

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder
```

```
In [2]: book = pd.read_csv('book.csv')
book
```

Out[2]:

	ChildBks	YouthBks	CookBks	DoItYBks	RefBks	ArtBks	GeogBks	ItalCook	ItalAtlas	ItalArt
0	0	1	0	1	0	0	1	0	0	0
1	1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	1	1	1	0	1	0	1	0	0	0
4	0	0	1	0	0	0	1	0	0	0
...
1995	0	0	1	0	0	1	1	1	1	0
1996	0	0	0	0	0	0	0	0	0	0
1997	0	0	0	0	0	0	0	0	0	0
1998	0	0	1	0	0	0	0	0	0	0
1999	0	0	0	0	0	0	0	0	0	0

2000 rows × 11 columns



```
In [3]: book.shape
```

Out[3]: (2000, 11)

```
In [4]: book.dtypes
```

```
Out[4]: ChildBks      int64
YouthBks      int64
CookBks      int64
DoItYBks      int64
RefBks      int64
ArtBks      int64
GeogBks      int64
ItalCook      int64
ItalAtlas      int64
ItalArt      int64
Florence      int64
dtype: object
```

In [5]: `book.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 11 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   ChildBks    2000 non-null   int64
1   YouthBks    2000 non-null   int64
2   CookBks     2000 non-null   int64
3   DoItYBks    2000 non-null   int64
4   RefBks      2000 non-null   int64
5   ArtBks      2000 non-null   int64
6   GeogBks     2000 non-null   int64
7   ItalCook    2000 non-null   int64
8   ItalAtlas   2000 non-null   int64
9   ItalArt     2000 non-null   int64
10  Florence    2000 non-null   int64
dtypes: int64(11)
memory usage: 171.9 KB
```

In [7]: `book.isna().sum()`

```
Out[7]: ChildBks      0
YouthBks      0
CookBks       0
DoItYBks      0
RefBks        0
ArtBks        0
GeogBks       0
ItalCook      0
ItalAtlas     0
ItalArt       0
Florence      0
dtype: int64
```

1. Value of support

```
In [45]: # with 5% support
freq_itemsets = apriori(book, min_support=0.05, use_colnames=True)
freq_itemsets
```

Out[45]:

	support	itemsets
0	0.4230	(ChildBks)
1	0.2475	(YouthBks)
2	0.4310	(CookBks)
3	0.2820	(DoltYBks)
4	0.2145	(RefBks)
...
95	0.0600	(CookBks, DoltYBks, GeogBks, YouthBks)
96	0.0560	(ArtBks, CookBks, GeogBks, YouthBks)
97	0.0650	(ArtBks, CookBks, DoltYBks, GeogBks)
98	0.0510	(CookBks, ChildBks, DoltYBks, GeogBks, YouthBks)
99	0.0535	(ArtBks, ChildBks, CookBks, DoltYBks, GeogBks)

100 rows × 2 columns

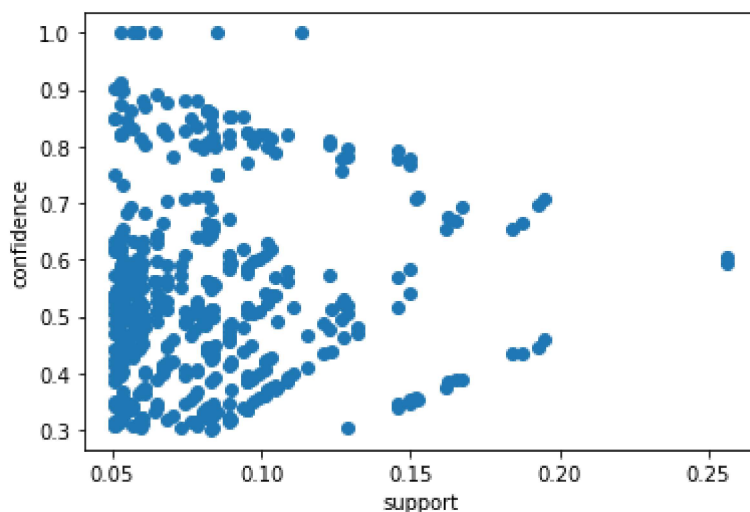
```
In [46]: # 30% confidence
AR1 = association_rules(freq_itemsets, metric='confidence', min_threshold=0.3)
AR1
```

