D212_DataMiningII_PA3_JWillis

January 8, 2023

0.1 D212 - Data Mining II - PA3

0.1.1 Background Info:

One of the most critical factors in patient relationship management that directly affects a hospital's long-term cost effectiveness is understanding its patients and the conditions leading to hospital admissions. When a hospital can better understand its patients' characteristics, it is better able to target treatment to patients, resulting in more effective cost of care for the hospital in the long term.

You are an analyst for a hospital that wants to better understand the characteristics of its patients. You have been asked to perform a market basket analysis to analyze patient data to identify key associations of your patients, ultimately allowing better business and strategic decision-making for the hospital.

Question: Can we ascertain the probability of certain medications (consequents) given a medication (antecedent) for our patients?

0.1.2 Import Libraries

[27]:
```
import pandas as pd
from pandas import DataFrame
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
import matplotlib.pyplot as plt
%matplotlib inline
```

0.1.3 Load Data From medical_clean.csv

[28]:
```
# File Open Dialog
#from tkinter.filedialog import askopenfilename
#df = pd.read_csv(askopenfilename())
```

[29]:
```
# load data file
df = pd.read_csv('./medical_market_basket.csv')
```

```python
# quick test the data is present and see the shape
df.head(5)
```

[29]:

```
      Presc01            Presc02                      Presc03       Presc04  \
0         NaN                NaN                          NaN           NaN
1  amlodipine  albuterol aerosol                  allopurinol  pantoprazole
2         NaN                NaN                          NaN           NaN
3  citalopram            benicar  amphetamine salt combo xr           NaN
4         NaN                NaN                          NaN           NaN

     Presc05     Presc06     Presc07      Presc08     Presc09      Presc10  \
0        NaN         NaN         NaN          NaN         NaN          NaN
1  lorazepam  omeprazole  mometasone  fluconozole  gabapentin  pravastatin
2        NaN         NaN         NaN          NaN         NaN          NaN
3        NaN         NaN         NaN          NaN         NaN          NaN
4        NaN         NaN         NaN          NaN         NaN          NaN

  Presc11   Presc12                  Presc13           Presc14  Presc15  \
0     NaN       NaN                      NaN               NaN      NaN
1  cialis  losartan  metoprolol succinate XL  sulfamethoxazole  abilify
2     NaN       NaN                      NaN               NaN      NaN
3     NaN       NaN                      NaN               NaN      NaN
4     NaN       NaN                      NaN               NaN      NaN

          Presc16        Presc17       Presc18       Presc19    Presc20
0             NaN            NaN           NaN           NaN        NaN
1  spironolactone  albuterol HFA  levofloxacin  promethazine  glipizide
2             NaN            NaN           NaN           NaN        NaN
3             NaN            NaN           NaN           NaN        NaN
4             NaN            NaN           NaN           NaN        NaN
```

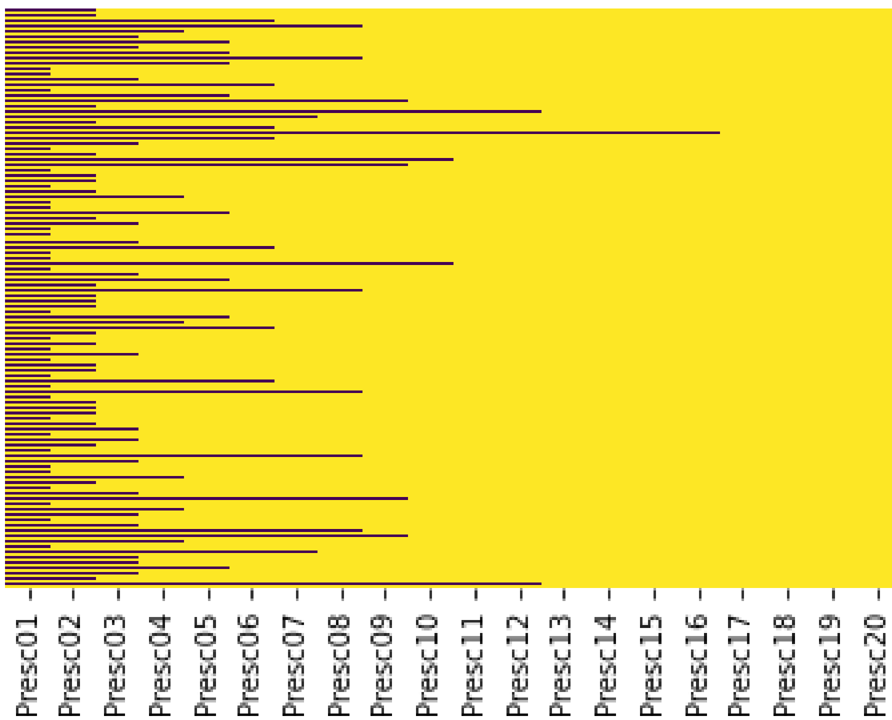
[30]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15002 entries, 0 to 15001
Data columns (total 20 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Presc01  7501 non-null   object
 1   Presc02  5747 non-null   object
 2   Presc03  4389 non-null   object
 3   Presc04  3345 non-null   object
 4   Presc05  2529 non-null   object
 5   Presc06  1864 non-null   object
 6   Presc07  1369 non-null   object
 7   Presc08  981 non-null    object
 8   Presc09  654 non-null    object
```

