- Mediante el algoritmo de K vecinos más cercanos determine el valor promedio de alcohol que tendrían los 5 vinos más parecidos a aquel con las características siguientes:

Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color_Intensity	Hue	OD280	Proline
14	2	2.5	16	115	3	2.5	0.4	2	9	1	3.5	800

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [4]:
```
wine = pd.read_csv('C:/Users/Isaac/Desktop/IHD/EBAC DT/CIENCIA DE DATOS/M30 DS/wine-clustering.csv')
wine.head()
```

Out[4]:

	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color_Intensity	Hue	OD280	Proli
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	5.64	1.04	3.92	10
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38	1.05	3.40	10
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.68	1.03	3.17	11
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.80	0.86	3.45	14
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.32	1.04	2.93	7

In [9]:
```
wine_arr = np.array(wine)
print(wine_arr)
```

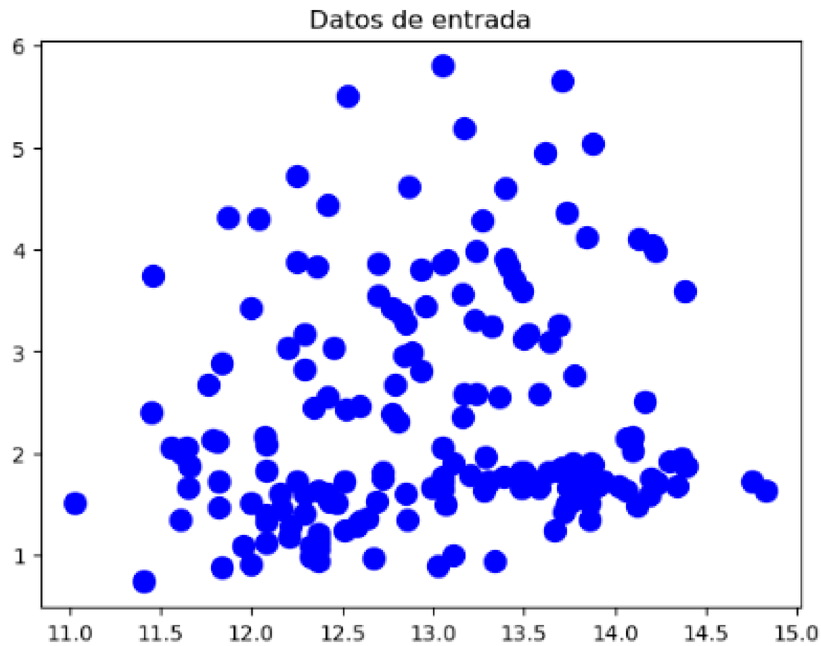
```
[[1.423e+01 1.710e+00 2.430e+00 ... 1.040e+00 3.920e+00 1.065e+03]
 [1.320e+01 1.780e+00 2.140e+00 ... 1.050e+00 3.400e+00 1.050e+03]
 [1.316e+01 2.360e+00 2.670e+00 ... 1.030e+00 3.170e+00 1.185e+03]
 ...
 [1.327e+01 4.280e+00 2.260e+00 ... 5.900e-01 1.560e+00 8.350e+02]
 [1.317e+01 2.590e+00 2.370e+00 ... 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 [5]:
```
k = 3

# puntos a relacionar

data = [14, 2, 2.5, 16, 115, 3, 2.5, 0.4, 2, 9, 1, 3.5, 800]
```

In [10]:

```
# visualizacion del apoblacion

plt.figure()
plt.title('Datos de entrada')
plt.scatter(wine_arr[:,0], wine_arr[:,1], marker = 'o', color = 'blue', s = 100)
```

Out[10]: <matplotlib.collections.PathCollection at 0x1f5615acfd0>



In [11]:

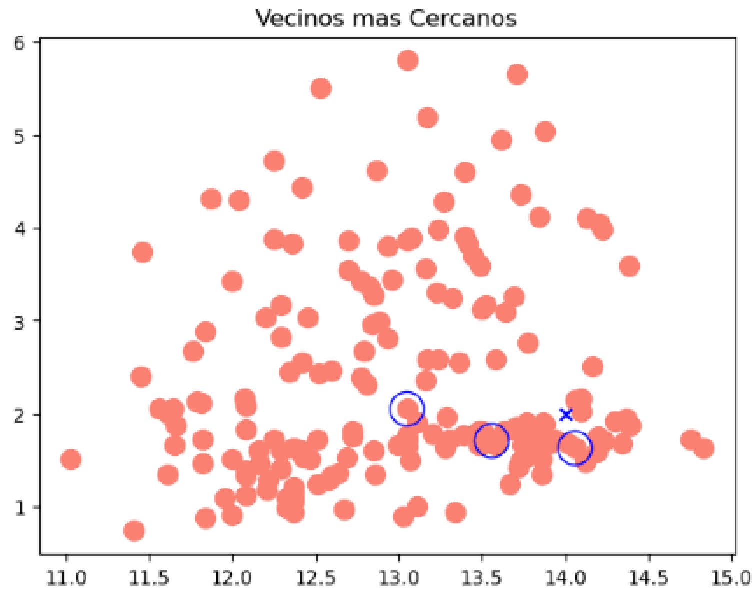
```
# algorimto KNN
from sklearn.neighbors import NearestNeighbors
knn_model = NearestNeighbors(n_neighbors = k, algorithm = 'auto')
knn_model.fit(wine_arr)

