	0.167539
16	(sausage)	(other vegetables)	0.167539
17	(whipped/sour cream)	(whole milk)	0.124245
18	(whipped/sour cream)	(other vegetables)	0.124245
19	(pastry)	(whole milk)	0.150624

	consequent support	support	confidence	lift	leverage	conviction
0	0.421869	0.110954	0.459933	1.090228	0.009183	1.070481
1	0.335079	0.085985	0.356427	1.063713	0.005150	1.033172
2	0.241240	0.057994	0.312026	1.293423	0.013156	1.102890
3	0.335079	0.071083	0.382449	1.141370	0.008804	1.076706
4	0.421869	0.083770	0.450704	1.068352	0.005359	1.052495
5	0.335079	0.148208	0.351313	1.048449	0.006849	1.025026
6	0.421869	0.148208	0.442308	1.048449	0.006849	1.036649
7	0.421869	0.112163	0.378654	0.897564	-0.012801	0.930450
8	0.421869	0.068063	0.366992	0.869921	-0.010177	0.913309
9	0.267217	0.057390	0.309446	1.158033	0.007832	1.061153
10	0.421869	0.060411	0.412655	0.978159	-0.001349	0.984313
11	0.335079	0.057189	0.390646	1.165836	0.008135	1.091192
12	0.335079	0.093838	0.477949	1.426378	0.028050	1.273671
13	0.421869	0.096859	0.493333	1.169400	0.014031	1.141049
14	0.296214	0.060612	0.361779	1.221342	0.010985	1.102730
15	0.421869	0.059203	0.353365	0.837619	-0.011477	0.894062
16	0.335079	0.053363	0.318510	0.950552	-0.002776	0.975687
17	0.421869	0.063834	0.513776	1.217858	0.011419	1.189023
18	0.335079	0.057189	0.460292	1.373683	0.015557	1.232002
19	0.421869	0.065848	0.437166	1.036260	0.002304	1.027179

Смысл метрик: - support - самое частое правило - lift - насколько часто можно встретить это правило во всех наборах, где есть второй член правила - confidence - насколько часто можно встретить это правило во всех наборах, где есть первый член правила

7. Построим граф для следующего анализа

[193]:
```
rules = association_rules(result, min_threshold = 0.4, metric='confidence')
```

```
rules["antecedents"] = rules["antecedents"].apply(lambda x: list(x)[0]).
 ↪astype("unicode")
rules["consequents"] = rules["consequents"].apply(lambda x: list(x)[0]).
 ↪astype("unicode")

rules
```

[193]:

