

Homework 3

October 3, 2024

0.0.1 Homework 3 - Emma Brown - 9/27/24

Christian helped me on question 2. He showed me how to apply the lambda function to the code to help pair down the output.

0.0.2 Homework Questions

```
[3]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os

import dhs_util
from dhs_util import *

os.chdir('/Users/emmabrown/Downloads/DS-Unit 1/')
df = pd.read_csv('dhs_service_records_synthesized_final copy.csv')

df = dhs_preprocessing(df)
df, service_map = add_service_label(df)
df = add_age_bin(df)

recipient = get_recipient_attribute(df)
```

```
[4]: import mlxtend
```

```
[5]: from mlxtend.preprocessing import TransactionEncoder
from mlxtend.preprocessing import *
from mlxtend.frequent_patterns import association_rules
from mlxtend.frequent_patterns import fpgrowth
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import fpmax
from mlxtend.frequent_patterns import hmine
```

```
[6]: serv_list = []
for groups in df.groupby('id').groups.values():
    serv_list.append(df.loc[groups]['serv'].tolist())
```

```
# following the tutorial example
def oneHotCoding(serv_list):
    te = TransactionEncoder()
    te_ary = te.fit(serv_list).transform(serv_list)
    te_df = pd.DataFrame(te_ary, columns=te.columns_)
    return te_df

serv_oneHot = oneHotCoding(serv_list)
```

```
[7]: def get_id_service_matrix(df):
    df_temp = df.groupby(["id", "serv"]).agg(
        num_serv = ('service', 'nunique')
    ).reset_index()
    df_serv = df_temp.pivot_table(
        values='num_serv', index=["id"],
        columns="serv", aggfunc=np.sum
    ).reset_index()
    return df_serv
```

```
[8]: df_id_serv = get_id_service_matrix(df)
df_id_serv.iloc[:,1:23] = df_id_serv.iloc[:,1:23] > 0
```

Number 1 - Frequent itemsets Extract service itemsets that have support greater than 0.01 using apriori.

Extract service itemsets that have support greater than 0.0001 using fpgrowth.

Extract service itemsets that have support greater than 0.0001 using hmine.

```
[10]: apriori(df_id_serv.iloc[:,1:23], use_colnames=True, min_support=0.01)\
    .sort_values(by="support", ascending=False)
```

```
[10]:
```

	support	itemsets
4	0.941422	(S12)
2	0.153844	(S09)
14	0.139131	(S12, S09)
15	0.103528	(S14, S09)
6	0.103528	(S14)
25	0.094436	(S12, S14, S09)
20	0.094436	(S12, S14)
3	0.040882	(S11)
18	0.032106	(S12, S11)
10	0.031396	(S19)
7	0.024002	(S15)
21	0.022561	(S12, S15)
16	0.019431	(S15, S09)
13	0.018307	(S09, S11)

26	0.018280	(S12, S15, S09)
24	0.016508	(S12, S09, S11)
0	0.013687	(S03)
9	0.013573	(S18)
17	0.013468	(S09, S18)
23	0.013460	(S14, S18)
28	0.013460	(S14, S09, S18)
11	0.013260	(S21)
8	0.012967	(S17)
1	0.012649	(S05)
12	0.012284	(S12, S03)
5	0.011915	(S13)
19	0.011448	(S12, S13)
22	0.010384	(S12, S18)
27	0.010285	(S12, S09, S18)
29	0.010277	(S12, S14, S18)
30	0.010277	(S12, S14, S09, S18)

```
[11]: fpgrowth(df_id_serv.iloc[:,1:23], use_colnames=True, min_support=0.0001)\
      .sort_values(by="support", ascending=False)
```

	support	itemsets
0	0.941422	(S12)
1	0.153844	(S09)
22	0.139131	(S12, S09)
3	0.103528	(S14)
30	0.103528	(S14, S09)
..
218	0.000101	(S12, S09, S21, S16, S18)
505	0.000101	(S15, S06, S12, S14, S09, S11)
504	0.000101	(S15, S06, S12, S14, S21, S11)
219	0.000101	(S12, S14, S21, S16, S18)
502	0.000101	(S15, S06, S12, S14, S11)