Out[46]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage
0	(ChildBks)	(YouthBks)	0.4230	0.2475	0.1650	0.390071	1.576044	0.060308
1	(YouthBks)	(ChildBks)	0.2475	0.4230	0.1650	0.666667	1.576044	0.060308
2	(ChildBks)	(CookBks)	0.4230	0.4310	0.2560	0.605201	1.404179	0.073687
3	(CookBks)	(ChildBks)	0.4310	0.4230	0.2560	0.593968	1.404179	0.073687
4	(ChildBks)	(DoltYBks)	0.4230	0.2820	0.1840	0.434988	1.542511	0.064714
...
473	(ChildBks, ArtBks)	(CookBks, DoltYBks, GeogBks)	0.1625	0.1085	0.0535	0.329231	3.034385	0.035869
474	(ArtBks, CookBks)	(ChildBks, DoltYBks, GeogBks)	0.1670	0.1045	0.0535	0.320359	3.065639	0.036048
475	(ArtBks, DoltYBks)	(ChildBks, GeogBks, CookBks)	0.1235	0.1495	0.0535	0.433198	2.897648	0.035037
476	(ArtBks, GeogBks)	(ChildBks, DoltYBks, CookBks)	0.1275	0.1460	0.0535	0.419608	2.874026	0.034885
477	(GeogBks, DoltYBks)	(ChildBks, ArtBks, CookBks)	0.1325	0.1265	0.0535	0.403774	3.191886	0.036739

478 rows × 9 columns

```
In [47]: plt.scatter(AR1['support'], AR1['confidence'])
plt.xlabel('support')
plt.ylabel('confidence')
plt.show()
```

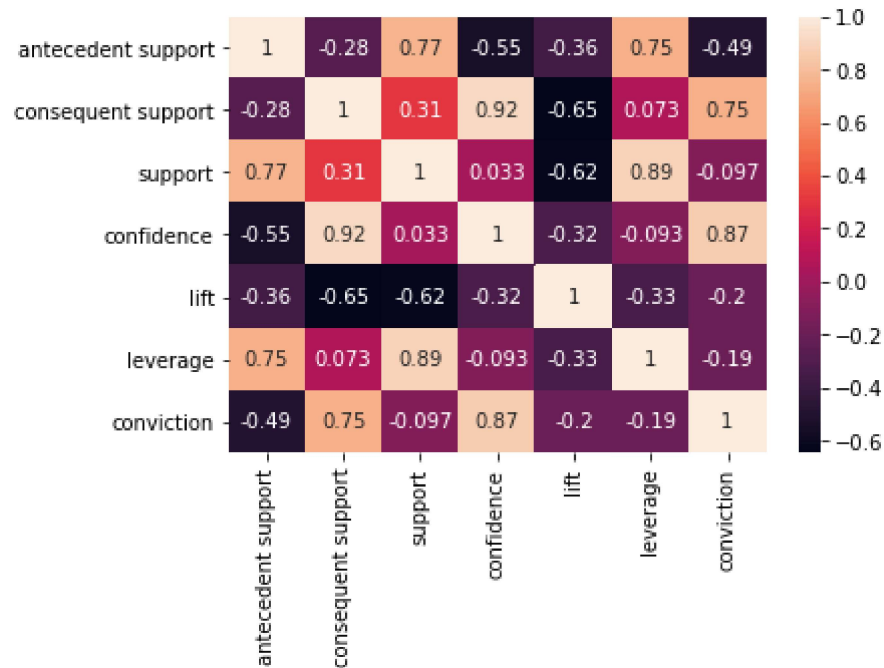


```
In [48]: corr_AR1 = AR1.corr()
corr_AR1
```

