In [ ]:

```
# 1.对数据集进行处理，转换成适合进行关联规则挖掘的形式
# ------------------------------------------------
import pandas as pd
path = './winemag-data_first150k.csv'
data = pd.read_csv(path)

# 处理country空值，根据designation确定对应country
designation2country = {
    "Askitikos":"Greece",
    "Shah":"US",
    "Piedra Feliz":"Chile",
}
for i in range(len(data)):
    country = data.iloc[i,1]
    if pd.isnull(country):
        designation = data.iloc[i,3]
        data.iloc[i,1] = designation2country[designation]

# 将price和points进行离散化
def points_discretization(value):
    return "points-" + str(int(value/5))

data.loc[:,'points'] = data['points'].map(lambda x:points_discretization(x))

def price_discretization(value):
    if value < 100:
        return "price-" + str(int(value/10))
    else:
        return "price-" + "10"

data.loc[:,'price'] = data['price'].map(lambda x:price_discretization(x))

# 仅保留country、points、price用于分析
data = data.drop(['Unnamed: 0','description','province','region_1', \
                  'region_2','variety','winery','designation'], axis = 1)

# 数据格式转换
def deal(data):
    return data.to_list()
data = data.apply(deal,axis=1).tolist()
from mlxtend.preprocessing import TransactionEncoder
te = TransactionEncoder()
tf = te.fit_transform(data)
new_data = pd.DataFrame(tf,columns=te.columns_)
```

In [ ]:

```
# 2.找出频繁模式
# ------------------------------------------------
# 使用apriori算法，找出频繁模式
from mlxtend.frequent_patterns import apriori
min_support = 0.03      # 最小支持度阈值取0.03
apriori_result = apriori(new_data, min_support=min_support, use_colnames=True, max_le
        .sort_values(by='support', ascending=False)
apriori_result
```

Out[ ]:

	support	itemsets
9	0.526887	(points-17)
7	0.413423	(US)
12	0.303419	(price-1)

	support	itemsets
10	0.299669	(points-18)
14	0.212986	(price-2)
37	0.201034	(points-17, price-1)
29	0.199788	(points-17, US)
4	0.155556	(Italy)
8	0.153694	(points-16)
3	0.139787	(France)
39	0.131604	(points-17, price-2)
30	0.128748	(points-18, US)
15	0.124554	(price-3)
13	0.118121	(price-10)
32	0.106460	(US, price-2)
31	0.101617	(US, price-1)
23	0.093964	(points-17, Italy)
16	0.082840	(price-4)
35	0.079454	(points-16, price-1)
33	0.076784	(price-3, US)
28	0.076048	(points-16, US)
19	0.066998	(points-17, France)
40	0.062327	(points-17, price-3)
50	0.060757	(points-17, price-2, US)
49	0.058424	(points-17, US, price-1)
20	0.054926	(points-18, France)
6	0.054780	(Spain)
42	0.051898	(points-18, price-10)
43	0.050957	(points-18, price-2)
44	0.049990	(points-18, price-3)
17	0.049990	(price-5)
24	0.049983	(points-18, Italy)
22	0.049930	(price-10, France)
34	0.049692	(price-4, US)
38	0.049102	(points-17, price-10)
45	0.043855	(points-18, price-4)
25	0.039422	(Italy, price-1)
2	0.038554	(Chile)
51	0.038064	(points-17, US, price-3)

	support	itemsets
0	0.037309	(Argentina)
26	0.036202	(price-10, Italy)
5	0.035261	(Portugal)
11	0.034188	(price-0)
48	0.033936	(points-16, US, price-1)
47	0.033426	(Italy, points-17, price-1)
41	0.033380	(points-17, price-4)
1	0.032843	(Australia)
18	0.031339	(price-6)
21	0.030842	(price-1, France)
27	0.030504	(points-17, Spain)
46	0.030405	(points-18, price-5)
36	0.030193	(points-16, price-2)

