

1.Import Library

```
In [1]: import pandas as pd
from mlxtend.frequent_patterns import association_rules,apriori
```

2.Import Datasets

```
In [2]: data=pd.read_csv("titnic.csv",sep=" ")
data.head()
```

Out[2]:

	Class	Gender	Age	Survived
1	3rd	Male	Child	No
2	3rd	Male	Child	No
3	3rd	Male	Child	No
4	3rd	Male	Child	No
5	3rd	Male	Child	No

3.Data Prepration

```
In [3]: dummy_data=pd.get_dummies(data)
dummy_data
```

Out[3]:

	Class_1st	Class_2nd	Class_3rd	Class_Crew	Gender_Female	Gender_Male	Age_Adult	Age_Child	Survived_No	Survived_Yes
1	0	0	1	0	0	1	0	1	1	0
2	0	0	1	0	0	1	0	1	1	0
3	0	0	1	0	0	1	0	1	1	0
4	0	0	1	0	0	1	0	1	1	0
5	0	0	1	0	0	1	0	1	1	0
...
2197	0	0	0	1	1	0	1	0	0	1
2198	0	0	0	1	1	0	1	0	0	1
2199	0	0	0	1	1	0	1	0	0	1
2200	0	0	0	1	1	0	1	0	0	1
2201	0	0	0	1	1	0	1	0	0	1

2201 rows × 10 columns

4.Apriori

```
In [4]: frequent_items=apriori(dummy_data,min_support=0.1,use_colnames=True)
frequent_items
```

Out[4]:

	support	itemsets
0	0.147660	(Class_1st)
1	0.129487	(Class_2nd)
2	0.320763	(Class_3rd)
3	0.402090	(Class_Crew)
4	0.213539	(Gender_Female)
5	0.786461	(Gender_Male)
6	0.950477	(Age_Adult)
7	0.676965	(Survived_No)
8	0.323035	(Survived_Yes)
9	0.144934	(Age_Adult, Class_1st)
10	0.118582	(Age_Adult, Class_2nd)
11	0.231713	(Gender_Male, Class_3rd)
12	0.284871	(Age_Adult, Class_3rd)
13	0.239891	(Survived_No, Class_3rd)
14	0.391640	(Gender_Male, Class_Crew)
15	0.402090	(Age_Adult, Class_Crew)
16	0.305770	(Survived_No, Class_Crew)
17	0.193094	(Gender_Female, Age_Adult)
18	0.156293	(Survived_Yes, Gender_Female)
19	0.757383	(Age_Adult, Gender_Male)
20	0.619718	(Survived_No, Gender_Male)
21	0.166742	(Survived_Yes, Gender_Male)
22	0.653339	(Survived_No, Age_Adult)
23	0.297138	(Survived_Yes, Age_Adult)
24	0.209905	(Age_Adult, Gender_Male, Class_3rd)
25	0.191731	(Survived_No, Gender_Male, Class_3rd)
26	0.216265	(Survived_No, Age_Adult, Class_3rd)

	support	itemsets
27	0.391640	(Age_Adult, Gender_Male, Class_Crew)
28	0.304407	(Survived_No, Gender_Male, Class_Crew)
29	0.305770	(Survived_No, Age_Adult, Class_Crew)
30	0.143571	(Age_Adult, Survived_Yes, Gender_Female)
31	0.603816	(Age_Adult, Survived_No, Gender_Male)
32	0.153567	(Age_Adult, Survived_Yes, Gender_Male)
33	0.175829	(Age_Adult, Survived_No, Gender_Male, Class_3rd)
34	0.304407	(Age_Adult, Survived_No, Gender_Male, Class_Crew)

4.Association rules

```
In [5]: rules=association_rules(frequent_items,min_threshold=0.7,    metric='lift')
rules
#Leverage values of 0 indicates independents value range between -1 to 1
```