```
 9   Presc10  395 non-null    object
 10  Presc11  256 non-null    object
 11  Presc12  154 non-null    object
 12  Presc13  87 non-null     object
 13  Presc14  47 non-null     object
 14  Presc15  25 non-null     object
 15  Presc16  8 non-null      object
 16  Presc17  4 non-null      object
 17  Presc18  4 non-null      object
 18  Presc19  3 non-null      object
 19  Presc20  1 non-null      object
dtypes: object(20)
memory usage: 2.3+ MB
```

[31]:
```python
# Mapping to view missing data...none present.
sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap='viridis');
```



0.1.4 Remove Empty Rows

[32]:
```python
# https://www.adamsmith.haus/python/answers/
↪how-to-drop-a-list-of-rows-from-a-pandas-dataframe-by-index-in-python
is_empty = df.index[df.isna().all(axis=1)].tolist()
#is_empty
```

```
df.drop(is_empty, inplace=True)

df.head(2)
```

[32]:

```
       Presc01            Presc02                     Presc03       Presc04  \
1  amlodipine  albuterol aerosol                 allopurinol  pantoprazole
3  citalopram            benicar  amphetamine salt combo xr           NaN

      Presc05     Presc06     Presc07      Presc08     Presc09      Presc10  \
1  lorazepam  omeprazole  mometasone  fluconozole  gabapentin  pravastatin
3        NaN         NaN         NaN          NaN         NaN          NaN

  Presc11   Presc12                Presc13           Presc14  Presc15  \
1  cialis  losartan  metoprolol succinate XL  sulfamethoxazole  abilify
3     NaN       NaN                      NaN               NaN      NaN

          Presc16        Presc17       Presc18       Presc19    Presc20
1  spironolactone  albuterol HFA  levofloxacin  promethazine  glipizide
3             NaN            NaN           NaN           NaN        NaN
```

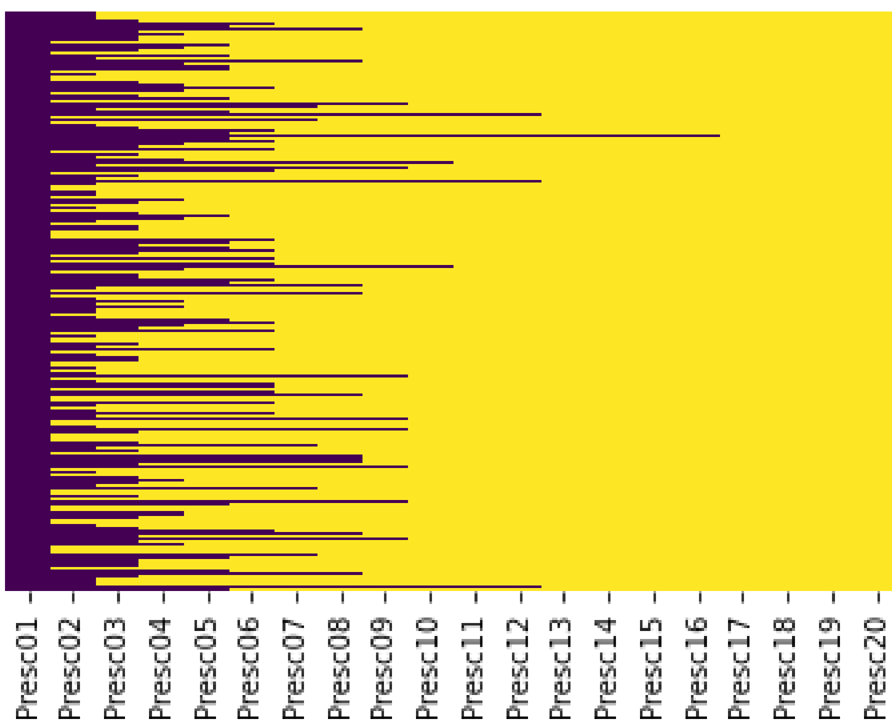
[33]:

