

Assignment 3

In [2]:

```
import os
import warnings
warnings.filterwarnings("ignore")
grocery_path = r'Grocery_Items_10.csv'

import pandas as pd
grocery_data= pd.read_csv(grocery_path)
groceries_list= [line.dropna().tolist() for idx, line in grocery_data.iterrows()]

from mlxtend.preprocessing import TransactionEncoder
te = TransactionEncoder()
te_ary = te.fit(groceries_list).transform(groceries_list)
final_groceries_df = pd.DataFrame(te_ary, columns=te.columns_)

final_groceries_df.head(3)
```

Out[2]:

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

3 rows × 167 columns

min\_sup = 0.01 and min\_conf 0.1

In [3]:

```
from mlxtend.frequent_patterns import apriori,association_rules
def gen_assoc_rules(df,i,j):
    frequent_items = apriori(df, min_support=i, use_colnames=True)
    ar=association_rules(frequent_items, metric="confidence", min_threshold=j)
    return ar
gen_assoc_rules(final_groceries_df,0.01,0.1)
```

Out[3]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(whole milk)	(other vegetables)	0.157500	0.11975	0.016000	0.101587	0.848328	-0.002861	0.979784
1	(other vegetables)	(whole milk)	0.119750	0.15750	0.016000	0.133612	0.848328	-0.002861	0.972428
2	(rolls/buns)	(whole milk)	0.111625	0.15750	0.014375	0.128779	0.817647	-0.003206	0.967034
3	(soda)	(whole milk)	0.098625	0.15750	0.012125	0.122940	0.780574	-0.003408	0.960596
4	(yogurt)	(whole milk)	0.088750	0.15750	0.012125	0.136620	0.867427	-0.001853	0.975816

(msv): 0.001, 0.005, 0.01 and (mct): 0.05, 0.075, 0.1. For each pair (msv, mct), find the number of association rules

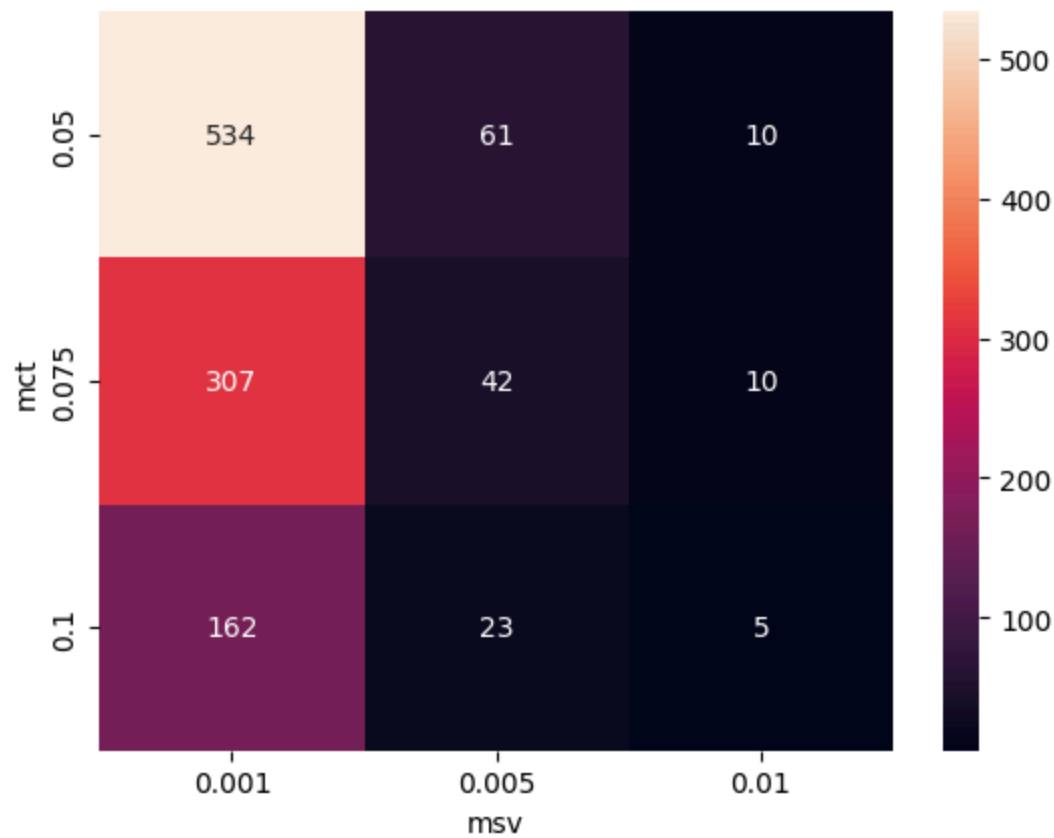
In [7]:

```
import seaborn as sns
msv =[0.001,0.005,0.01]
mct =[0.05,0.075,0.1]

pair_df = pd.DataFrame(columns=['msv', 'mct', 'count'])
for i in msv:
    for j in mct:
        pair_df = pair_df.append({'msv': i, 'mct': j, 'count': len(gen_assoc_rules(final_groceries_df,i,j))}, ignore_index=True)
heatmap = pair_df.pivot("mct", "msv", "count")
sns.heatmap(heatmap,annot=True,fmt=".0f")
```

Out[7]:

<AxesSubplot:xlabel='msv', ylabel='mct'>



Split the dataset into 50:50 (i.e., 2 equal subsets) and extract association rules for each data subset for minimum support = 0.005 and minimum confident threshold = 0.075.

```
In [8]: subset1 = final_groceries_df.iloc[:len(final_groceries_df)//2]
subset2 = final_groceries_df.iloc[len(final_groceries_df)//2:]
```

```
In [9]: gen_assoc_rules(subset1,0.005,0.075)
```

