

```
In [3]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.neighbors import NearestNeighbors
import os
os.chdir('/Users/Lenovo/Desktop/EBAC')
import warnings
warnings.filterwarnings('ignore')
```

```
In [13]: datos = pd.read_csv('wine-clustering.csv')
datos.head()
```

Out[13]:

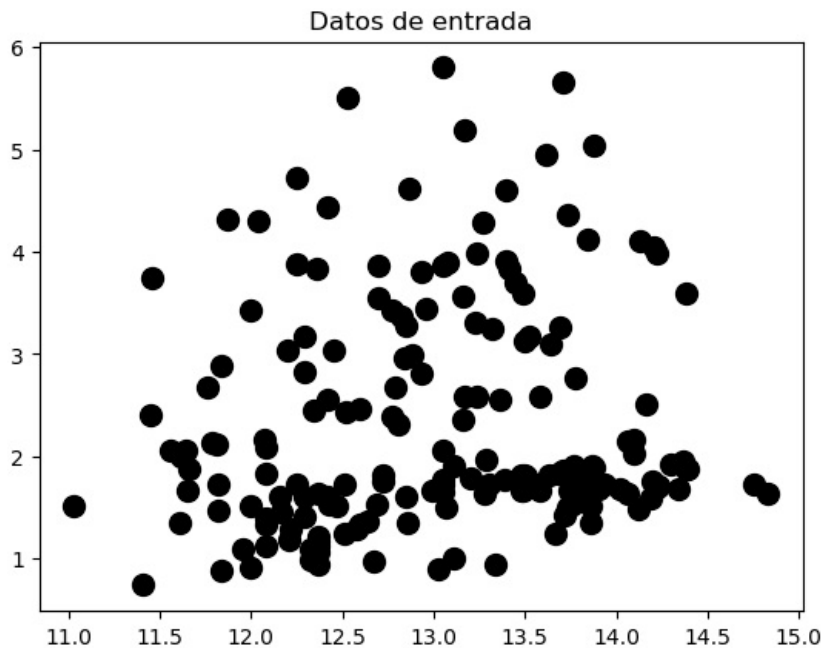
	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	

```
In [15]: # Convertimos a array para poder trabajarlo
wine_array = datos.values
wine_array
```

```
Out[15]: array([[1.423e+01, 1.710e+00, 2.430e+00, ..., 1.040e+00, 3.920e+00,
1.065e+03],
[1.320e+01, 1.780e+00, 2.140e+00, ..., 1.050e+00, 3.400e+00,
1.050e+03],
[1.316e+01, 2.360e+00, 2.670e+00, ..., 1.030e+00, 3.170e+00,
1.185e+03],
...,
[1.327e+01, 4.280e+00, 2.260e+00, ..., 5.900e-01, 1.560e+00,
8.350e+02],
[1.317e+01, 2.590e+00, 2.370e+00, ..., 6.000e-01, 1.620e+00,
8.400e+02],
[1.413e+01, 4.100e+00, 2.740e+00, ..., 6.100e-01, 1.600e+00,
5.600e+02]])
```

```
In [25]: # Visualizacion de los puntos de la poblacion
plt.figure()
plt.title('Datos de entrada')
plt.scatter(wine_array[:,0], wine_array[:,1], marker = 'o', s = 100, color = 'black')
```

```
Out[25]: <matplotlib.collections.PathCollection at 0x1ff0ebe1ee0>
```



```
In [21]: # Definir el numero de vecinos
k = 5
# Definir punto a relacionar
test_data = pd.DataFrame({
    'Alcohol': [14], 'Malic_Acid': [2], 'Ash': [2.5], 'Ash_Alcanity': [16], 'Magnesium': [115],
    'Total_Phenols': [3], 'Flavanoids': [2.5], 'Nonflavanoid_Phenols': [0.4],
```

```

        'Proanthocyanins': [2], 'Color_Intensity': [9], 'Hue': [1], 'OD280': [3.5], 'Proline': [800]
    })
    test = test_data.values
    test