Out[48]:

	antecedent support	consequent support	support	confidence	lift	leverage	conviction
antecedent support	1.000000	-0.275429	0.768106	-0.546549	-0.355572	0.749441	-0.490575
consequent support	-0.275429	1.000000	0.309742	0.917072	-0.645453	0.073186	0.753839
support	0.768106	0.309742	1.000000	0.032897	-0.624631	0.892221	-0.096799
confidence	-0.546549	0.917072	0.032897	1.000000	-0.321874	-0.092935	0.866620
lift	-0.355572	-0.645453	-0.624631	-0.321874	1.000000	-0.325328	-0.201533
leverage	0.749441	0.073186	0.892221	-0.092935	-0.325328	1.000000	-0.191227
conviction	-0.490575	0.753839	-0.096799	0.866620	-0.201533	-0.191227	1.000000

```
In [49]: sns.heatmap(data=corr_AR1, annot=True)
plt.show()
```



```
In [ ]:
```

2. Value of support

```
In [50]: # with 10% support
freq_itemsets_2 = apriori(book, min_support=0.10, use_colnames=True)
freq_itemsets_2
```

Out[50]:

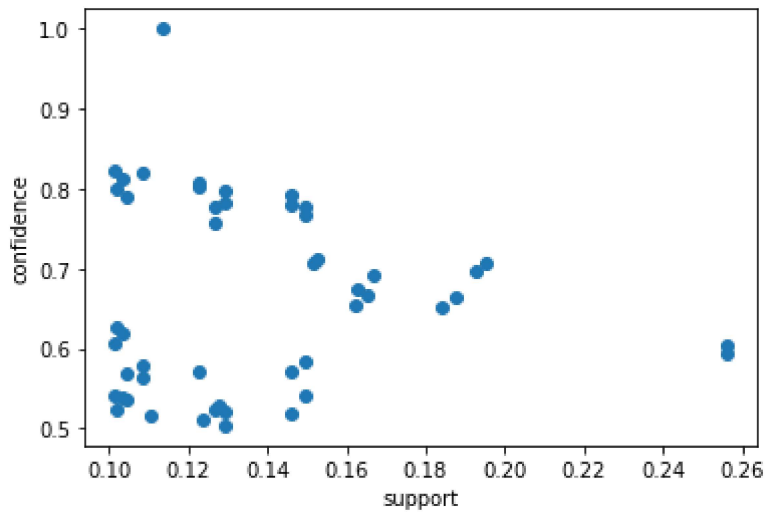
	support	itemsets
0	0.4230	(ChildBks)
1	0.2475	(YouthBks)
2	0.4310	(CookBks)
3	0.2820	(DoltYBks)
4	0.2145	(RefBks)
5	0.2410	(ArtBks)
6	0.2760	(GeogBks)
7	0.1135	(ItalCook)
8	0.1085	(Florence)
9	0.1650	(ChildBks, YouthBks)
10	0.2560	(ChildBks, CookBks)
11	0.1840	(ChildBks, DoltYBks)
12	0.1515	(ChildBks, RefBks)
13	0.1625	(ArtBks, ChildBks)
14	0.1950	(ChildBks, GeogBks)
15	0.1620	(CookBks, YouthBks)
16	0.1155	(DoltYBks, YouthBks)
17	0.1010	(ArtBks, YouthBks)
18	0.1205	(GeogBks, YouthBks)
19	0.1875	(CookBks, DoltYBks)
20	0.1525	(CookBks, RefBks)
21	0.1670	(ArtBks, CookBks)
22	0.1925	(CookBks, GeogBks)
23	0.1135	(ItalCook, CookBks)
24	0.1055	(RefBks, DoltYBks)
25	0.1235	(ArtBks, DoltYBks)
26	0.1325	(GeogBks, DoltYBks)
27	0.1105	(GeogBks, RefBks)
28	0.1275	(ArtBks, GeogBks)
29	0.1290	(CookBks, ChildBks, YouthBks)
30	0.1460	(ChildBks, DoltYBks, CookBks)
31	0.1225	(ChildBks, RefBks, CookBks)