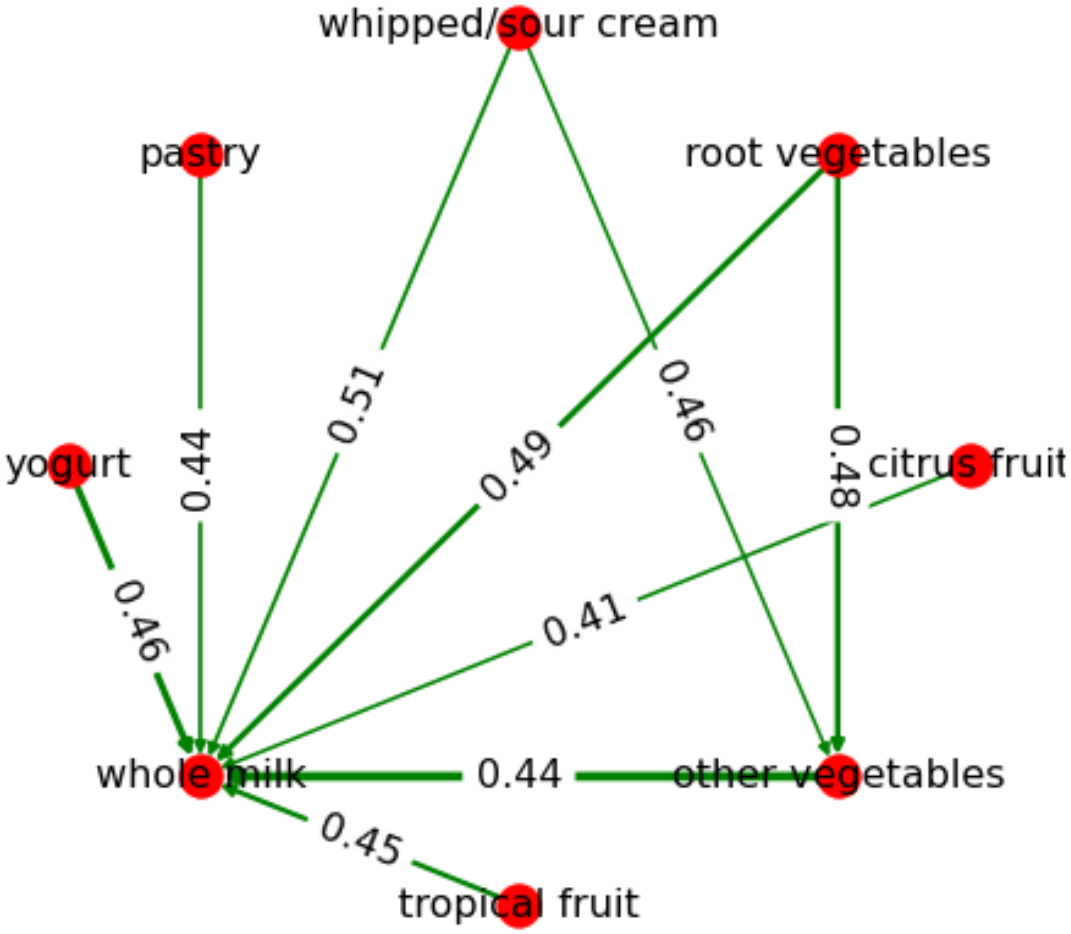
	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	yogurt	whole milk	0.241240	0.421869	0.110954	0.459933	1.090228	0.009183	1.070481
1	tropical fruit	whole milk	0.185864	0.421869	0.083770	0.450704	1.068352	0.005359	1.052495
2	other vegetables	whole milk	0.335079	0.421869	0.148208	0.442308	1.048449	0.006849	1.036649
3	citrus fruit	whole milk	0.146395	0.421869	0.060411	0.412655	0.978159	-0.001349	0.984313
4	root vegetables	other vegetables	0.196335	0.335079	0.093838	0.477949	1.426378	0.028050	1.273671
5	root vegetables	whole milk	0.196335	0.421869	0.096859	0.493333	1.169400	0.014031	1.141049
6	whipped/sour cream	whole milk	0.124245	0.421869	0.063834	0.513776	1.217858	0.011419	1.189023
7	whipped/sour cream	other vegetables	0.124245	0.335079	0.057189	0.460292	1.373683	0.015557	1.232002
8	pastry	whole milk	0.150624	0.421869	0.065848	0.437166	1.036260	0.002304	1.027179

[194]:
```
import networkx as nx
from matplotlib.pyplot import figure

G = nx.from_pandas_edgelist(rules, 'antecedents', 'consequents', ['confidence',␣
 ↪'support'], create_using=nx.DiGraph())

labels = {}
for u, v, data in G.edges(data=True):
    labels[(u, v)] = round(data['confidence'], 2)

figure(figsize=(8, 8))
pos = nx.shell_layout(G)
nx.draw_networkx_edge_labels(G, pos, edge_labels=labels, font_size=16,␣
 ↪font_color='black')
nx.draw_networkx_labels(G, pos, font_size=16, font_color='black')
nx.draw(G, pos, arrows=True, width=rules['support'] * 25, node_color='red',␣
 ↪edge_color='green')
```



8. Какую информацию из него можно извлечь? На данном графике, к примеру, видно, какие объекты входят в наибольшее количество правил, какое правило является самым сильным