```
df.shape
```

[33]: (7501, 20)

[34]:

```
sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap='viridis');
```



0.2 Preparing & Transforming Data

[35]:
```
# https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?
 ↪id=5aefcf2b-73cd-41f5-b4d3-aea0011efd05

trans = []
for i in range(0,7501):
    trans.append([str(df.values[i,j]) for j in range(0,20)])

# Transform list of lists into Numpy array
TE = TransactionEncoder()
array = TE.fit(trans).transform(trans)
```

[36]:
```
# Display First Transaction
ex_trans = trans[:1]
print(ex_trans)
```

```
[['amlodipine', 'albuterol aerosol', 'allopurinol', 'pantoprazole', 'lorazepam',
'omeprazole', 'mometasone', 'fluconozole', 'gabapentin', 'pravastatin',
'cialis', 'losartan', 'metoprolol succinate XL', 'sulfamethoxazole', 'abilify',
'spironolactone', 'albuterol HFA', 'levofloxacin', 'promethazine', 'glipizide']]
```

[37]:
```
# Create/Build df for Cleaning
cleaned_df = pd.DataFrame(array, columns = TE.columns_)
cleaned_df
```

[37]:
```
      Duloxetine  Premarin    Yaz  abilify  acetaminophen  actonel  \
0          False     False  False     True          False    False
1          False     False  False    False          False    False
2          False     False  False    False          False    False
3          False     False  False    False          False    False
4          False     False  False     True          False    False
…          …       …   …      …              …       …
7496       False     False  False    False          False    False
7497       False     False  False    False          False    False
7498       False     False  False    False          False    False
7499       False     False  False    False          False    False
7500       False     False  False    False          False    False

      albuterol HFA  albuterol aerosol  alendronate  allopurinol  …  \
0              True               True        False         True  …
1             False              False        False        False  …
2             False              False        False        False  …
3             False              False        False         True  …
```

```
4           False              False      False      False   …
…           …                …         …         …  …
7496        False              False      False      False   …
7497        False              False      False      False   …
7498        False              False      False      False   …
7499        False              False      False      False   …
7500        False              False      False      False   …

     trazodone HCI  triamcinolone Ace topical  triamterene  trimethoprim DS  \
0           False                      False        False            False
1           False                      False        False            False
2           False                      False        False            False
3           False                      False        False            False
4           False                      False        False            False
…           …                       …        …            …
7496        False                      False        False            False
7497        False                      False        False            False
7498        False                      False        False            False
7499        False                      False        False            False
7500        False                      False        False            False

     valaciclovir  valsartan  venlafaxine XR  verapamil SR  viagra  zolpidem
0           False      False           False         False   False     False
1           False      False           False         False   False     False
2           False      False           False         False   False     False
3           False      False           False         False   False     False
4           False      False           False         False   False     False
…           …       …           …        …       …     …
7496        False      False           False         False   False     False
7497        False      False           False         False   False     False
7498        False      False           False         False   False     False
7499        False      False           False         False   False     False
7500        False      False           False         False   False     False