	support	itemsets
32	0.1265	(ArtBks, ChildBks, CookBks)
33	0.1495	(ChildBks, GeogBks, CookBks)
34	0.1045	(ChildBks, DoltYBks, GeogBks)
35	0.1020	(ArtBks, ChildBks, GeogBks)
36	0.1015	(ArtBks, CookBks, DoltYBks)
37	0.1085	(CookBks, DoltYBks, GeogBks)
38	0.1035	(ArtBks, CookBks, GeogBks)

```
In [51]: # 50% confidence
AR2 = association_rules(freq_itemsets_2, metric='confidence', min_threshold=0.5)
AR2
```

9	(RefBks)	(CookBks)	0.2145	0.4310	0.1525	0.710956	1.649549	0.060050
10	(ArtBks)	(CookBks)	0.2410	0.4310	0.1670	0.692946	1.607763	0.063129
11	(GeogBks)	(CookBks)	0.2760	0.4310	0.1925	0.697464	1.618245	0.073544
12	(ItalCook)	(CookBks)	0.1135	0.4310	0.1135	1.000000	2.320186	0.064582
13	(ArtBks)	(DoltYBks)	0.2410	0.2820	0.1235	0.512448	1.817192	0.055538
14	(RefBks)	(GeogBks)	0.2145	0.2760	0.1105	0.515152	1.866491	0.051298
15	(ArtBks)	(GeogBks)	0.2410	0.2760	0.1275	0.529046	1.916832	0.060984
16	(ChildBks, CookBks)	(YouthBks)	0.2560	0.2475	0.1290	0.503906	2.035985	0.065640
17	(CookBks, YouthBks)	(ChildBks)	0.1620	0.4230	0.1290	0.796296	1.882497	0.060474
18	(ChildBks, YouthBks)	(CookBks)	0.1650	0.4310	0.1290	0.781818	1.813963	0.057885


```
In [52]: plt.scatter(AR2['support'], AR2['confidence'])
plt.xlabel('support')
plt.ylabel('confidence')
plt.show()
```

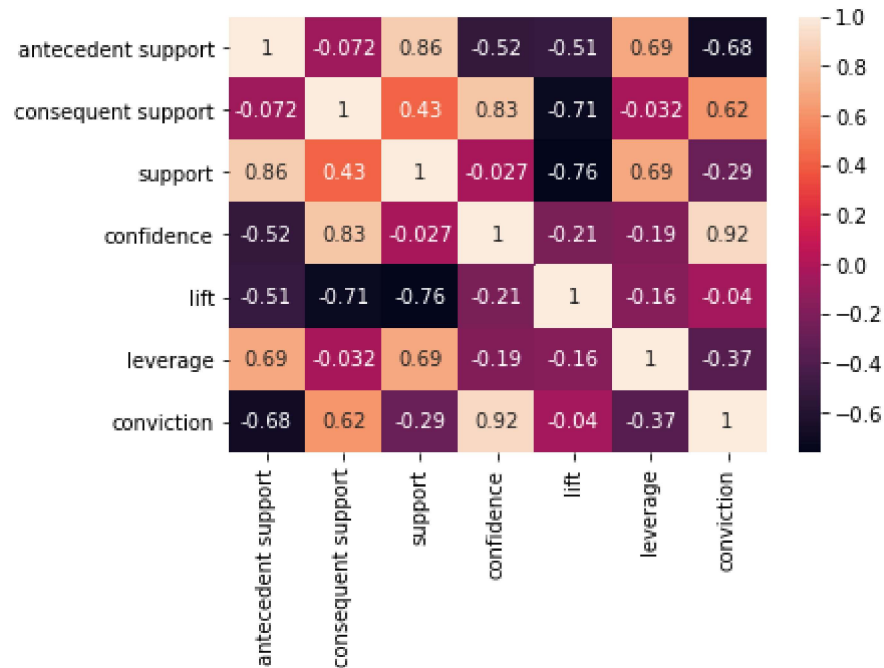


```
In [53]: corr_AR2 = AR2.corr()
corr_AR2
```