Out[9]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(beef)	(whole milk)	0.02900	0.15925	0.00500	0.172414	1.082661	0.000382	1.015906
1	(bottled beer)	(whole milk)	0.03900	0.15925	0.00825	0.211538	1.328342	0.002039	1.066317
2	(bottled water)	(whole milk)	0.05950	0.15925	0.00600	0.100840	0.633220	-0.003475	0.935040

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
3	(brown bread)	(whole milk)	0.04025	0.15925	0.00500	0.124224	0.780054	-0.001410	0.960005
4	(citrus fruit)	(other vegetables)	0.05625	0.12025	0.00525	0.093333	0.776161	-0.001514	0.970313
5	(citrus fruit)	(whole milk)	0.05625	0.15925	0.00800	0.142222	0.893075	-0.000958	0.980149
6	(citrus fruit)	(yogurt)	0.05625	0.08400	0.00525	0.093333	1.111111	0.000525	1.010294
7	(domestic eggs)	(whole milk)	0.03725	0.15925	0.00550	0.147651	0.927165	-0.000432	0.986392
8	(newspapers)	(whole milk)	0.03625	0.15925	0.00500	0.137931	0.866129	-0.000773	0.975270
9	(rolls/buns)	(other vegetables)	0.10725	0.12025	0.01025	0.095571	0.794770	-0.002647	0.972713
10	(other vegetables)	(rolls/buns)	0.12025	0.10725	0.01025	0.085239	0.794770	-0.002647	0.975938
11	(sausage)	(other vegetables)	0.05725	0.12025	0.00700	0.122271	1.016805	0.000116	1.002302
12	(soda)	(other vegetables)	0.09825	0.12025	0.01175	0.119593	0.994535	-0.000065	0.999254
13	(other vegetables)	(soda)	0.12025	0.09825	0.01175	0.097713	0.994535	-0.000065	0.999405
14	(tropical fruit)	(other vegetables)	0.07075	0.12025	0.00675	0.095406	0.793400	-0.001758	0.972536
15	(whole milk)	(other vegetables)	0.15925	0.12025	0.01550	0.097331	0.809407	-0.003650	0.974610
16	(other vegetables)	(whole milk)	0.12025	0.15925	0.01550	0.128898	0.809407	-0.003650	0.965157
17	(yogurt)	(other vegetables)	0.08400	0.12025	0.00825	0.098214	0.816751	-0.001851	0.975564
18	(pastry)	(whole milk)	0.04950	0.15925	0.00650	0.131313	0.824572	-0.001383	0.967840
19	(pip fruit)	(rolls/buns)	0.04575	0.10725	0.00650	0.142077	1.324723	0.001593	1.040594
20	(pip fruit)	(whole milk)	0.04575	0.15925	0.00575	0.125683	0.789219	-0.001536	0.961608
21	(pork)	(whole milk)	0.03700	0.15925	0.00650	0.175676	1.103144	0.000608	1.019926
22	(root vegetables)	(rolls/buns)	0.07225	0.10725	0.00600	0.083045	0.774312	-0.001749	0.973603
23	(soda)	(rolls/buns)	0.09825	0.10725	0.00825	0.083969	0.782932	-0.002287	0.974585
24	(rolls/buns)	(soda)	0.10725	0.09825	0.00825	0.076923	0.782932	-0.002287	0.976896
25	(whole milk)	(rolls/buns)	0.15925	0.10725	0.01575	0.098901	0.922155	-0.001330	0.990735
26	(rolls/buns)	(whole milk)	0.10725	0.15925	0.01575	0.146853	0.922155	-0.001330	0.985469
27	(yogurt)	(rolls/buns)	0.08400	0.10725	0.00875	0.104167	0.971251	-0.000259	0.996558

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
28	(rolls/buns)	(yogurt)	0.10725	0.08400	0.00875	0.081585	0.971251	-0.000259	0.997371
29	(root vegetables)	(whole milk)	0.07225	0.15925	0.00875	0.121107	0.760485	-0.002756	0.956601
30	(root vegetables)	(yogurt)	0.07225	0.08400	0.00625	0.086505	1.029824	0.000181	1.002742
31	(sausage)	(soda)	0.05725	0.09825	0.00500	0.087336	0.888919	-0.000625	0.988042
32	(sausage)	(whole milk)	0.05725	0.15925	0.00750	0.131004	0.822633	-0.001617	0.967496
33	(sausage)	(yogurt)	0.05725	0.08400	0.00500	0.087336	1.039717	0.000191	1.003656
34	(shopping bags)	(whole milk)	0.05000	0.15925	0.00725	0.145000	0.910518	-0.000713	0.983333
35	(tropical fruit)	(soda)	0.07075	0.09825	0.00650	0.091873	0.935092	-0.000451	0.992978
36	(soda)	(whole milk)	0.09825	0.15925	0.01075	0.109415	0.687063	-0.004896	0.944042
37	(tropical fruit)	(whole milk)	0.07075	0.15925	0.00825	0.116608	0.732231	-0.003017	0.951729
38	(yogurt)	(whole milk)	0.08400	0.15925	0.01100	0.130952	0.822307	-0.002377	0.967438

In [10]:

```
gen_assoc_rules(subset2,0.005,0.075)
```

Out[10]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(bottled beer)	(whole milk)	0.04525	0.15575	0.00800	0.176796	1.135124	0.000952	1.025565
1	(bottled water)	(other vegetables)	0.05725	0.11925	0.00525	0.091703	0.768998	-0.001577	0.969672
2	(bottled water)	(rolls/buns)	0.05725	0.11600	0.00650	0.113537	0.978768	-0.000141	0.997222
3	(bottled water)	(soda)	0.05725	0.09900	0.00600	0.104803	1.058621	0.000332	1.006483
4	(bottled water)	(whole milk)	0.05725	0.15575	0.00900	0.157205	1.009343	0.000083	1.001727
5	(butter)	(whole milk)	0.03675	0.15575	0.00575	0.156463	1.004575	0.000026	1.000845
6	(canned beer)	(whole milk)	0.04800	0.15575	0.00800	0.166667	1.070091	0.000524	1.013100
7	(citrus fruit)	(other vegetables)	0.05225	0.11925	0.00525	0.100478	0.842587	-0.000981	0.979132
8	(citrus fruit)	(whole milk)	0.05225	0.15575	0.00725	0.138756	0.890889	-0.000888	0.980268
9	(citrus fruit)	(yogurt)	0.05225	0.09350	0.00525	0.100478	1.074636	0.000365	1.007758
10	(domestic eggs)	(whole milk)	0.03675	0.15575	0.00575	0.156463	1.004575	0.000026	1.000845