[935 rows x 2 columns]

```
[12]: hmine(df_id_serv.iloc[:,1:23], use_colnames=True, min_support=0.0001)\
      .sort_values(by="support", ascending=False)
```

	support	itemsets
784	0.941422	(S12)
458	0.153844	(S09)
548	0.139131	(S12, S09)
633	0.103528	(S14, S09)
872	0.103528	(S14)
..
479	0.000101	(S09, S17, S10)

```

379  0.000101          (S07, S10)
380  0.000101      (S07, S11, S10)
715  0.000101          (S19, S10)
815  0.000101  (S12, S14, S21, S16, S18)

```

[935 rows x 2 columns]

Make observations of the difference between them.

The three of these all give you the same support numbers and itemsets in order, but their indices are different. Apriori also only gives you 31 values whereas fpgrowth and hmine give you 935.

```
[14]: fpmix(df_id_serv.iloc[:,1:23], use_colnames=True, min_support=0.0001)\
      .sort_values(by="support", ascending=False)
```

```
[14]:      support      itemsets
56  0.000326  (S15, S12, S14, S09, S17, S18)
1   0.000305      (S12, S01)
34  0.000253  (S07, S12, S14, S09, S16, S11, S18)
63  0.000247      (S12, S14, S09, S19, S11)
11  0.000223  (S02, S12, S14, S09, S03, S18)
..   ...
16  0.000101      (S07, S11, S10)
15  0.000101      (S19, S10)
29  0.000101  (S15, S06, S12, S14, S09, S21, S11)
17  0.000101      (S09, S17, S10)
40  0.000101  (S12, S14, S09, S21, S16, S18)

```

[64 rows x 2 columns]

Make observations between fpmix and others.

fpmix gives you completely different support and itemsets. Their supports start a lot lower than apriori, fpgrowth and hmine. fpmix contains more rows than apriori, but significantly less than fpgrowth and hmine.

Number 2 - Frequent itemsets with length (size of the itemsets) Extract length-1 service itemsets that have support greater than 0.01 using apriori.

Extract length-2 service itemsets that have support greater than 0.005 using hmine.

Extract length-5 service itemsets that have support greater than 0.0001 using fpmix.

I used the 'iloc' command to "grab" the first 12 rows of data because the function listed the results in increasing lengths of itemsets. I printed out all of ext_apr_1 and used this observation to grab the rows I needed.

```
[18]: ext_apr_1 = apriori(serv_oneHot,min_support=0.01,use_colnames=True)
      ext_apr_1.iloc[0:12, :]
```

```
[18]:      support  itemsets
0    0.013687    (S03)
1    0.012649    (S05)
2    0.153844    (S09)
3    0.040882    (S11)
4    0.941422    (S12)
5    0.011915    (S13)
6    0.103528    (S14)
7    0.024002    (S15)
8    0.012967    (S17)
9    0.013573    (S18)
10   0.031396    (S19)
11   0.013260    (S21)
```

```
[19]: ext_hmine = hmine(serv_oneHot, min_support=0.005, use_colnames=True)
ext_hmine_2 = ext_hmine[ext_hmine['itemsets'].apply(lambda x: len(x)==2)]
ext_hmine_2
```

```
[19]:      support      itemsets
1    0.005274  (S03, S09)
3    0.012284  (S12, S03)
5    0.008057  (S12, S05)
8    0.006398  (S07, S11)
10   0.005105  (S12, S07)
12   0.018307  (S09, S11)
16   0.139131  (S12, S09)
27   0.008419  (S09, S13)
28   0.103528  (S14, S09)
32   0.019431  (S15, S09)
33   0.009372  (S16, S09)
34   0.006731  (S09, S17)
35   0.013468  (S09, S18)
36   0.005268  (S19, S09)
37   0.007949  (S21, S09)
39   0.005238  (S12, S10)
41   0.032106  (S12, S11)
43   0.009374  (S14, S11)
45   0.011448  (S12, S13)
46   0.094436  (S12, S14)
50   0.022561  (S12, S15)
51   0.00683   (S12, S16)
52   0.008674  (S12, S17)
53   0.010384  (S12, S18)
54   0.009949  (S12, S19)
55   0.008848  (S12, S21)
58   0.009888  (S14, S15)
59   0.009371  (S14, S16)
```