Out[53]:

	antecedent support	consequent support	support	confidence	lift	leverage	conviction
antecedent support	1.000000	-0.071635	0.858437	-0.519173	-0.512713	0.690605	-0.683617
consequent support	-0.071635	1.000000	0.426340	0.831627	-0.711482	-0.031692	0.621042
support	0.858437	0.426340	1.000000	-0.027358	-0.762058	0.692109	-0.291754
confidence	-0.519173	0.831627	-0.027358	1.000000	-0.208019	-0.185236	0.917344
lift	-0.512713	-0.711482	-0.762058	-0.208019	1.000000	-0.157036	-0.040188
leverage	0.690605	-0.031692	0.692109	-0.185236	-0.157036	1.000000	-0.365942
conviction	-0.683617	0.621042	-0.291754	0.917344	-0.040188	-0.365942	1.000000

```
In [54]: sns.heatmap(data=corr_AR2, annot=True)
plt.show()
```



In []:

3. Value of support

```
In [55]: # with 15% support
freq_itemsets_3 = apriori(book, min_support=0.15, use_colnames=True)
freq_itemsets_3
```

Out[55]:

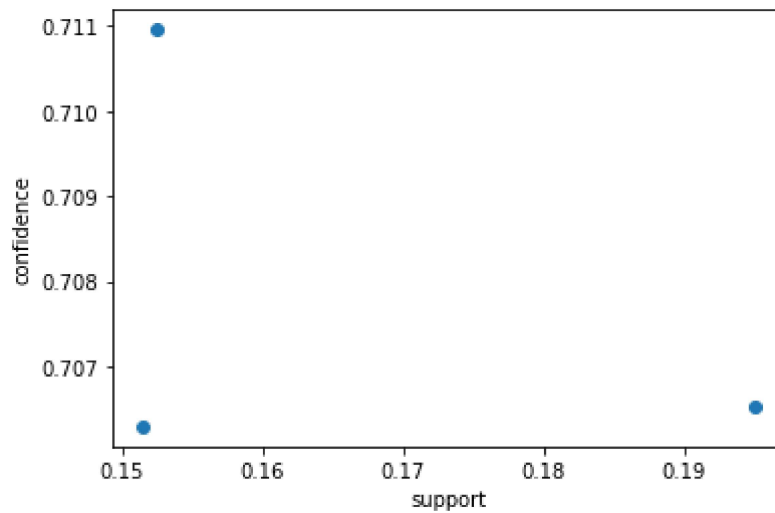
	support	itemsets
0	0.4230	(ChildBks)
1	0.2475	(YouthBks)
2	0.4310	(CookBks)
3	0.2820	(DoltYBks)
4	0.2145	(RefBks)
5	0.2410	(ArtBks)
6	0.2760	(GeogBks)
7	0.1650	(ChildBks, YouthBks)
8	0.2560	(ChildBks, CookBks)
9	0.1840	(ChildBks, DoltYBks)
10	0.1515	(ChildBks, RefBks)
11	0.1625	(ArtBks, ChildBks)
12	0.1950	(ChildBks, GeogBks)
13	0.1620	(CookBks, YouthBks)
14	0.1875	(CookBks, DoltYBks)
15	0.1525	(CookBks, RefBks)
16	0.1670	(ArtBks, CookBks)
17	0.1925	(CookBks, GeogBks)

```
In [56]: # 70% confidence
AR3 = association_rules(freq_itemsets_3, metric='confidence', min_threshold=0.7)
AR3
```