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
11	(frankfurter)	(other vegetables)	0.03525	0.11925	0.00525	0.148936	1.248941	0.001046	1.034881
12	(frankfurter)	(whole milk)	0.03525	0.15575	0.00550	0.156028	1.001787	0.000010	1.000330
13	(newspapers)	(whole milk)	0.03800	0.15575	0.00625	0.164474	1.056011	0.000332	1.010441
14	(rolls/buns)	(other vegetables)	0.11600	0.11925	0.01125	0.096983	0.813273	-0.002583	0.975341
15	(other vegetables)	(rolls/buns)	0.11925	0.11600	0.01125	0.094340	0.813273	-0.002583	0.976083
16	(sausage)	(other vegetables)	0.06100	0.11925	0.00550	0.090164	0.756092	-0.001774	0.968032
17	(shopping bags)	(other vegetables)	0.04650	0.11925	0.00500	0.107527	0.901693	-0.000545	0.986864
18	(tropical fruit)	(other vegetables)	0.06825	0.11925	0.00700	0.102564	0.860076	-0.001139	0.981407
19	(whole milk)	(other vegetables)	0.15575	0.11925	0.01650	0.105939	0.888377	-0.002073	0.985112
20	(other vegetables)	(whole milk)	0.11925	0.15575	0.01650	0.138365	0.888377	-0.002073	0.979823
21	(yogurt)	(other vegetables)	0.09350	0.11925	0.01025	0.109626	0.919293	-0.000900	0.989191
22	(other vegetables)	(yogurt)	0.11925	0.09350	0.01025	0.085954	0.919293	-0.000900	0.991744
23	(pastry)	(whole milk)	0.05300	0.15575	0.00650	0.122642	0.787425	-0.001755	0.962263
24	(pip fruit)	(whole milk)	0.05125	0.15575	0.00725	0.141463	0.908272	-0.000732	0.983359
25	(pip fruit)	(yogurt)	0.05125	0.09350	0.00500	0.097561	1.043433	0.000208	1.004500
26	(root vegetables)	(rolls/buns)	0.06800	0.11600	0.00600	0.088235	0.760649	-0.001888	0.969548
27	(shopping bags)	(rolls/buns)	0.04650	0.11600	0.00525	0.112903	0.973304	-0.000144	0.996509
28	(soda)	(rolls/buns)	0.09900	0.11600	0.00850	0.085859	0.740160	-0.002984	0.967028
29	(tropical fruit)	(rolls/buns)	0.06825	0.11600	0.00600	0.087912	0.757863	-0.001917	0.969205
30	(whole milk)	(rolls/buns)	0.15575	0.11600	0.01300	0.083467	0.719544	-0.005067	0.964504
31	(rolls/buns)	(whole milk)	0.11600	0.15575	0.01300	0.112069	0.719544	-0.005067	0.950806
32	(yogurt)	(rolls/buns)	0.09350	0.11600	0.00725	0.077540	0.668449	-0.003596	0.958307
33	(root vegetables)	(soda)	0.06800	0.09900	0.00650	0.095588	0.965538	-0.000232	0.996228
34	(root vegetables)	(whole milk)	0.06800	0.15575	0.00800	0.117647	0.755358	-0.002591	0.956817
35	(sausage)	(soda)	0.06100	0.09900	0.00600	0.098361	0.993542	-0.000039	0.999291

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
36	(whole milk)	(sausage)	0.15575	0.06100	0.01175	0.075441	1.236744	0.002249	1.015620
37	(sausage)	(whole milk)	0.06100	0.15575	0.01175	0.192623	1.236744	0.002249	1.045670
38	(yogurt)	(sausage)	0.09350	0.06100	0.00725	0.077540	1.271149	0.001547	1.017930
39	(sausage)	(yogurt)	0.06100	0.09350	0.00725	0.118852	1.271149	0.001547	1.028772
40	(shopping bags)	(whole milk)	0.04650	0.15575	0.00750	0.161290	1.035572	0.000258	1.006606
41	(tropical fruit)	(soda)	0.06825	0.09900	0.00600	0.087912	0.888001	-0.000757	0.987843
42	(soda)	(whole milk)	0.09900	0.15575	0.01350	0.136364	0.875529	-0.001919	0.977553
43	(whole milk)	(soda)	0.15575	0.09900	0.01350	0.086677	0.875529	-0.001919	0.986508
44	(tropical fruit)	(whole milk)	0.06825	0.15575	0.00825	0.120879	0.776110	-0.002380	0.960334
45	(tropical fruit)	(yogurt)	0.06825	0.09350	0.00525	0.076923	0.822707	-0.001131	0.982042
46	(yogurt)	(whole milk)	0.09350	0.15575	0.01325	0.141711	0.909863	-0.001313	0.983643
47	(whole milk)	(yogurt)	0.15575	0.09350	0.01325	0.085072	0.909863	-0.001313	0.990789

In [11]:

```
pd.merge(gen_assoc_rules(subset1,0.005,0.075), gen_assoc_rules(subset2,0.005,0.075),on=['antecedents', 'consequents'])
```