[7501 rows x 120 columns]
```

[38]:
```
np.where(pd.isnull(df))
```

[38]:
```
(array([   1,    1,    1, …, 7500, 7500, 7500]),
 array([ 3,  4,  5, …, 17, 18, 19]))
```

0.2.1 Any Rows Missing Values?

[39]:
```
cleaned_df.isnull().all(axis=1).any()
```

[39]:
```
False
```

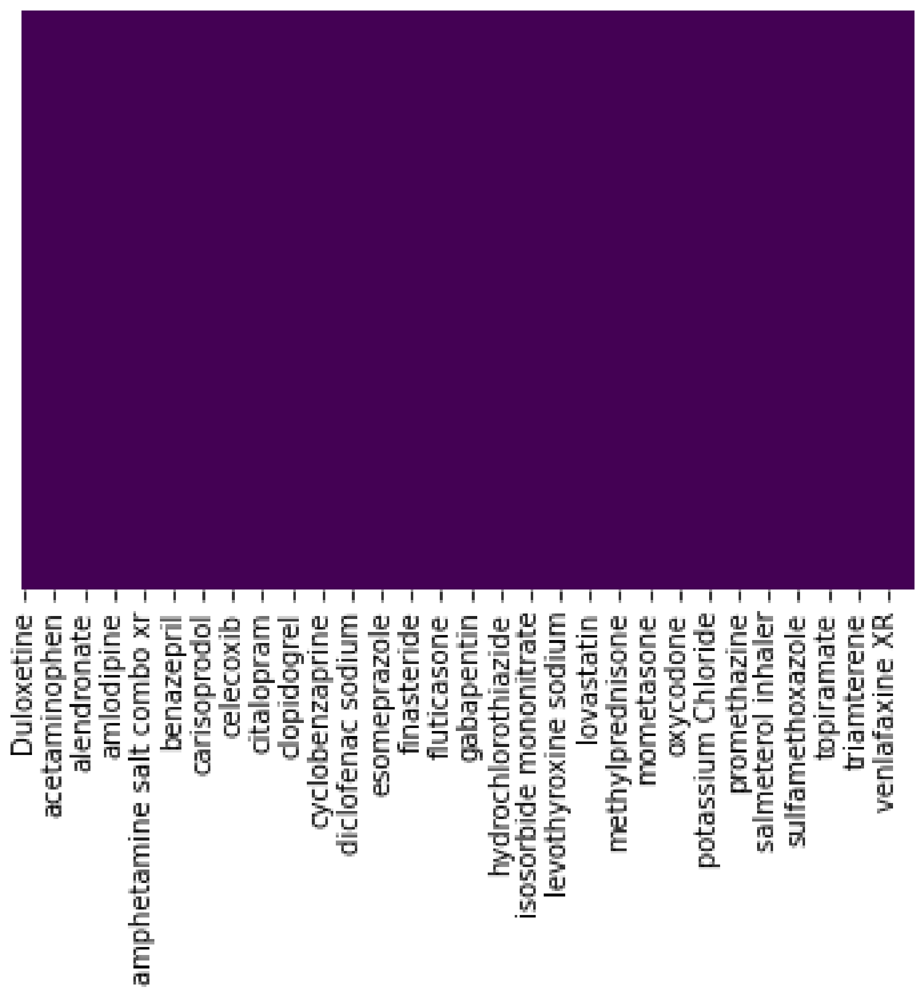
0.2.2 Any Columns Missing Values?

[40]:
```
cleaned_df.loc[:, cleaned_df.isnull().any()]
```

[40]:
```
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39,
40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59,
60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79,
80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99,
…]

[7501 rows x 0 columns]
```

[41]:
```
sns.heatmap(cleaned_df.isnull(), yticklabels=False, cbar=False, cmap='viridis');
```



[42]:
```
print(cleaned_df.dtypes)
```

```
Duloxetine          bool
Premarin            bool
Yaz                 bool
abilify             bool
acetaminophen       bool
                    …
valsartan           bool
venlafaxine XR      bool
verapamil SR        bool
viagra              bool
zolpidem            bool
Length: 120, dtype: object
```

0.2.3 Look for Empty Column

[43]:
```
for col in cleaned_df.columns:
    print(col)
```