Out[56]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(RefBks)	(ChildBks)	0.2145	0.423	0.1515	0.706294	1.669725	0.060767	
1	(GeogBks)	(ChildBks)	0.2760	0.423	0.1950	0.706522	1.670264	0.078252	
2	(RefBks)	(CookBks)	0.2145	0.431	0.1525	0.710956	1.649549	0.060050	

```
In [57]: plt.scatter(AR3['support'], AR3['confidence'])
plt.xlabel('support')
plt.ylabel('confidence')
plt.show()
```

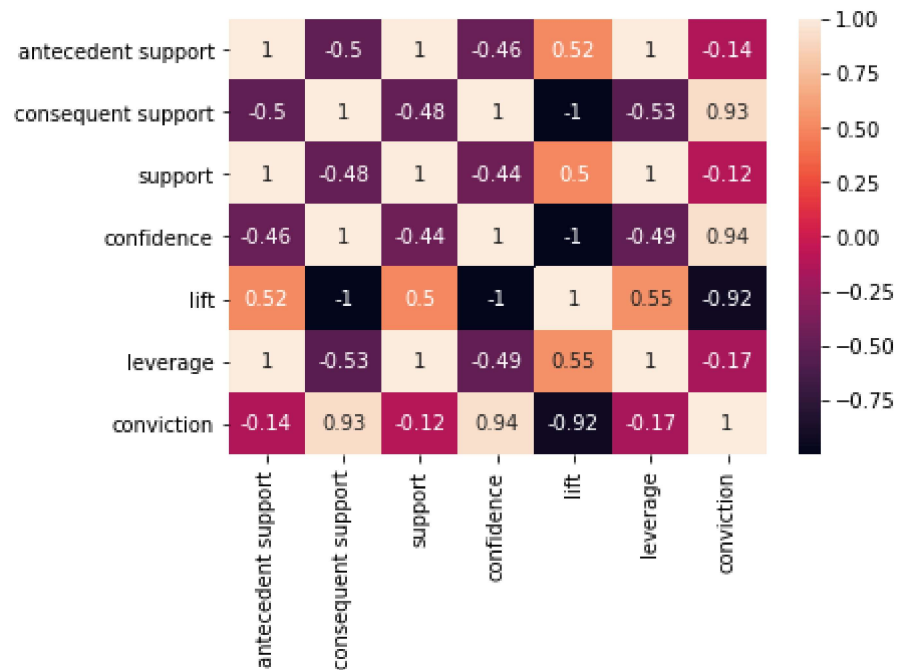


```
In [58]: corr_AR3 = AR3.corr()
corr_AR3
```

Out[58]:

	antecedent support	consequent support	support	confidence	lift	leverage	conviction
antecedent support	1.000000	-0.500000	0.999797	-0.461960	0.519640	0.999397	-0.136385
consequent support	-0.500000	1.000000	-0.482460	0.999059	-0.999739	-0.529775	0.926126
support	0.999797	-0.482460	1.000000	-0.444008	0.502331	0.998495	-0.116410
confidence	-0.461960	0.999059	-0.444008	1.000000	-0.997808	-0.492483	0.941618
lift	0.519640	-0.999739	0.502331	-0.997808	1.000000	0.548999	-0.917273
leverage	0.999397	-0.529775	0.998495	-0.492483	0.548999	1.000000	-0.170708
conviction	-0.136385	0.926126	-0.116410	0.941618	-0.917273	-0.170708	1.000000

```
In [59]: sns.heatmap(data=corr_AR3, annot=True)  
plt.show()
```



```
In [ ]:
```