Out[11]:

	antecedents	consequents	antecedent support_x	consequent support_x	support_x	confidence_x	lift_x	leverage_x	conviction_x	antecedent support_y	consequent support_y	support_y	confidence_y	lift_y	leverage_y	cc
0	(bottled beer)	(whole milk)	0.03900	0.15925	0.00825	0.211538	1.328342	0.002039	1.066317	0.04525	0.15575	0.00800	0.176796	1.135124	0.000952	
1	(bottled water)	(whole milk)	0.05950	0.15925	0.00600	0.100840	0.633220	-0.003475	0.935040	0.05725	0.15575	0.00900	0.157205	1.009343	0.000083	
2	(citrus fruit)	(other vegetables)	0.05625	0.12025	0.00525	0.093333	0.776161	-0.001514	0.970313	0.05225	0.11925	0.00525	0.100478	0.842587	-0.000981	
3	(citrus fruit)	(whole milk)	0.05625	0.15925	0.00800	0.142222	0.893075	-0.000958	0.980149	0.05225	0.15575	0.00725	0.138756	0.890889	-0.000888	
4	(citrus fruit)	(yogurt)	0.05625	0.08400	0.00525	0.093333	1.111111	0.000525	1.010294	0.05225	0.09350	0.00525	0.100478	1.074636	0.000365	
5	(domestic eggs)	(whole milk)	0.03725	0.15925	0.00550	0.147651	0.927165	-0.000432	0.986392	0.03675	0.15575	0.00575	0.156463	1.004575	0.000026	
6	(newspapers)	(whole milk)	0.03625	0.15925	0.00500	0.137931	0.866129	-0.000773	0.975270	0.03800	0.15575	0.00625	0.164474	1.056011	0.000332	

	antecedents	consequents	antecedent support_x	consequent support_x	support_x	confidence_x	lift_x	leverage_x	conviction_x	antecedent support_y	consequent support_y	support_y	confidence_y	lift_y	leverage_y	cc
7	(rolls/buns)	(other vegetables)	0.10725	0.12025	0.01025	0.095571	0.794770	-0.002647	0.972713	0.11600	0.11925	0.01125	0.096983	0.813273	-0.002583	
8	(other vegetables)	(rolls/buns)	0.12025	0.10725	0.01025	0.085239	0.794770	-0.002647	0.975938	0.11925	0.11600	0.01125	0.094340	0.813273	-0.002583	
9	(sausage)	(other vegetables)	0.05725	0.12025	0.00700	0.122271	1.016805	0.000116	1.002302	0.06100	0.11925	0.00550	0.090164	0.756092	-0.001774	
10	(tropical fruit)	(other vegetables)	0.07075	0.12025	0.00675	0.095406	0.793400	-0.001758	0.972536	0.06825	0.11925	0.00700	0.102564	0.860076	-0.001139	
11	(whole milk)	(other vegetables)	0.15925	0.12025	0.01550	0.097331	0.809407	-0.003650	0.974610	0.15575	0.11925	0.01650	0.105939	0.888377	-0.002073	
12	(other vegetables)	(whole milk)	0.12025	0.15925	0.01550	0.128898	0.809407	-0.003650	0.965157	0.11925	0.15575	0.01650	0.138365	0.888377	-0.002073	
13	(yogurt)	(other vegetables)	0.08400	0.12025	0.00825	0.098214	0.816751	-0.001851	0.975564	0.09350	0.11925	0.01025	0.109626	0.919293	-0.000900	
14	(pastry)	(whole milk)	0.04950	0.15925	0.00650	0.131313	0.824572	-0.001383	0.967840	0.05300	0.15575	0.00650	0.122642	0.787425	-0.001755	
15	(pip fruit)	(whole milk)	0.04575	0.15925	0.00575	0.125683	0.789219	-0.001536	0.961608	0.05125	0.15575	0.00725	0.141463	0.908272	-0.000732	
16	(root vegetables)	(rolls/buns)	0.07225	0.10725	0.00600	0.083045	0.774312	-0.001749	0.973603	0.06800	0.11600	0.00600	0.088235	0.760649	-0.001888	
17	(soda)	(rolls/buns)	0.09825	0.10725	0.00825	0.083969	0.782932	-0.002287	0.974585	0.09900	0.11600	0.00850	0.085859	0.740160	-0.002984	
18	(whole milk)	(rolls/buns)	0.15925	0.10725	0.01575	0.098901	0.922155	-0.001330	0.990735	0.15575	0.11600	0.01300	0.083467	0.719544	-0.005067	
19	(rolls/buns)	(whole milk)	0.10725	0.15925	0.01575	0.146853	0.922155	-0.001330	0.985469	0.11600	0.15575	0.01300	0.112069	0.719544	-0.005067	
20	(yogurt)	(rolls/buns)	0.08400	0.10725	0.00875	0.104167	0.971251	-0.000259	0.996558	0.09350	0.11600	0.00725	0.077540	0.668449	-0.003596	
21	(root vegetables)	(whole milk)	0.07225	0.15925	0.00875	0.121107	0.760485	-0.002756	0.956601	0.06800	0.15575	0.00800	0.117647	0.755358	-0.002591	
22	(sausage)	(soda)	0.05725	0.09825	0.00500	0.087336	0.888919	-0.000625	0.988042	0.06100	0.09900	0.00600	0.098361	0.993542	-0.000039	
23	(sausage)	(whole milk)	0.05725	0.15925	0.00750	0.131004	0.822633	-0.001617	0.967496	0.06100	0.15575	0.01175	0.192623	1.236744	0.002249	
24	(sausage)	(yogurt)	0.05725	0.08400	0.00500	0.087336	1.039717	0.000191	1.003656	0.06100	0.09350	0.00725	0.118852	1.271149	0.001547	
25	(shopping bags)	(whole milk)	0.05000	0.15925	0.00725	0.145000	0.910518	-0.000713	0.983333	0.04650	0.15575	0.00750	0.161290	1.035572	0.000258	