In [ ]:

```
# 3.导出关联规则，计算其支持度和置信度
# --------------------------------------------
# 使用association_rules方法，导出关联规则，同时获得支持度及置信度
from mlxtend.frequent_patterns import association_rules
min_threshold = 0.4     # 置信度阈值设为0.4
rules =  association_rules(apriori_result, metric ='confidence',min_threshold = min_t
rules = rules.drop(['leverage','conviction'], axis = 1)

# 输出支持度、置信度
for index, row in rules.iterrows():
    #print(row)
    antecedents = tuple(row['antecedents'])
    consequents = tuple(row['consequents'])
    print("%s ⇒ %s (suupport = %f, confidence = %f )" % (antecedents, consequents, \
          row['support'], row['confidence']))
```

```
('price-1',) ⇒ ('points-17',) (suupport = 0.201034, confidence = 0.662561 )
('US',) ⇒ ('points-17',) (suupport = 0.199788, confidence = 0.483253 )
('price-2',) ⇒ ('points-17',) (suupport = 0.131604, confidence = 0.617900 )
('points-18',) ⇒ ('US',) (suupport = 0.128748, confidence = 0.429636 )
('price-2',) ⇒ ('US',) (suupport = 0.106460, confidence = 0.499844 )
('Italy',) ⇒ ('points-17',) (suupport = 0.093964, confidence = 0.604055 )
('points-16',) ⇒ ('price-1',) (suupport = 0.079454, confidence = 0.516963 )
('price-3',) ⇒ ('US',) (suupport = 0.076784, confidence = 0.616469 )
('points-16',) ⇒ ('US',) (suupport = 0.076048, confidence = 0.494805 )
('France',) ⇒ ('points-17',) (suupport = 0.066998, confidence = 0.479287 )
('price-3',) ⇒ ('points-17',) (suupport = 0.062327, confidence = 0.500399 )
('points-17', 'price-2') ⇒ ('US',) (suupport = 0.060757, confidence = 0.461662 )
('US', 'price-2') ⇒ ('points-17',) (suupport = 0.060757, confidence = 0.570700 )
('US', 'price-1') ⇒ ('points-17',) (suupport = 0.058424, confidence = 0.574949 )
('price-10',) ⇒ ('points-18',) (suupport = 0.051898, confidence = 0.439365 )
('price-3',) ⇒ ('points-18',) (suupport = 0.049990, confidence = 0.401351 )
('price-10',) ⇒ ('France',) (suupport = 0.049930, confidence = 0.422706 )
('price-4',) ⇒ ('US',) (suupport = 0.049692, confidence = 0.599856 )
('price-10',) ⇒ ('points-17',) (suupport = 0.049102, confidence = 0.415694 )
('price-4',) ⇒ ('points-18',) (suupport = 0.043855, confidence = 0.529393 )
('points-17', 'price-3') ⇒ ('US',) (suupport = 0.038064, confidence = 0.610715 )
```

```
('US', 'price-3') ⇒ ('points-17',) (suupport = 0.038064, confidence = 0.495729 )
('points-16', 'US') ⇒ ('price-1',) (suupport = 0.033936, confidence = 0.446245 )
('points-16', 'price-1') ⇒ ('US',) (suupport = 0.033936, confidence = 0.427118 )
('Italy', 'price-1') ⇒ ('points-17',) (suupport = 0.033426, confidence = 0.847899 )
('price-4',) ⇒ ('points-17',) (suupport = 0.033380, confidence = 0.402943 )
('Spain',) ⇒ ('points-17',) (suupport = 0.030504, confidence = 0.556846 )
('price-5',) ⇒ ('points-18',) (suupport = 0.030405, confidence = 0.608217 )
```

In [ ]:

```
# 4.对规则进行评价，可使用Lift、卡方和其它教材中提及的指标，至少2种
# ------------------------------------------------
# 这里使用提升度Lift和全置信度allconf
def allconf(x):
    return x.support/max(x['antecedent support'],x['consequent support'])
allconf_list = []
for index, row in rules.iterrows():
    allconf_list.append(allconf(row))
rules['allconf'] = allconf_list
rules.drop(['antecedent support','consequent support'],axis=1,inplace=False)
final_rules = rules.iloc[:]
from sklearn.preprocessing import LabelEncoder
for index, row in final_rules.iterrows():
    #print(row)
    if row['allconf'] < 0.1:    # 过滤allconf小于0.1的规则
        final_rules.drop(index=index,inplace=True)
final_rules = final_rules.sort_values(by=['lift'], ascending=False)[:16] # 按照lift从

final_rules
```