# calculamos distancias e indices

distances, indices = knn_model.kneighbors([data])
```

In [13]:

```
print('K vecinos mas cercanos')
for i, index, in enumerate(indices[0][:k], start = 1):
    print(str(i) + ' is', wine_arr[index])
```

```
K vecinos mas cercanos
1 is [1.356e+01 1.710e+00 2.310e+00 1.620e+01 1.170e+02 3.150e+00 3.290e+00
 3.400e-01 2.340e+00 6.130e+00 9.500e-01 3.380e+00 7.950e+02]
2 is [1.406e+01 1.630e+00 2.280e+00 1.600e+01 1.260e+02 3.000e+00 3.170e+00
 2.400e-01 2.100e+00 5.650e+00 1.090e+00 3.710e+00 7.800e+02]
3 is [1.305e+01 2.050e+00 3.220e+00 2.500e+01 1.240e+02 2.630e+00 2.680e+00
 4.700e-01 1.920e+00 3.580e+00 1.130e+00 3.200e+00 8.300e+02]
```

In [26]:
```
# visualización  puntos asociados a los puntos de interes
plt.figure()
plt.title('Vecinos mas Cercanos')
plt.scatter(wine_arr[:,0], wine_arr[:,1], marker ='o', color = 'salmon', s = 100)
plt.scatter(wine_arr[indices][0][:][:,0], wine_arr[indices][0][:][:,1], marker = 'o', s = 300,
            color = 'blue', facecolors = 'none')
plt.scatter(data[0], data[1], marker ='x', color = 'blue')
plt.show()
```



Market basket

In [28]:
```
my_basket = [['bread','butter','wine','bananas','coffe','carrots'],
             ['tomatoes','onion','cheese','milk','potatoes'],
             ['beer','chips','asparagus','salsa','milk','apples'],
             ['olive oil','bread','butter','tomatoes','steak','carrots'],
             ['tomatoes','onion','chips','wine','ketchup','orange juice'],
             ['bread','butter','beer','chips','milk'],
             ['butter','tomatoes','carrots','coffe','sugar'],
             ['tomatoes','onion','cheese','milk','potatoes'],
             ['bread','butter','ketchup','coffe','chicken wings'],
             ['butter','beer','chips','asparagus','apples'],
             ['tomatoes','onion','beer','chips','milk','coffe']]
```

In [37]:
```
from mlxtend.preprocessing import TransactionEncoder
```

In [59]:
```
mb = TransactionEncoder()
mb_arr = mb.fit(my_basket).transform(my_basket)
df = pd.DataFrame(mb_arr, columns = mb.columns_)
df = df.astype(int)
df
```

Out[59]:

	apples	asparagus	bananas	beer	bread	butter	carrots	cheese	chicken wings	chips	...	milk	olive oil	onion	orange juice	potatoes	salsa	steak	sugar	tomatoes
0	0	0	1	0	1	1	1	0	0	0	...	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	1	0	0	...	1	0	1	0	1	0	0	0	1
2	1	1	0	1	0	0	0	0	0	1	...	1	0	0	0	0	1	0	0	0
3	0	0	0	0	1	1	1	0	0	0	...	0	1	0	0	0	0	1	0	1
4	0	0	0	0	0	0	0	0	0	1	...	0	0	1	1	0	0	0	0	1
5	0	0	0	1	1	1	0	0	0	1	...	1	0	0	0	0	0	0	0	0
6	0	0	0	0	0	1	1	0	0	0	...	0	0	0	0	0	0	0	1	1
7	0	0	0	0	0	0	0	1	0	0	...	1	0	1	0	1	0	0	0	1
8	0	0	0	0	1	1	0	0	1	0	...	0	0	0	0	0	0	0	0	0
9	1	1	0	1	0	1	0	0	0	1	...	0	0	0	0	0	0	0	0	0
10	0	0	0	1	0	0	0	0	0	1	...	1	0	1	0	0	0	0	0	1

11 rows × 22 columns

In [47]:
```python
# algoritmo apriori
from mlxtend.frequent_patterns import apriori
articulos_frecuentes = apriori(df, min_support = 0.03, use_colnames = True)
articulos_frecuentes['length'] = articulos_frecuentes['itemsets'].apply(lambda x:len(x))
articulos_frecuentes
```