	antecedents	consequents	antecedent support_x	consequent support_x	support_x	confidence_x	lift_x	leverage_x	conviction_x	antecedent support_y	consequent support_y	support_y	confidence_y	lift_y	leverage_y	cc
26	(tropical fruit)	(soda)	0.07075	0.09825	0.00650	0.091873	0.935092	-0.000451	0.992978	0.06825	0.09900	0.00600	0.087912	0.888001	-0.000757	
27	(soda)	(whole milk)	0.09825	0.15925	0.01075	0.109415	0.687063	-0.004896	0.944042	0.09900	0.15575	0.01350	0.136364	0.875529	-0.001919	
28	(tropical fruit)	(whole milk)	0.07075	0.15925	0.00825	0.116608	0.732231	-0.003017	0.951729	0.06825	0.15575	0.00825	0.120879	0.776110	-0.002380	
29	(yogurt)	(whole milk)	0.08400	0.15925	0.01100	0.130952	0.822307	-0.002377	0.967438	0.09350	0.15575	0.01325	0.141711	0.909863	-0.001313	

Image processing, getting images and labels

In [20]:

```
from glob import glob
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.image import ImageDataGenerator

dog_images=r'output folder'

hist_images = []
labels = []
for index,breed in enumerate(os.listdir(dog_images)):
    image_folder=os.path.join(dog_images,breed)
    images=glob(os.path.join(image_folder, '*.jpg'))
    hist_images.extend(images)
    labels.extend([breed] * len(images))

dog_df = pd.DataFrame({'image_path': hist_images, 'breed': labels})

training_data, validation_data = train_test_split(dog_df, test_size=0.2, random_state=42)

train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2)
val_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2)

train = train_datagen.flow_from_dataframe(training_data,x_col='image_path',y_col='breed',target_size=(128, 128),batch_size=16,class_mode='categorical')
validation = val_datagen.flow_from_dataframe(validation_data,x_col='image_path',y_col='breed',target_size=(128, 128),batch_size=16,class_mode='categorical')
```

Found 556 validated image filenames belonging to 4 classes.  
Found 140 validated image filenames belonging to 4 classes.

classification model as per the given parameters

In [27]:

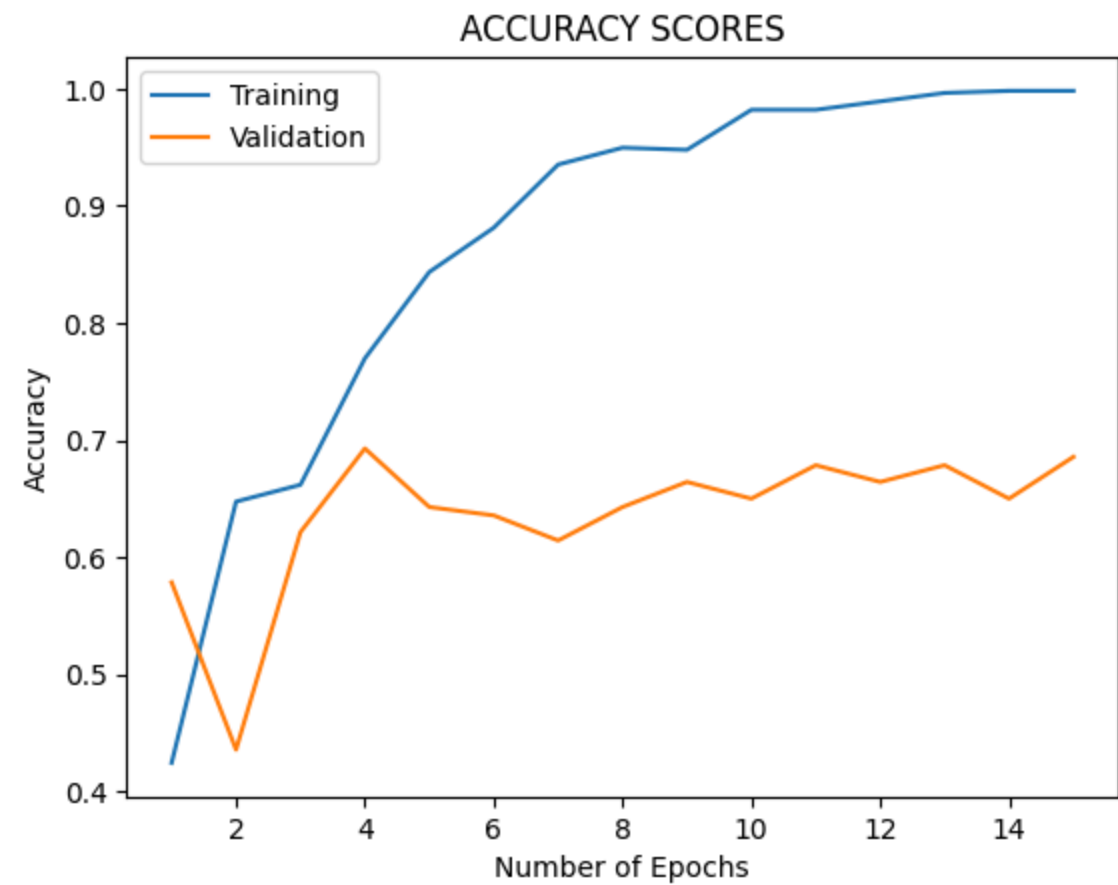
```
from tensorflow.keras.layers import Dense,Conv2D,Flatten,MaxPooling2D
from tensorflow.keras.models import Sequential
import matplotlib.pyplot as plt

warnings.filterwarnings("ignore", category=DeprecationWarning)

model=Sequential([
    Conv2D(8,(3,3),activation='relu',input_shape = (128,128,3)),
    MaxPooling2D(pool_size=(2,2)) ,
    Flatten(),
    Dense(16,activation='relu'),
    Dense(4,activation = 'softmax')
])
model.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model.fit(train,steps_per_epoch=len(train),epochs=15,validation_data=validation,validation_steps=len(validation) )
training = history.history['accuracy']
validate = history.history['val_accuracy']
epochs = range(1, len(training) + 1)
plt.plot(epochs, training , label='Training')
plt.plot(epochs, validate, label='Validation')
plt.title("ACCURACY SCORES")
plt.xlabel('Number of Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

WARNING:tensorflow:sample\_weight modes were coerced from  
...  
to  
['...']  
WARNING:tensorflow:sample\_weight modes were coerced from  
...  
to  
['...']  
Train for 35 steps, validate for 9 steps  
Epoch 1/15  
35/35 [=====] - 4s 118ms/step - loss: 1.5857 - accuracy: 0.4245 - val\_loss: 1.0482 - val\_accuracy: 0.5786  
Epoch 2/15  
35/35 [=====] - 4s 105ms/step - loss: 0.8763 - accuracy: 0.6475 - val\_loss: 1.2784 - val\_accuracy: 0.4357  
Epoch 3/15  
35/35 [=====] - 4s 105ms/step - loss: 0.7887 - accuracy: 0.6619 - val\_loss: 1.0064 - val\_accuracy: 0.6214  
Epoch 4/15