60 0.01346 (S14, S18)

```
[20]: ext_fpmax = fpmax(serv_oneHot, min_support=0.0001, use_colnames=True)
ext_fpmax_5 = ext_fpmax[ext_fpmax['itemsets'].apply(lambda x: len(x)==5)]
ext_fpmax_5
```

```
[20]:
```

	support	itemsets
4	0.000131	(S12, S14, S09, S04, S03)
18	0.000163	(S12, S14, S09, S10, S18)
19	0.000157	(S06, S12, S09, S21, S10)
21	0.000124	(S15, S12, S09, S21, S10)
22	0.000208	(S15, S12, S14, S09, S10)
23	0.000139	(S12, S14, S09, S21, S10)
24	0.000197	(S12, S14, S09, S10, S11)
25	0.000103	(S06, S14, S09, S21, S16)
31	0.000103	(S07, S12, S09, S19, S11)
33	0.000120	(S07, S12, S09, S03, S11)
37	0.000131	(S14, S09, S19, S16, S18)
38	0.000142	(S12, S14, S09, S19, S16)
45	0.000120	(S12, S14, S09, S03, S13)
46	0.000111	(S12, S14, S09, S17, S13)
47	0.000150	(S15, S12, S14, S09, S13)
49	0.000150	(S12, S14, S09, S13, S11)
50	0.000111	(S12, S14, S09, S05, S18)
53	0.000109	(S12, S09, S21, S17, S11)
61	0.000204	(S12, S14, S09, S19, S18)
62	0.000169	(S15, S12, S14, S09, S19)
63	0.000247	(S12, S14, S09, S19, S11)

Number 3 - Association Rules Extract association rules that have lift greater than 0.5, using itemsets from fpgrowth with support greater than 0.05.

Extract association rules that have support greater than 0.0003, using itemsets from fpmax with support greater than 0.0001.

```
[22]: def serv_rules(freq_itemsets, metrics, threshold):
        asso_rules = association_rules(freq_itemsets, metric=metrics,
        ↪ min_threshold=threshold)
        return asso_rules.sort_values(by='lift', ascending=False)[['antecedents',
        ↪ 'consequents', 'support', 'confidence', 'lift']]
```

```
[23]: min_freq = 1000 # if we want to set threshold by frequency of the itemsets
min_support = min_freq/serv_oneHot.shape[0]
min_confidence = 0.6
min_rule_support = 0.2
min_lift = 0.15
```

```
[24]: freq_itemset_fpgrowth =   
      ↪ fpgrowth(serv_oneHot,min_support=min_support,use_colnames=True)
```

```
[25]: rule_fpgrowth = serv_rules(freq_itemset_fpgrowth,"support",0.05)
```

```
[26]: rule_fpgrowth[rule_fpgrowth['lift'].apply(lambda x: x>0.5)]
```

```
[26]:
```

	antecedents	consequents	support	confidence	lift
7	(S12, S09)	(S14)	0.094436	0.678758	6.556292
10	(S14)	(S12, S09)	0.094436	0.912184	6.556292
2	(S14)	(S09)	0.103528	1.000000	6.500073
3	(S09)	(S14)	0.103528	0.672938	6.500073
6	(S12, S14)	(S09)	0.094436	1.000000	6.500073
11	(S09)	(S12, S14)	0.094436	0.613843	6.500073
4	(S12)	(S14)	0.094436	0.100312	0.968942
5	(S14)	(S12)	0.094436	0.912184	0.968942
8	(S14, S09)	(S12)	0.094436	0.912184	0.968942
9	(S12)	(S14, S09)	0.094436	0.100312	0.968942
0	(S12)	(S09)	0.139131	0.147788	0.960634
1	(S09)	(S12)	0.139131	0.904362	0.960634

```
[27]: freq_itemset_fpmax = fpmax(serv_oneHot,min_support=0.0001, use_colnames=True)
```

```
[28]: asso_rules = association_rules(freq_itemset_fpmax, metric='lift',   
      ↪ min_threshold=0.0003, support_only=True)   
      asso_rules.sort_values(by='lift', ascending=False)[['antecedents',   
      ↪ 'consequents', 'support', 'confidence', 'lift']]
```

```
[28]:
```