```
Duloxetine
Premarin
Yaz
abilify
acetaminophen
actonel
albuterol HFA
albuterol aerosol
alendronate
allopurinol
alprazolam
amitriptyline
amlodipine
amoxicillin
amphetamine
amphetamine salt combo
amphetamine salt combo xr
atenolol
atorvastatin
azithromycin
benazepril
benicar
boniva
bupropion sr
carisoprodol
carvedilol
cefdinir
celebrex
```

celecoxib
cephalexin
cialis
ciprofloxacin
citalopram
clavulanate K+
clonazepam
clonidine HCI
clopidogrel
clotrimazole
codeine
crestor
cyclobenzaprine
cymbalta
dextroamphetamine XR
diazepam
diclofenac sodium
doxycycline hyclate
enalapril
escitalopram
esomeprazole
ezetimibe
fenofibrate
fexofenadine
finasteride
flovent hfa 110mcg inhaler
fluconozole
fluoxetine HCI
fluticasone
fluticasone nasal spray
folic acid
furosemide
gabapentin
glimepiride
glipizide
glyburide
hydrochlorothiazide
hydrocodone
hydrocortisone 2.5% cream
ibuprophen
isosorbide mononitrate
lansoprazole
lantus
levofloxacin
levothyroxine sodium
lisinopril
lorazepam
losartan

lovastatin
meloxicam
metformin
metformin HCI
methylprednisone
metoprolol
metoprolol succinate XL
metoprolol tartrate
mometasone
nan
naproxen
omeprazole
oxycodone
pantoprazole
paroxetine
pioglitazone
potassium Chloride
pravastatin
prednisone
pregabalin
promethazine
quetiapine
ranitidine
rosuvastatin
salmeterol inhaler
sertraline HCI
simvastatin
spironolactone
sulfamethoxazole
synthroid
tamsulosin
temezepam
topiramate
tramadol
trazodone HCI
triamcinolone Ace topical
triamterene
trimethoprim DS
valaciclovir
valsartan
venlafaxine XR
verapamil SR
viagra
zolpidem

0.2.4 Remove Empty Column

[44]:
```
# https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?
↪id=5aefcf2b-73cd-41f5-b4d3-aea0011efd05
# drop empty column
cleaned_df = cleaned_df.drop(['nan'], axis=1)
```

[45]:
```
# Shape
print("Shape: " + str(cleaned_df.shape))
print("---------"*5)

#Verify
for col in cleaned_df.columns:
    print(col)
```

```
Shape: (7501, 119)
---------------------------------------------
Duloxetine
Premarin
Yaz
abilify
acetaminophen
actonel
albuterol HFA
albuterol aerosol
alendronate
allopurinol
alprazolam
amitriptyline
amlodipine
amoxicillin
amphetamine
amphetamine salt combo
amphetamine salt combo xr
atenolol
atorvastatin
azithromycin
benazepril
benicar
boniva
bupropion sr
carisoprodol
carvedilol
cefdinir
celebrex
celecoxib
cephalexin
cialis
```

ciprofloxacin
citalopram
clavulanate K+
clonazepam
clonidine HCI
clopidogrel
clotrimazole
codeine
crestor
cyclobenzaprine
cymbalta
dextroamphetamine XR
diazepam
diclofenac sodium
doxycycline hyclate
enalapril
escitalopram
esomeprazole
ezetimibe
fenofibrate
fexofenadine
finasteride
flovent hfa 110mcg inhaler
fluconozole
fluoxetine HCI
fluticasone
fluticasone nasal spray
folic acid
furosemide
gabapentin
glimepiride
glipizide
glyburide
hydrochlorothiazide
hydrocodone
hydrocortisone 2.5% cream
ibuprophen
isosorbide mononitrate
lansoprazole
lantus
levofloxacin
levothyroxine sodium
lisinopril
lorazepam
losartan
lovastatin
meloxicam
metformin