```

```

Out[21]: array([[1.40e+01, 2.00e+00, 2.50e+00, 1.60e+01, 1.15e+02, 3.00e+00,
                2.50e+00, 4.00e-01, 2.00e+00, 9.00e+00, 1.00e+00, 3.50e+00,
                8.00e+02]])

```

```

In [27]: #Ejecucion del algoritmo KNN
knn_model = NearestNeighbors(n_neighbors = k, algorithm = 'auto').fit(wine_array)
distances, indices = knn_model.kneighbors(test)

```

```

In [43]: vinos_parecidos = datos.iloc[indices[0]]
print(vinos_parecidos)

```

	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	\
40	13.56	1.71	2.31	16.2	117	3.15	
20	14.06	1.63	2.28	16.0	126	3.00	
25	13.05	2.05	3.22	25.0	124	2.63	
21	12.93	3.80	2.65	18.6	102	2.41	
141	13.36	2.56	2.35	20.0	89	1.40	

	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color_Intensity	Hue	\
40	3.29		0.34	2.34	6.13	0.95
20	3.17		0.24	2.10	5.65	1.09
25	2.68		0.47	1.92	3.58	1.13
21	2.41		0.25	1.98	4.50	1.03
141	0.50		0.37	0.64	5.60	0.70

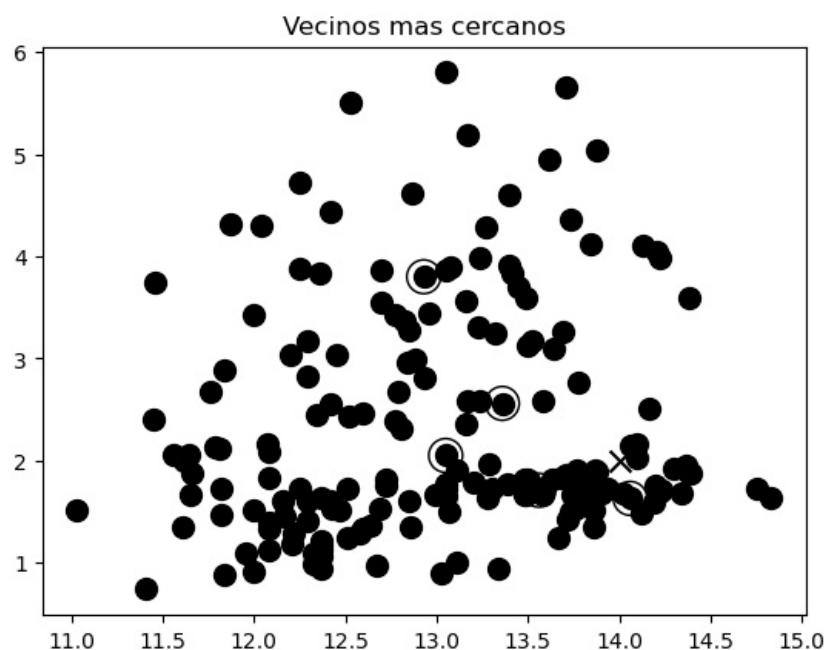
  

	OD280	Proline
40	3.38	795
20	3.71	780
25	3.20	830
21	3.52	770
141	2.47	780

```

In [47]: # Visualizacion de puntos asociados al punto de interes
plt.figure()
plt.title('Vecinos mas cercanos')
plt.scatter(wine_array[:,0], wine_array[:,1], marker = 'o', s = 100, color = 'black')
plt.scatter(wine_array[indices[0][:][:,0], wine_array[indices[0][:][:,1], marker = 'o', s = 250, color = 'black')
plt.scatter(test[0, 0], test[0, 1], marker = 'x', s = 100, color = 'black')
plt.show()

```



## Conclucion

En este caso pudimos encontrar 5 Vinos que son bastante parecidos al que tenemos como muestra, y las concentraciones de alcohol son las siguientes: Vino #40: 13.56, Vino #20: 14.06, Vino #25: 13.05, Vino #21: 12.93, Vino #141: 13.36.

