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

In [2]:
```python
data=pd.read_csv('MarketBasketAnalysis_kaggle.csv')
data.head()
```

Out[2]:

	Member_number	Date	itemDescription
0	1808	21-07-2015	tropical fruit
1	2552	05-01-2015	whole milk
2	2300	19-09-2015	pip fruit
3	1187	12-12-2015	other vegetables
4	3037	01-02-2015	whole milk

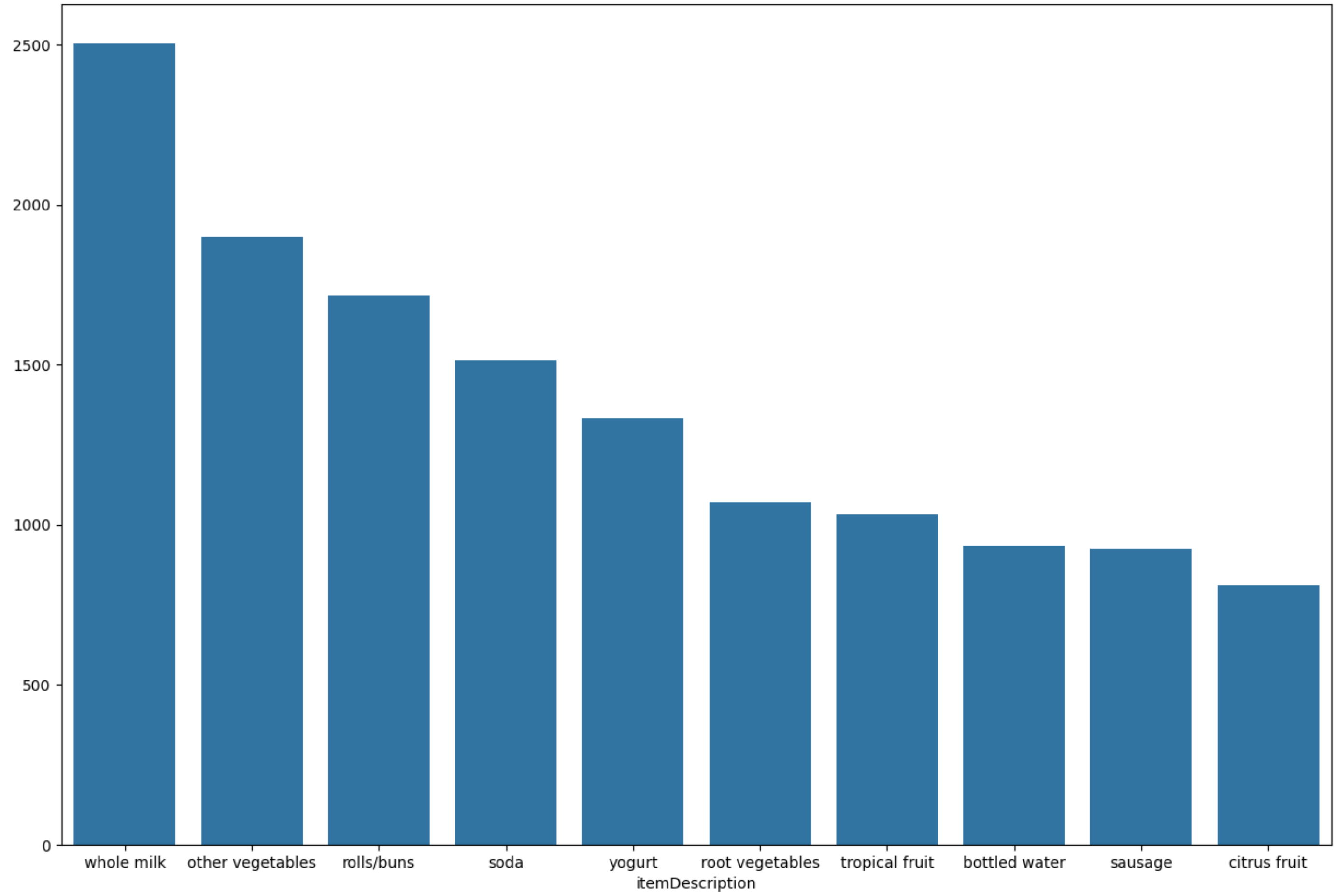
In [3]:
```python
x=data['itemDescription'].value_counts().sort_values(ascending=False)[:10]
#Arranging data in ascending order with Top 10 Item sold
```

In [4]:
```python
x
```

Out[4]:
```
itemDescription
whole milk          2502
other vegetables    1898
rolls/buns          1716
soda                1514
yogurt              1334
root vegetables     1071
tropical fruit      1032
bottled water        933
sausage              924
citrus fruit         812
Name: count, dtype: int64
```

In [5]:
```python
plt.figure(figsize=(15,10))
sns.barplot(x=x.index,y=x.values)
```