```
metformin HCI
methylprednisone
metoprolol
metoprolol succinate XL
metoprolol tartrate
mometasone
naproxen
omeprazole
oxycodone
pantoprazole
paroxetine
pioglitazone
potassium Chloride
pravastatin
prednisone
pregabalin
promethazine
quetiapine
ranitidine
rosuvastatin
salmeterol inhaler
sertraline HCI
simvastatin
spironolactone
sulfamethoxazole
synthroid
tamsulosin
temezepam
topiramate
tramadol
trazodone HCI
triamcinolone Ace topical
triamterene
trimethoprim DS
valaciclovir
valsartan
venlafaxine XR
verapamil SR
viagra
zolpidem
```

0.2.5 Export Cleaned Data

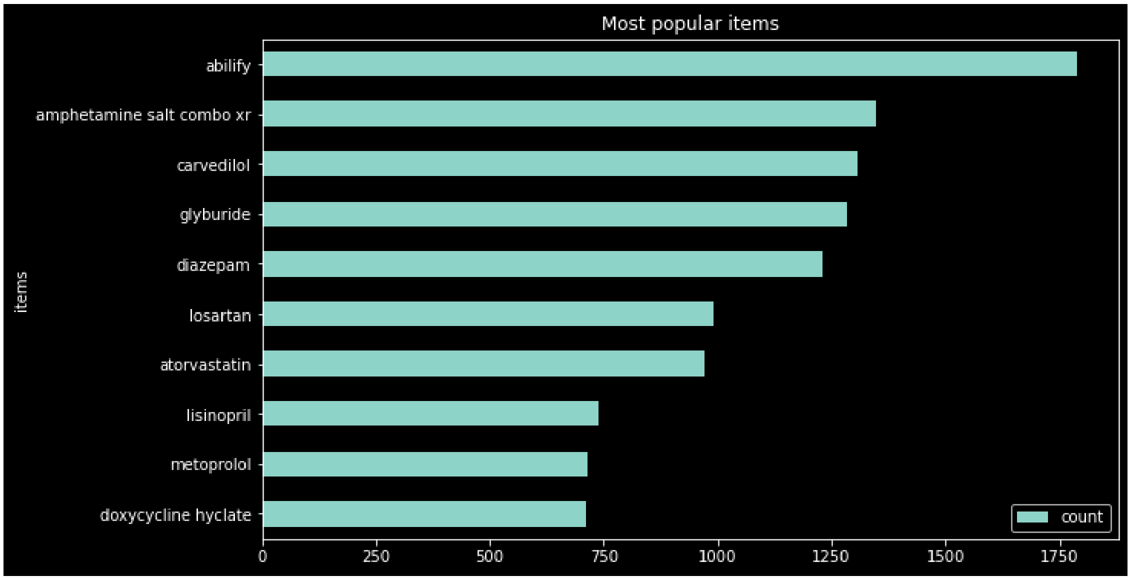
[46]:
```python
cleaned_df.to_csv('cleaned_df.csv', index=False)
cleaned_df.shape
```

[46]:
```
(7501, 119)
```

0.2.6 List Popular Meds

[47]:
```
# https://sarakmair.medium.com/market-basket-analysis-8dc699b7e27
#most popular Meds
count = cleaned_df.loc[:,:].sum()
freq_pharm = count.sort_values(ascending=False).head(10)
freq_pharm = freq_pharm.to_frame()
freq_pharm = freq_pharm.reset_index()
freq_pharm = freq_pharm.rename(columns = {'index': 'items',0: 'count'})

#Data Visualization
plt.rcParams['figure.figsize'] = (10, 6)
plt.style.use('dark_background')
ax = freq_pharm.plot.barh(x = 'items', y = 'count')
plt.title('Most popular items')
plt.gca().invert_yaxis()
```



[48]:
```
print("Frequest Transactions: " + str(freq_pharm))
```

```
Frequest Transactions:                            items  count
0                    abilify   1788
1  amphetamine salt combo xr   1348
2                 carvedilol   1306
3                  glyburide   1282
4                   diazepam   1229
5                   losartan    991
6               atorvastatin    972
7                 lisinopril    737
8                 metoprolol    715
```