```
35/35 [=====] - 4s 106ms/step - loss: 0.6465 - accuracy: 0.7698 - val_loss: 0.8478 - val_accuracy: 0.6929
Epoch 5/15
35/35 [=====] - 4s 106ms/step - loss: 0.4626 - accuracy: 0.8435 - val_loss: 0.8863 - val_accuracy: 0.6429
Epoch 6/15
35/35 [=====] - 4s 120ms/step - loss: 0.4175 - accuracy: 0.8813 - val_loss: 0.9007 - val_accuracy: 0.6357
Epoch 7/15
35/35 [=====] - 4s 119ms/step - loss: 0.2904 - accuracy: 0.9353 - val_loss: 0.8835 - val_accuracy: 0.6143
Epoch 8/15
35/35 [=====] - 4s 121ms/step - loss: 0.2479 - accuracy: 0.9496 - val_loss: 0.9372 - val_accuracy: 0.6429
Epoch 9/15
35/35 [=====] - 4s 111ms/step - loss: 0.2088 - accuracy: 0.9478 - val_loss: 0.8572 - val_accuracy: 0.6643
Epoch 10/15
35/35 [=====] - 4s 105ms/step - loss: 0.1525 - accuracy: 0.9820 - val_loss: 0.8845 - val_accuracy: 0.6500
Epoch 11/15
35/35 [=====] - 5s 130ms/step - loss: 0.1269 - accuracy: 0.9820 - val_loss: 0.8881 - val_accuracy: 0.6786
Epoch 12/15
35/35 [=====] - 4s 122ms/step - loss: 0.1043 - accuracy: 0.9892 - val_loss: 1.0284 - val_accuracy: 0.6643
Epoch 13/15
35/35 [=====] - 4s 107ms/step - loss: 0.0772 - accuracy: 0.9964 - val_loss: 0.9741 - val_accuracy: 0.6786
Epoch 14/15
35/35 [=====] - 4s 114ms/step - loss: 0.0557 - accuracy: 0.9982 - val_loss: 0.9564 - val_accuracy: 0.6500
Epoch 15/15
35/35 [=====] - 4s 106ms/step - loss: 0.0451 - accuracy: 0.9982 - val_loss: 0.9903 - val_accuracy: 0.6857
```



916461327

In [31]:

```
model=Sequential([
    Conv2D(8,(3,3),activation='relu',input_shape = (128,128,3)),
    MaxPooling2D(pool_size=(2,2)) ,
    Flatten(),
    Dense(8,activation='relu'),
    Dense(4,activation = 'softmax')
])
model.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model.fit(train,steps_per_epoch=len(train),epochs=15,validation_data=validation,validation_steps=len(validation) )
training = history.history['accuracy']
validate = history.history['val_accuracy']
epochs = range(1, len(training) + 1)
plt.plot(epochs, training , label='Training')
```

```
plt.plot(epochs, validate, label='Validation')
plt.title("ACCURACY SCORES")
plt.xlabel('Number of Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

WARNING:tensorflow:sample\_weight modes were coerced from

...  
to  
['...']

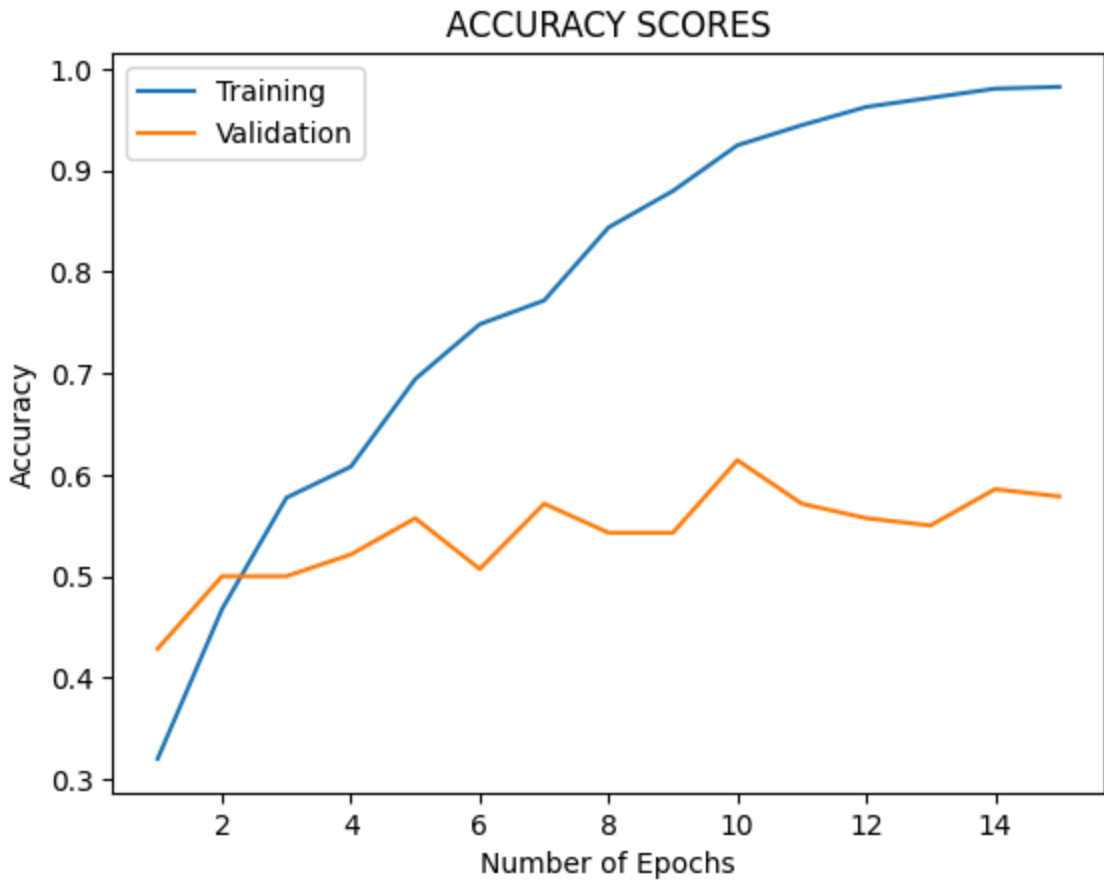
WARNING:tensorflow:sample\_weight modes were coerced from