Out[5]:
```
<Axes: xlabel='itemDescription'>
```



In [6]:
```
data['Quantity']=1
```

In [7]:
```
trans=data.groupby(['Member_number','itemDescription'])['Quantity'].sum().unstack().reset_index(
# making Pivot table and grouping valuable data
```

In [8]:
```
trans=trans.fillna(0) # replacing NaN values with 0
```

In [9]:
```
trans
```

Out[9]:

itemDescription	Instant food products	UHT-milk	abrasive cleaner	artif. sweetener	baby cosmetics	bags	baking powder	bathroom cleaner	beef	berries	...	t
Member_number												
1000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
1001	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	...	
1002	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
1003	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
1004	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
4996	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
4997	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
4998	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
4999	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	...	
5000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	

3898 rows × 167 columns

In [10]:

```
def encode(x):
    if x<=0:
        return 0
    elif x>0:
        return 1
basket=trans.map(encode)
```

In [11]:

```
basket
```

Out[11]:

itemDescription	Instant food products	UHT-milk	abrasive cleaner	artif. sweetener	baby cosmetics	bags	baking powder	bathroom cleaner	beef	berries	...	t
Member_number												
1000	0	0	0	0	0	0	0	0	0	0	...	
1001	0	0	0	0	0	0	0	0	1	0	...	
1002	0	0	0	0	0	0	0	0	0	0	...	
1003	0	0	0	0	0	0	0	0	0	0	...	
1004	0	0	0	0	0	0	0	0	0	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
4996	0	0	0	0	0	0	0	0	0	0	...	
4997	0	0	0	0	0	0	0	0	0	0	...	
4998	0	0	0	0	0	0	0	0	0	0	...	
4999	0	0	0	0	0	0	0	0	0	1	...	
5000	0	0	0	0	0	0	0	0	0	0	...	

3898 rows × 167 columns

In [12]:
```
freq=apriori(basket,min_support=0.06,use_colnames=True)
rules=association_rules(freq,metric='lift',min_threshold=1)
```

```
C:\Users\mohda\AppData\Local\Programs\Python\Python311\Lib\site-packages\mlxtend\frequent_patter
ns\fpcommon.py:110: DeprecationWarning: DataFrames with non-bool types result in worse computati
onalperformance and their support might be discontinued in the future.Please use a DataFrame wit
h bool type
  warnings.warn(
```

In [13]:
```
rules.head()
```

Out[13]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhan
0	(whole milk)	(beef)	0.458184	0.119548	0.064135	0.139978	1.170886	0.009360	1.023754	
1	(beef)	(whole milk)	0.119548	0.458184	0.064135	0.536481	1.170886	0.009360	1.168919	
2	(other vegetables)	(bottled beer)	0.376603	0.158799	0.068497	0.181880	1.145345	0.008692	1.028212	
3	(bottled beer)	(other vegetables)	0.158799	0.376603	0.068497	0.431341	1.145345	0.008692	1.096257	
4	(rolls/buns)	(bottled beer)	0.349666	0.158799	0.063109	0.180484	1.136555	0.007582	1.026461	

In [14]:
```
rules[(rules['confidence']>0.4)&(rules['lift']>1.0)]
```

Out[14]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
1	(beef)	(whole milk)	0.119548	0.458184	0.064135	0.536481	1.170886	0.009360	1.168919
3	(bottled beer)	(other vegetables)	0.158799	0.376603	0.068497	0.431341	1.145345	0.008692	1.096257
6	(bottled beer)	(whole milk)	0.158799	0.458184	0.085428	0.537964	1.174124	0.012669	1.172672
8	(bottled water)	(other vegetables)	0.213699	0.376603	0.093894	0.439376	1.166680	0.013414	1.111969
14	(bottled water)	(whole milk)	0.213699	0.458184	0.112365	0.525810	1.147597	0.014452	1.142615
19	(brown bread)	(whole milk)	0.135967	0.458184	0.069779	0.513208	1.120091	0.007481	1.113034
20	(butter)	(whole milk)	0.126475	0.458184	0.066188	0.523327	1.142176	0.008239	1.136661
22	(canned beer)	(other vegetables)	0.165213	0.376603	0.067214	0.406832	1.080267	0.004994	1.050962
24	(canned beer)	(rolls/buns)	0.165213	0.349666	0.066701	0.403727	1.154605	0.008931	1.090663
26	(canned beer)	(whole milk)	0.165213	0.458184	0.087224	0.527950	1.152268	0.011526	1.147795
29	(citrus fruit)	(other vegetables)	0.185480	0.376603	0.077476	0.417704	1.109135	0.007623	1.070584
35	(citrus fruit)	(whole milk)	0.185480	0.458184	0.092355	0.497925	1.086737	0.007371	1.079155
37	(curd)	(whole milk)	0.120831	0.458184	0.063622	0.526539	1.149188	0.008259	1.144374
38	(domestic eggs)	(whole milk)	0.133145	0.458184	0.070292	0.527938	1.152242	0.009287	1.147766
41	(frankfurter)	(other vegetables)	0.137506	0.376603	0.061057	0.444030	1.179038	0.009272	1.121277
43	(frankfurter)	(whole milk)	0.137506	0.458184	0.067984	0.494403	1.079050	0.004980	1.071637
45	(fruit/vegetable juice)	(whole milk)	0.124936	0.458184	0.062340	0.498973	1.089025	0.005096	1.081412
46	(newspapers)	(whole milk)	0.139815	0.458184	0.072345	0.517431	1.129310	0.008284	1.122775
48	(pastry)	(other vegetables)	0.177527	0.376603	0.071575	0.403179	1.070567	0.004718	1.044529
51	(pip fruit)	(other vegetables)	0.170600	0.376603	0.072345	0.424060	1.126013	0.008096	1.082399
53	(rolls/buns)	(other vegetables)	0.349666	0.376603	0.146742	0.419663	1.114335	0.015056	1.074197
55	(root vegetables)	(other vegetables)	0.230631	0.376603	0.094151	0.408231	1.083982	0.007294	1.053447
57	(sausage)	(other vegetables)	0.206003	0.376603	0.092868	0.450809	1.197040	0.015287	1.135119
59	(shopping bags)	(other vegetables)	0.168291	0.376603	0.073114	0.434451	1.153604	0.009735	1.102286
65	(whipped/sour cream)	(other vegetables)	0.154695	0.376603	0.066957	0.432836	1.149315	0.008699	1.099147
66	(other vegetables)	(whole milk)	0.376603	0.458184	0.191380	0.508174	1.109106	0.018827	1.101643