```
C:\Users\Isaac\anaconda3\Lib\site-packages\mlxtend\frequent_patterns\fpcommon.py:109: Deprecation
ool types result in worse computationalperformance and their support might be discontinued in the
with bool type
  warnings.warn(
```

Out[47]:

	support	itemsets	length
0	0.181818	(apples)	1
1	0.181818	(asparagus)	1
2	0.090909	(bananas)	1
3	0.363636	(beer)	1
4	0.363636	(bread)	1
...	...	...	...
385	0.090909	(asparagus, beer, apples, chips, salsa, milk)	6
386	0.090909	(bananas, wine, bread, carrots, butter, coffe)	6
387	0.090909	(beer, tomatoes, onion, chips, coffe, milk)	6
388	0.090909	(tomatoes, steak, olive oil, bread, carrots, b...	6
389	0.090909	(wine, tomatoes, onion, ketchup, chips, orange...	6

390 rows × 3 columns

In [48]:
```python
# reglas de asociacion
from mlxtend.frequent_patterns import association_rules
```

In [56]:
```python
asso_rules = association_rules
asso_rules(articulos_frecuentes, metric = 'confidence', min_threshold = 0.5,).reset_index(drop = True)
```

Out[56]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(asparagus)	(apples)	0.181818	0.181818	0.181818	1.0	5.500000	0.148760	inf	1.000000
1	(apples)	(asparagus)	0.181818	0.181818	0.181818	1.0	5.500000	0.148760	inf	1.000000
2	(beer)	(apples)	0.363636	0.181818	0.181818	0.5	2.750000	0.115702	1.636364	1.000000
3	(apples)	(beer)	0.181818	0.363636	0.181818	1.0	2.750000	0.115702	inf	0.777778
4	(apples)	(butter)	0.181818	0.545455	0.090909	0.5	0.916667	-0.008264	0.909091	-0.100000
...	...	...	...	...	...	...	...	...	...	...
2737	(ketchup, orange juice)	(tomatoes, onion, chips, wine)	0.090909	0.090909	0.090909	1.0	11.000000	0.082645	inf	1.000000
2738	(orange juice, chips)	(tomatoes, ketchup, onion, wine)	0.090909	0.090909	0.090909	1.0	11.000000	0.082645	inf	1.000000
2739	(wine)	(tomatoes, onion, ketchup, chips, orange juice)	0.181818	0.090909	0.090909	0.5	5.500000	0.074380	1.818182	1.000000
2740	(ketchup)	(wine, tomatoes, onion, chips, orange juice)	0.181818	0.090909	0.090909	0.5	5.500000	0.074380	1.818182	1.000000
2741	(orange juice)	(wine, tomatoes, onion, ketchup, chips)	0.090909	0.090909	0.090909	1.0	11.000000	0.082645	inf	1.000000

2742 rows × 10 columns

In [57]:
```
asso_rules(articulos_frecuentes, metric = 'lift', min_threshold = 1.01,).reset_index(drop = True)
```

Out[57]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(asparagus)	(apples)	0.181818	0.181818	0.181818	1.000000	5.500000	0.148760	inf	1.000000
1	(apples)	(asparagus)	0.181818	0.181818	0.181818	1.000000	5.500000	0.148760	inf	1.000000
2	(beer)	(apples)	0.363636	0.181818	0.181818	0.500000	2.750000	0.115702	1.636364	1.000000
3	(apples)	(beer)	0.181818	0.363636	0.181818	1.000000	2.750000	0.115702	inf	0.777778
4	(apples)	(chips)	0.181818	0.454545	0.181818	1.000000	2.200000	0.099174	inf	0.666667
...	...	...	...	...	...	...	...	...	...	...
3579	(tomatoes)	(wine, onion, ketchup, chips, orange juice)	0.545455	0.090909	0.090909	0.166667	1.833333	0.041322	1.090909	1.000000
3580	(onion)	(wine, tomatoes, ketchup, chips, orange juice)	0.363636	0.090909	0.090909	0.250000	2.750000	0.057851	1.212121	1.000000
3581	(ketchup)	(wine, tomatoes, onion, chips, orange juice)	0.181818	0.090909	0.090909	0.500000	5.500000	0.074380	1.818182	1.000000
3582	(chips)	(wine, tomatoes, onion, ketchup, orange juice)	0.454545	0.090909	0.090909	0.200000	2.200000	0.049587	1.136364	1.000000
3583	(orange juice)	(wine, tomatoes, onion, ketchup, chips)	0.090909	0.090909	0.090909	1.000000	11.000000	0.082645	inf	1.000000

3584 rows × 10 columns