	antecedents	consequents	support	\
0	(S12)	(S01)	0.000305	
1	(S01)	(S12)	0.000305	
2	(S15, S12, S14, S09, S17)	(S18)	0.000326	
3	(S15, S12, S14, S09, S18)	(S17)	0.000326	
4	(S15, S12, S14, S17, S18)	(S09)	0.000326	
..	
59	(S12)	(S15, S14, S09, S17, S18)	0.000326	
60	(S14)	(S15, S12, S09, S17, S18)	0.000326	
61	(S09)	(S15, S12, S14, S17, S18)	0.000326	
62	(S17)	(S15, S12, S14, S09, S18)	0.000326	
63	(S18)	(S15, S12, S14, S09, S17)	0.000326	

	confidence	lift
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

```

..      ...  ...
59      NaN  NaN
60      NaN  NaN
61      NaN  NaN
62      NaN  NaN
63      NaN  NaN

```

[64 rows x 5 columns]

Number 4 - Make Predictions (draw conclusion) If you were to make suggestions for DHS to consider increase the offering of one service, say, “Families_ Receiving_ Child_ Welfare_ Services” (S06), what other services would you suggest to offer together with?

Run `predict({'S06'}, rules, consequents_only=False)`, with rules generated from different thresholds and algorithms.

```

[30]: asso_rules = association_rules(freq_itemset_fpmix, metric='lift',
    ↪ min_threshold=0.000001, support_only=True)
    asso_rules.sort_values(by='lift', ascending=False)[['antecedents',
    ↪ 'consequents', 'support', 'confidence', 'lift']]

```

```

[30]:      antecedents      consequents      support      confidence      lift
0      (S12)      (S08)  0.000199      NaN      NaN
1      (S08)      (S12)  0.000199      NaN      NaN
2      (S12)      (S01)  0.000305      NaN      NaN
3      (S01)      (S12)  0.000305      NaN      NaN
4      (S12)      (S22)  0.000124      NaN      NaN
...
2455      (S12)  (S14, S19, S09, S11)  0.000247      NaN      NaN
2456      (S14)  (S12, S19, S09, S11)  0.000247      NaN      NaN
2457      (S09)  (S12, S14, S19, S11)  0.000247      NaN      NaN
2458      (S19)  (S12, S14, S09, S11)  0.000247      NaN      NaN
2459      (S11)  (S12, S14, S19, S09)  0.000247      NaN      NaN

```

[2460 rows x 5 columns]

```

[31]: def predict(antecedent, rules, consequents_only = False):
    # get the rules for this antecedent
    preds = rules[rules['antecedents'] == antecedent]
    if consequents_only:
        # a way to convert a frozen set with one element to string
        preds = preds['consequents'].apply(iter).apply(next)
    return preds

```

```

[32]: predict({'S06'}, asso_rules, consequents_only=False)

```



```
[32]:
```

	antecedents	consequents	antecedent support	\
399	(S06)	(S12, S21, S09, S10)	NaN	
563	(S06)	(S14, S21, S16, S09)	NaN	
624	(S06)	(S12, S14, S09, S21, S18)	NaN	
686	(S06)	(S12, S14, S09, S21, S17)	NaN	
749	(S06)	(S15, S12, S09, S21, S17)	NaN	
874	(S06)	(S15, S12, S14, S09, S21, S11)	NaN	