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
67	(whole milk)	(other vegetables)	0.458184	0.376603	0.191380	0.417693	1.109106	0.018827	1.070564
69	(yogurt)	(other vegetables)	0.282966	0.376603	0.120318	0.425204	1.129050	0.013752	1.084553
74	(pastry)	(whole milk)	0.177527	0.458184	0.091072	0.513006	1.119651	0.009732	1.112572
81	(pip fruit)	(whole milk)	0.170600	0.458184	0.086968	0.509774	1.112598	0.008801	1.105239
82	(pork)	(whole milk)	0.132376	0.458184	0.066957	0.505814	1.103955	0.006305	1.096381
89	(shopping bags)	(rolls/buns)	0.168291	0.349666	0.068753	0.408537	1.168361	0.009907	1.099533
94	(rolls/buns)	(whole milk)	0.349666	0.458184	0.178553	0.510638	1.114484	0.018342	1.107190
100	(root vegetables)	(whole milk)	0.230631	0.458184	0.113135	0.490545	1.070630	0.007464	1.063522
107	(sausage)	(whole milk)	0.206003	0.458184	0.106978	0.519303	1.133394	0.012591	1.127146
113	(shopping bags)	(whole milk)	0.168291	0.458184	0.091329	0.542683	1.184422	0.014220	1.184772
116	(soda)	(whole milk)	0.313494	0.458184	0.151103	0.481997	1.051973	0.007465	1.045971
121	(tropical fruit)	(whole milk)	0.233710	0.458184	0.116470	0.498353	1.087672	0.009388	1.080076
124	(whipped/sour cream)	(whole milk)	0.154695	0.458184	0.079785	0.515755	1.125650	0.008906	1.118888
127	(yogurt)	(whole milk)	0.282966	0.458184	0.150590	0.532185	1.161510	0.020940	1.158185
128	(other vegetables, rolls/buns)	(whole milk)	0.146742	0.458184	0.082093	0.559441	1.220996	0.014859	1.229837
129	(other vegetables, whole milk)	(rolls/buns)	0.191380	0.349666	0.082093	0.428954	1.226753	0.015174	1.138847
130	(rolls/buns, whole milk)	(other vegetables)	0.178553	0.376603	0.082093	0.459770	1.220834	0.014850	1.153947
134	(soda, other vegetables)	(whole milk)	0.124166	0.458184	0.069266	0.557851	1.217528	0.012375	1.225416
136	(soda, whole milk)	(other vegetables)	0.151103	0.376603	0.069266	0.458404	1.217206	0.012360	1.151036
141	(other vegetables, yogurt)	(whole milk)	0.120318	0.458184	0.071832	0.597015	1.303003	0.016704	1.344507
142	(whole milk, yogurt)	(other vegetables)	0.150590	0.376603	0.071832	0.477002	1.266589	0.015119	1.191967
146	(soda, rolls/buns)	(whole milk)	0.119805	0.458184	0.065162	0.543897	1.187072	0.010269	1.187926
147	(soda, whole milk)	(rolls/buns)	0.151103	0.349666	0.065162	0.431239	1.233288	0.012326	1.143422
153	(rolls/buns, yogurt)	(whole milk)	0.111339	0.458184	0.065931	0.592166	1.292420	0.014917	1.328521

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
154	(whole milk, yogurt)	(rolls/buns)	0.150590	0.349666	0.065931	0.437819	1.252106	0.013275	1.156805

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