...  
to  
['...']

Train for 35 steps, validate for 9 steps

Epoch 1/15	
35/35 [=====]	- 4s 115ms/step - loss: 1.3761 - accuracy: 0.3201 - val_loss: 1.2769 - val_accuracy: 0.4286
Epoch 2/15	
35/35 [=====]	- 4s 112ms/step - loss: 1.1586 - accuracy: 0.4676 - val_loss: 1.0770 - val_accuracy: 0.5000
Epoch 3/15	
35/35 [=====]	- 4s 118ms/step - loss: 0.9557 - accuracy: 0.5773 - val_loss: 1.1336 - val_accuracy: 0.5000
Epoch 4/15	
35/35 [=====]	- 4s 118ms/step - loss: 0.8792 - accuracy: 0.6079 - val_loss: 0.9820 - val_accuracy: 0.5214
Epoch 5/15	
35/35 [=====]	- 4s 113ms/step - loss: 0.6651 - accuracy: 0.6942 - val_loss: 0.9597 - val_accuracy: 0.5571
Epoch 6/15	
35/35 [=====]	- 4s 113ms/step - loss: 0.5727 - accuracy: 0.7482 - val_loss: 1.0857 - val_accuracy: 0.5071
Epoch 7/15	
35/35 [=====]	- 4s 118ms/step - loss: 0.4737 - accuracy: 0.7716 - val_loss: 0.9823 - val_accuracy: 0.5714
Epoch 8/15	
35/35 [=====]	- 4s 119ms/step - loss: 0.4129 - accuracy: 0.8435 - val_loss: 1.2853 - val_accuracy: 0.5429
Epoch 9/15	
35/35 [=====]	- 4s 112ms/step - loss: 0.3999 - accuracy: 0.8795 - val_loss: 1.1484 - val_accuracy: 0.5429
Epoch 10/15	
35/35 [=====]	- 4s 117ms/step - loss: 0.3042 - accuracy: 0.9245 - val_loss: 1.0337 - val_accuracy: 0.6143
Epoch 11/15	
35/35 [=====]	- 4s 115ms/step - loss: 0.2475 - accuracy: 0.9442 - val_loss: 1.2213 - val_accuracy: 0.5714
Epoch 12/15	
35/35 [=====]	- 4s 113ms/step - loss: 0.1959 - accuracy: 0.9622 - val_loss: 1.4754 - val_accuracy: 0.5571
Epoch 13/15	
35/35 [=====]	- 4s 116ms/step - loss: 0.1575 - accuracy: 0.9712 - val_loss: 1.4844 - val_accuracy: 0.5500
Epoch 14/15	
35/35 [=====]	- 4s 116ms/step - loss: 0.1325 - accuracy: 0.9802 - val_loss: 1.3893 - val_accuracy: 0.5857

Epoch 15/15  
35/35 [=====] - 4s 115ms/step - loss: 0.0991 - accuracy: 0.9820 - val\_loss: 1.6109 - val\_accuracy: 0.5786