	consequent support	support	confidence	lift	leverage	conviction	\
399	NaN	0.000157	NaN	NaN	NaN	NaN	
563	NaN	0.000103	NaN	NaN	NaN	NaN	
624	NaN	0.000146	NaN	NaN	NaN	NaN	
686	NaN	0.000105	NaN	NaN	NaN	NaN	
749	NaN	0.000114	NaN	NaN	NaN	NaN	
874	NaN	0.000101	NaN	NaN	NaN	NaN	

	zhangs_metric
399	NaN
563	NaN
624	NaN
686	NaN
749	NaN
874	NaN

Based on the above table, if DHS was considering increasing the offering of “Families_Receiving_Child_Welfare_Services” I would suggest they also offer support in the areas of “Income_Support” (S12) and “Individuals_Receiving_Mental_Health_Services”(S14) (also S09 and S21, but these are already accounted for in S06).

```
[34]: asso_rules = association_rules(freq_itemset_fpmax, metric='lift',
    ↪min_threshold=0.0002, support_only=True)
asso_rules.sort_values(by='lift', ascending=False)[['antecedents',
    ↪'consequents', 'support', 'confidence', 'lift']]
```

```
[34]:
```

	antecedents	consequents	support	confidence	\
0	(S12)	(S01)	0.000305	NaN	
1	(S01)	(S12)	0.000305	NaN	
2	(S02, S12, S14, S09, S03)	(S18)	0.000223	NaN	
3	(S02, S12, S14, S09, S18)	(S03)	0.000223	NaN	
4	(S02, S12, S14, S03, S18)	(S09)	0.000223	NaN	
..	
587	(S12)	(S14, S19, S09, S11)	0.000247	NaN	
588	(S14)	(S12, S19, S09, S11)	0.000247	NaN	
589	(S09)	(S12, S14, S19, S11)	0.000247	NaN	
590	(S19)	(S12, S14, S09, S11)	0.000247	NaN	
591	(S11)	(S12, S14, S19, S09)	0.000247	NaN	

lift

```

0      NaN
1      NaN
2      NaN
3      NaN
4      NaN
..     ...
587    NaN
588    NaN
589    NaN
590    NaN
591    NaN

```

[592 rows x 5 columns]

```
[35]: predict({'S14'}, asso_rules, consequents_only=False)
```

```
[35]:
```

	antecedents	consequents	antecedent support	\
60	(S14)	(S02, S12, S09, S03, S18)		NaN
91	(S14)	(S12, S15, S09, S10)		NaN
215	(S14)	(S07, S12, S09, S16, S11, S18)		NaN
342	(S14)	(S15, S07, S12, S09, S11, S18)		NaN
404	(S14)	(S15, S12, S09, S21, S17)		NaN
466	(S14)	(S15, S12, S09, S17, S18)		NaN
528	(S14)	(S15, S12, S09, S21, S18)		NaN
558	(S14)	(S12, S19, S09, S18)		NaN
588	(S14)	(S12, S19, S09, S11)		NaN

	consequent support	support	confidence	lift	leverage	conviction	\
60	NaN	0.000223	NaN	NaN	NaN	NaN	
91	NaN	0.000208	NaN	NaN	NaN	NaN	
215	NaN	0.000253	NaN	NaN	NaN	NaN	
342	NaN	0.000223	NaN	NaN	NaN	NaN	
404	NaN	0.000210	NaN	NaN	NaN	NaN	
466	NaN	0.000326	NaN	NaN	NaN	NaN	
528	NaN	0.000210	NaN	NaN	NaN	NaN	
558	NaN	0.000204	NaN	NaN	NaN	NaN	
588	NaN	0.000247	NaN	NaN	NaN	NaN	

	zhangs_metric
60	NaN
91	NaN
215	NaN
342	NaN
404	NaN
466	NaN
528	NaN
558	NaN

Based on the above table, if DHS was considering increasing the offering of “Individuals_Receiving_Mental_Health_Services” I would suggest they also offer support in the areas of “Income_Support” (S12), “Mental_Health_Crisis” (S18), and “Individuals_Receiving_Substance_Use_Disorder_Services” (S15).