```
9        doxycycline hyclate    713
```

0.2.7 Apply Apriori Algorithm

[49]:
```python
# Apply the A Priori Algorithm
a_rules = apriori(cleaned_df, min_support = 0.02, use_colnames=True)
a_rules.head()
```

[49]:

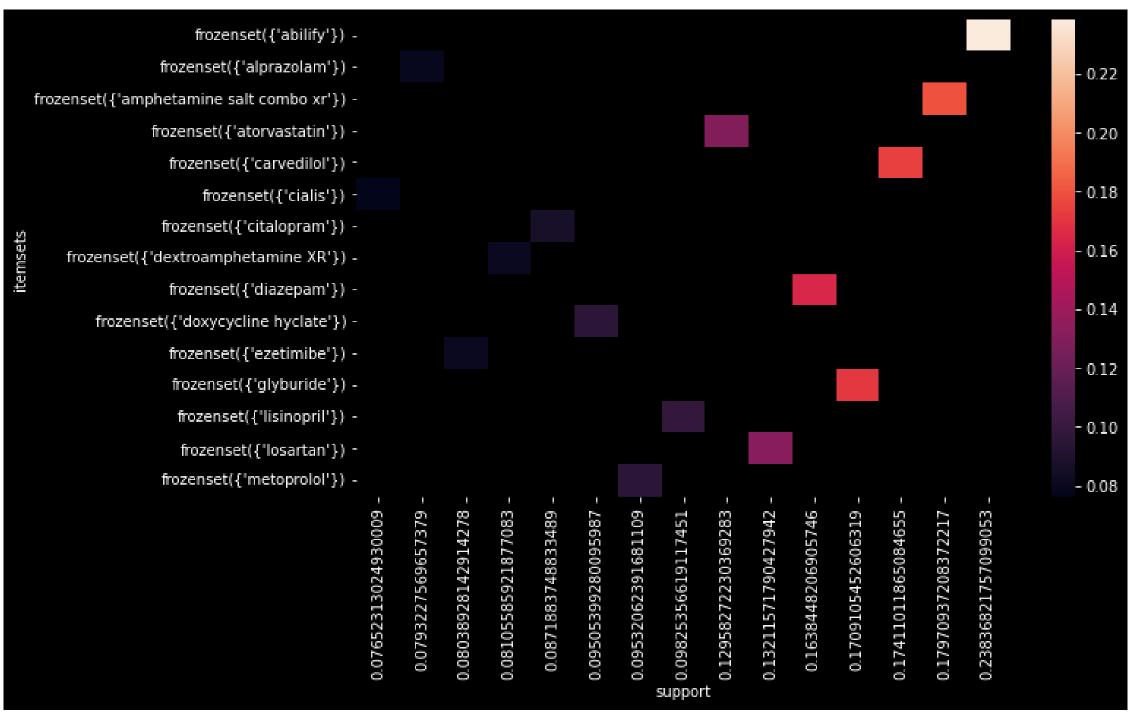
	support	itemsets
0	0.046794	(Premarin)
1	0.238368	(abilify)
2	0.020397	(albuterol aerosol)
3	0.033329	(allopurinol)
4	0.079323	(alprazolam)

[50]:
```python
a_rules_results = list(a_rules)
print(a_rules_results)
```

```
['support', 'itemsets']
```

0.2.8 Heatmap Only Showing Support Above 0.05

[51]:
```python
support_table = a_rules[a_rules['support'] > 0.075].pivot(index='itemsets',␣
↪columns='support', values='support')
sns.heatmap(support_table);
```



0.2.9 Association Rules

[52]:
```
# https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?
↪id=5aefcf2b-73cd-41f5-b4d3-aea0011efd05
ass_r = association_rules(a_rules, metric='lift', min_threshold=1)
ass_r.sort_values(by=['antecedents','consequents'], ascending=True).head(10)
```

[52]:

	antecedents	consequents	antecedent support	consequent support	\
0	(abilify)	(amlodipine)	0.238368	0.071457	
35	(abilify)	(naproxen)	0.238368	0.058526	
33	(abilify)	(metoprolol)	0.238368	0.095321	
30	(abilify)	(metformin)	0.238368	0.050527	
29	(abilify)	(lisinopril)	0.238368	0.098254	
26	(abilify)	(levofloxacin)	0.238368	0.063325	
25	(abilify)	(glipizide)	0.238368	0.065858	
22	(abilify)	(fenofibrate)	0.238368	0.051060	
21	(abilify)	(doxycycline hyclate)	0.238368	0.095054	
18	(abilify)	(diazepam)	0.238368	0.163845	

	support	confidence	lift	leverage	conviction
0	0.023597	0.098993	1.385352	0.006564	1.030562
35	0.020131	0.084452	1.442993	0.006180	1.028318
33	0.035729	0.149888	1.572463	0.013007	1.064189
30	0.023064	0.096756	1.914955	0.011020	1.051182
29	0.040928	0.171700	1.747522	0.017507	1.088672
26	0.020264	0.085011	1.342461	0.005169	1.023701
25	0.027596	0.115772	1.757904	0.011898	1.056449
22	0.020131	0.084452	1.653978	0.007960	1.036472
21	0.033729	0.141499	1.488616	0.011071	1.054100
18	0.052660	0.220917	1.348332	0.013604	1.073256

[53]:
```
ass_r.shape
```

[53]: (94, 9)

0.3 Top 3 Rules by Support

[54]:
```
# Support: frequency value for a medication within our dataset.

ass_r.sort_values(by=['support'],ascending=False).head(3)
```

[54]:

	antecedents	consequents	antecedent support	consequent support	\
8	(carvedilol)	(abilify)	0.174110	0.238368	
9	(abilify)	(carvedilol)	0.238368	0.174110	
19	(diazepam)	(abilify)	0.163845	0.238368	

	support	confidence	lift	leverage	conviction