In [30]:

```
model=Sequential([
    Conv2D(8,(3,3),activation='relu',input_shape = (128,128,3)),
    MaxPooling2D(pool_size=(2,2)) ,
    Flatten(),
    Dense(32,activation='relu'),
    Dense(4,activation = 'softmax')
])
model.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['accuracy'])
history = model.fit(train,steps_per_epoch=len(train),epochs=15,validation_data=validation,validation_steps=len(validation) )
training = history.history['accuracy']
validate = history.history['val_accuracy']
epochs = range(1, len(training) + 1)
plt.plot(epochs, training , label='Training')
```

```
plt.plot(epochs, validate, label='Validation')
plt.title("ACCURACY SCORES")
plt.xlabel('Number of Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

WARNING:tensorflow:sample\_weight modes were coerced from

...  
to  
['...']

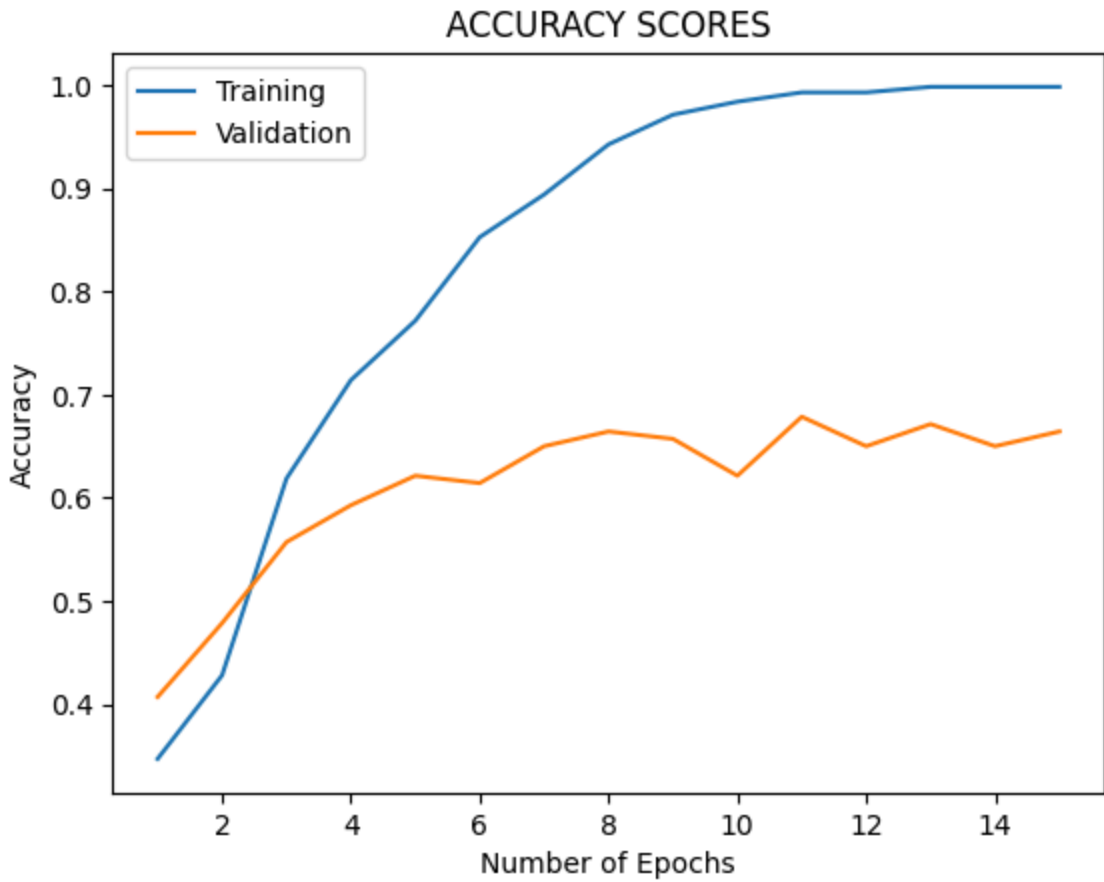
WARNING:tensorflow:sample\_weight modes were coerced from

...  
to  
['...']

Train for 35 steps, validate for 9 steps

Epoch 1/15	35/35 [=====]	- 4s 114ms/step	- loss: 1.7120	- accuracy: 0.3471	- val_loss: 1.2061	- val_accuracy: 0.4071
Epoch 2/15	35/35 [=====]	- 4s 121ms/step	- loss: 1.1592	- accuracy: 0.4281	- val_loss: 1.1586	- val_accuracy: 0.4786
Epoch 3/15	35/35 [=====]	- 4s 116ms/step	- loss: 0.9636	- accuracy: 0.6187	- val_loss: 1.2392	- val_accuracy: 0.5571
Epoch 4/15	35/35 [=====]	- 4s 120ms/step	- loss: 0.7744	- accuracy: 0.7140	- val_loss: 0.9795	- val_accuracy: 0.5929
Epoch 5/15	35/35 [=====]	- 4s 116ms/step	- loss: 0.6030	- accuracy: 0.7716	- val_loss: 0.9346	- val_accuracy: 0.6214
Epoch 6/15	35/35 [=====]	- 4s 111ms/step	- loss: 0.4527	- accuracy: 0.8525	- val_loss: 0.8945	- val_accuracy: 0.6143
Epoch 7/15	35/35 [=====]	- 4s 120ms/step	- loss: 0.3734	- accuracy: 0.8939	- val_loss: 0.9114	- val_accuracy: 0.6500
Epoch 8/15	35/35 [=====]	- 4s 111ms/step	- loss: 0.2620	- accuracy: 0.9424	- val_loss: 0.8783	- val_accuracy: 0.6643
Epoch 9/15	35/35 [=====]	- 4s 127ms/step	- loss: 0.1883	- accuracy: 0.9712	- val_loss: 0.9116	- val_accuracy: 0.6571
Epoch 10/15	35/35 [=====]	- 4s 119ms/step	- loss: 0.1300	- accuracy: 0.9838	- val_loss: 1.0538	- val_accuracy: 0.6214
Epoch 11/15	35/35 [=====]	- 4s 123ms/step	- loss: 0.1009	- accuracy: 0.9928	- val_loss: 0.9435	- val_accuracy: 0.6786
Epoch 12/15	35/35 [=====]	- 4s 120ms/step	- loss: 0.0739	- accuracy: 0.9928	- val_loss: 0.9438	- val_accuracy: 0.6500
Epoch 13/15	35/35 [=====]	- 4s 125ms/step	- loss: 0.0483	- accuracy: 0.9982	- val_loss: 0.9634	- val_accuracy: 0.6714
Epoch 14/15	35/35 [=====]	- 4s 127ms/step	- loss: 0.0384	- accuracy: 0.9982	- val_loss: 0.9903	- val_accuracy: 0.6500

Epoch 15/15  
35/35 [=====] - 4s 113ms/step - loss: 0.0312 - accuracy: 0.9982 - val\_loss: 1.0859 - val\_accuracy: 0.6643



3 models are overfitting Model 1 generally outperforms Model 2,3 in terms of both training and validation accuracy. model 3 is better than model 2.

```
In [ ]: References :      https://seaborn.pydata.org/generated/seaborn.heatmap.html
          http://rasbt.github.io/mlxtend/user_guide/frequent_patterns/association_rules/
```