Out[5]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(Age_Adult)	(Class_1st)	0.950477	0.147660	0.144934	0.152486	1.032680	0.004587	1.005694
1	(Class_1st)	(Age_Adult)	0.147660	0.950477	0.144934	0.981538	1.032680	0.004587	2.682493
2	(Age_Adult)	(Class_2nd)	0.950477	0.129487	0.118582	0.124761	0.963505	-0.004492	0.994601
3	(Class_2nd)	(Age_Adult)	0.129487	0.950477	0.118582	0.915789	0.963505	-0.004492	0.588085
4	(Gender_Male)	(Class_3rd)	0.786461	0.320763	0.231713	0.294627	0.918520	-0.020555	0.962947
...
101	(Gender_Male, Class_Crew)	(Survived_No, Age_Adult)	0.391640	0.653339	0.304407	0.777262	1.189676	0.048533	1.556362
102	(Age_Adult)	(Survived_No, Gender_Male, Class_Crew)	0.950477	0.304407	0.304407	0.320268	1.052103	0.015075	1.023334
103	(Survived_No)	(Class_Crew, Age_Adult, Gender_Male)	0.676965	0.391640	0.304407	0.449664	1.148157	0.039280	1.105434
104	(Gender_Male)	(Survived_No, Age_Adult, Class_Crew)	0.786461	0.305770	0.304407	0.387060	1.265851	0.063931	1.132622
105	(Class_Crew)	(Survived_No, Age_Adult, Gender_Male)	0.402090	0.603816	0.304407	0.757062	1.253795	0.061619	1.630802

106 rows × 9 columns

In [6]:

rules.sort_values("lift",ascending=False)[0:20]

Out[6]:

	antecedents		consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
65	(Gender_Female, Age_Adult)		(Survived_Yes)	0.193094	0.323035	0.143571	0.743529	2.301699	0.081195	2.639542
68	(Survived_Yes)	(Gender_Female, Age_Adult)		0.323035	0.193094	0.143571	0.444444	2.301699	0.081195	1.452431
18	(Survived_Yes)	(Gender_Female)		0.323035	0.213539	0.156293	0.483826	2.265745	0.087312	1.523634
19	(Gender_Female)		(Survived_Yes)	0.213539	0.323035	0.156293	0.731915	2.265745	0.087312	2.525187
69	(Gender_Female)		(Survived_Yes, Age_Adult)	0.213539	0.297138	0.143571	0.672340	2.262724	0.080121	2.145099
64	(Survived_Yes, Age_Adult)		(Gender_Female)	0.297138	0.213539	0.143571	0.483180	2.262724	0.080121	1.521732
100	(Survived_No, Class_Crew)		(Age_Adult, Gender_Male)	0.305770	0.757383	0.304407	0.995542	1.314450	0.072822	54.427079
97	(Age_Adult, Gender_Male)		(Survived_No, Class_Crew)	0.757383	0.305770	0.304407	0.401920	1.314450	0.072822	1.160764
51	(Class_Crew)		(Age_Adult, Gender_Male)	0.402090	0.757383	0.391640	0.974011	1.286022	0.087104	9.335480
46	(Age_Adult, Gender_Male)		(Class_Crew)	0.757383	0.402090	0.391640	0.517097	1.286022	0.087104	1.238157
53	(Survived_No, Class_Crew)		(Gender_Male)	0.305770	0.786461	0.304407	0.995542	1.265851	0.063931	47.903983
104	(Gender_Male)	(Survived_No, Age_Adult, Class_Crew)		0.786461	0.305770	0.304407	0.387060	1.265851	0.063931	1.132622
93	(Survived_No, Age_Adult, Class_Crew)		(Gender_Male)	0.305770	0.786461	0.304407	0.995542	1.265851	0.063931	47.903983
56	(Gender_Male)		(Survived_No, Class_Crew)	0.786461	0.305770	0.304407	0.387060	1.265851	0.063931	1.132622
105	(Class_Crew)		(Survived_No, Age_Adult, Gender_Male)	0.402090	0.603816	0.304407	0.757062	1.253795	0.061619	1.630802
92	(Survived_No, Age_Adult, Gender_Male)		(Class_Crew)	0.603816	0.402090	0.304407	0.504138	1.253795	0.061619	1.205800
50	(Gender_Male)		(Age_Adult, Class_Crew)	0.786461	0.402090	0.391640	0.497978	1.238474	0.075412	1.191004
11	(Class_Crew)		(Gender_Male)	0.402090	0.786461	0.391640	0.974011	1.238474	0.075412	8.216621
47	(Age_Adult, Class_Crew)		(Gender_Male)	0.402090	0.786461	0.391640	0.974011	1.238474	0.075412	8.216621
10	(Gender_Male)		(Class_Crew)	0.786461	0.402090	0.391640	0.497978	1.238474	0.075412	1.191004