```
8   0.059725    0.343032  1.439085  0.018223    1.159314
9   0.059725    0.250559  1.439085  0.018223    1.102008
19  0.052660    0.321400  1.348332  0.013604    1.122357
```

0.4 Top 3 Rules by Confidence

[55]:
```
# Confidence: measures the association value if another medication is␣
 ↪prescribed.

ass_r.sort_values(by=['confidence'],ascending=False).head(3)
```

[55]:
```
     antecedents consequents  antecedent support  consequent support  \
31   (metformin)   (abilify)            0.050527            0.238368
24   (glipizide)   (abilify)            0.065858            0.238368
28  (lisinopril)   (abilify)            0.098254            0.238368

     support  confidence      lift  leverage  conviction
31  0.023064    0.456464  1.914955  0.011020    1.401255
24  0.027596    0.419028  1.757904  0.011898    1.310962
28  0.040928    0.416554  1.747522  0.017507    1.305401
```

0.5 Top 3 Rules by Lift

[56]:
```
# Lift: measures the level of importance for the specific rule.

ass_r.sort_values(by=['lift'],ascending=False).head(3)
```

[56]:
```
     antecedents   consequents  antecedent support  consequent support  \
75  (carvedilol)  (lisinopril)            0.174110            0.098254
74  (lisinopril)  (carvedilol)            0.098254            0.174110
72   (glipizide)  (carvedilol)            0.065858            0.174110

     support  confidence      lift  leverage  conviction
75  0.039195    0.225115  2.291162  0.022088    1.163716
74  0.039195    0.398915  2.291162  0.022088    1.373997
72  0.022930    0.348178  1.999758  0.011464    1.267048
```

0.5.1 Pruning to Keep Rules

[57]:
```
pru_r_s=ass_r[ass_r['support'] > 0.03]
# ex: only 94 meds (pru_r) are left. means only x rows above y% range
print("only {} meds (pru_r_s) are left.".format(len(pru_r_s)))
```

```
only 32 meds (pru_r_s) are left.
```

[58]:
```
pru_r_c=pru_r_s[pru_r_s['confidence'] > 0.2]
# ex: only 94 meds (pru_r) are left. means only x rows above y% range
print("Using the above support fiter and this confidence filter, only {} meds␣
↪(pru_r_c) are left.".format(len(pru_r_c)))
```

```
Using the above support fiter and this confidence filter, only 26 meds (pru_r_c)
are left.
```

[59]:
```
pru_r_l=pru_r_c[pru_r_c['lift'] > 1.5]
# ex: only 94 meds (pru_r) are left. means only x rows above y% range
print("Using all three filters, only {} meds (pru_r_l) are left.".
↪format(len(pru_r_l)))
```

```
Using all three filters, only 9 meds (pru_r_l) are left.
```

[60]:
```
# Final List after Pruning
final_list = pru_r_l
final_list.head(10)
```

[60]:

	antecedents	consequents	antecedent support	consequent support	\
6	(abilify)	(atorvastatin)	0.238368	0.129583	
7	(atorvastatin)	(abilify)	0.129583	0.238368	
28	(lisinopril)	(abilify)	0.098254	0.238368	
32	(metoprolol)	(abilify)	0.095321	0.238368	
56	(carvedilol)	(atorvastatin)	0.174110	0.129583	
57	(atorvastatin)	(carvedilol)	0.129583	0.174110	
59	(atorvastatin)	(diazepam)	0.129583	0.163845	
74	(lisinopril)	(carvedilol)	0.098254	0.174110	
75	(carvedilol)	(lisinopril)	0.174110	0.098254	

	support	confidence	lift	leverage	conviction
6	0.047994	0.201342	1.553774	0.017105	1.089850
7	0.047994	0.370370	1.553774	0.017105	1.209650
28	0.040928	0.416554	1.747522	0.017507	1.305401
32	0.035729	0.374825	1.572463	0.013007	1.218270
56	0.035462	0.203675	1.571779	0.012900	1.093043
57	0.035462	0.273663	1.571779	0.012900	1.137061
59	0.032129	0.247942	1.513276	0.010898	1.111823
74	0.039195	0.398915	2.291162	0.022088	1.373997
75	0.039195	0.225115	2.291162	0.022088	1.163716

[61]:
```
final_list.to_csv('final_list.csv', index=False)
final_list.shape
```

[61]: (9, 9)