## Problema # 2

```

In [26]: from mlxtend.frequent_patterns import apriori, association_rules

```

```
my_basket = [['bread', 'butter', 'wine', 'bananas', 'coffee', 'carrots'],
             ['tomatoes', 'onions', 'cheese', 'milk', 'potatoes'],
             ['beer', 'chips', 'asparagus', 'salsa', 'milk', 'apples'],
             ['olive oil', 'bread', 'butter', 'tomatoes', 'steak', 'carrots'],
             ['tomatoes', 'onions', 'chips', 'wine', 'ketchup', 'orange juice'],
             ['bread', 'butter', 'beer', 'chips', 'milk'],
             ['butter', 'tomatoes', 'carrots', 'coffee', 'sugar'],
             ['tomatoes', 'onions', 'cheese', 'milk', 'potatoes'],
             ['bread', 'butter', 'ketchup', 'coffee', 'chicken wings'],
             ['butter', 'beer', 'chips', 'asparagus', 'apples'],
             ['tomatoes', 'onions', 'beer', 'chips', 'milk', 'coffee']]
```

```
In [28]: # Obtener artículos únicos
articulos = sorted(set(item for basket in my_basket for item in basket))
```

```
In [30]: canasta = []
for basket in my_basket:
    basket_dict = {item: (item in basket) for item in articulos}
    canasta.append(basket_dict)
```

```
In [32]: df_basket = pd.DataFrame(canasta).astype(int)
```

```
In [34]: # Apriori
frecuencia = apriori(df_basket, min_support=0.3, use_colnames=True)

print(frecuencia)
```

	support	itemsets
0	0.363636	(beer)
1	0.363636	(bread)
2	0.545455	(butter)
3	0.454545	(chips)
4	0.363636	(coffee)
5	0.454545	(milk)
6	0.363636	(onions)
7	0.545455	(tomatoes)
8	0.363636	(beer, chips)
9	0.363636	(bread, butter)
10	0.363636	(onions, tomatoes)

C:\Users\Lenovo\anaconda3\Lib\site-packages\mlxtend\frequent\_patterns\fpcommon.py:161: DeprecationWarning: DataFrames with non-bool types result in worse computational performance and their support might be discontinued in the future. Please use a DataFrame with bool type

warnings.warn()

```
In [36]: association_rules(frecuencia, metric = 'confidence',
                        min_threshold = 0.5).sort_values('confidence', ascending = False).reset_index(drop = True)
```

```
Out[36]:
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhan
0	(beer)	(chips)	0.363636	0.454545	0.363636	1.000000	2.200000	1.0	0.198347	inf	
1	(bread)	(butter)	0.363636	0.545455	0.363636	1.000000	1.833333	1.0	0.165289	inf	
2	(onions)	(tomatoes)	0.363636	0.545455	0.363636	1.000000	1.833333	1.0	0.165289	inf	
3	(chips)	(beer)	0.454545	0.363636	0.363636	0.800000	2.200000	1.0	0.198347	3.181818	
4	(butter)	(bread)	0.545455	0.363636	0.363636	0.666667	1.833333	1.0	0.165289	1.909091	
5	(tomatoes)	(onions)	0.545455	0.363636	0.363636	0.666667	1.833333	1.0	0.165289	1.909091	

## Conclusion

Tomando en cuenta los resultados, podemos concluir que en esta lista de compras tenemos varias combinaciones en donde es muy probable que cuando tengamos el antecedente volvamos a tener el consecuente, tal como el vaso de Beer > Chips o Bread > Butter. Con esto podemos tomar decisiones en cuanto a promociones conjuntas o el acomodo del producto dentro de la tienda. La confianza en estos casos son muy altos, por lo que podemos tener la certeza de que en un pronostico tendríamos alto porcentaje de acertividad.