Out[ ]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	allconf
16	(price-10)	(France)	0.118121	0.139787	0.049930	0.422706	3.023936	0.357190
27	(price-5)	(points-18)	0.049990	0.299669	0.030405	0.608217	2.029632	0.101461
19	(price-4)	(points-18)	0.082840	0.299669	0.043855	0.529393	1.766594	0.146344
6	(points-16)	(price-1)	0.153694	0.303419	0.079454	0.516963	1.703795	0.261863
7	(price-3)	(US)	0.124554	0.413423	0.076784	0.616469	1.491132	0.185727
22	(points-16, US)	(price-1)	0.076048	0.303419	0.033936	0.446245	1.470723	0.111846
14	(price-10)	(points-18)	0.118121	0.299669	0.051898	0.439365	1.466169	0.173185
17	(price-4)	(US)	0.082840	0.413423	0.049692	0.599856	1.450948	0.120196
15	(price-3)	(points-18)	0.124554	0.299669	0.049990	0.401351	1.339316	0.166818
0	(price-1)	(points-17)	0.303419	0.526887	0.201034	0.662561	1.257503	0.381550
4	(price-2)	(US)	0.212986	0.413423	0.106460	0.499844	1.209038	0.257508
8	(points-16)	(US)	0.153694	0.413423	0.076048	0.494805	1.196849	0.183948
2	(price-2)	(points-17)	0.212986	0.526887	0.131604	0.617900	1.172737	0.249777
5	(Italy)	(points-17)	0.155556	0.526887	0.093964	0.604055	1.146461	0.178338
11	(points-17, price-2)	(US)	0.131604	0.413423	0.060757	0.461662	1.116682	0.146960
13	(US, price-1)	(points-17)	0.101617	0.526887	0.058424	0.574949	1.091220	0.110886

In [ ]:

```
# 5.对挖掘结果进行分析
```

```
# ------------------------------------------------
idx = 0
for _, row in final_rules.iterrows():
    idx += 1
    t1 = tuple(row['antecedents'])
    t2 = tuple(row['consequents'])
    print("%d : %s ⇒ %s (support = %f, confidence = %f )"%(idx,t1,t2,row['support'],r
```

```
1 : ('price-10',) ⇒ ('France',) (support = 0.049930, confidence = 0.422706 )
2 : ('price-5',) ⇒ ('points-18',) (support = 0.030405, confidence = 0.608217 )
3 : ('price-4',) ⇒ ('points-18',) (support = 0.043855, confidence = 0.529393 )
4 : ('points-16',) ⇒ ('price-1',) (support = 0.079454, confidence = 0.516963 )
5 : ('price-3',) ⇒ ('US',) (support = 0.076784, confidence = 0.616469 )
6 : ('points-16', 'US') ⇒ ('price-1',) (support = 0.033936, confidence = 0.446245 )
7 : ('price-10',) ⇒ ('points-18',) (support = 0.051898, confidence = 0.439365 )
8 : ('price-4',) ⇒ ('US',) (support = 0.049692, confidence = 0.599856 )
9 : ('price-3',) ⇒ ('points-18',) (support = 0.049990, confidence = 0.401351 )
10 : ('price-1',) ⇒ ('points-17',) (support = 0.201034, confidence = 0.662561 )
11 : ('price-2',) ⇒ ('US',) (support = 0.106460, confidence = 0.499844 )
12 : ('points-16',) ⇒ ('US',) (support = 0.076048, confidence = 0.494805 )
13 : ('price-2',) ⇒ ('points-17',) (support = 0.131604, confidence = 0.617900 )
14 : ('Italy',) ⇒ ('points-17',) (support = 0.093964, confidence = 0.604055 )
15 : ('points-17', 'price-2') ⇒ ('US',) (support = 0.060757, confidence = 0.461662 )
16 : ('US', 'price-1') ⇒ ('points-17',) (support = 0.058424, confidence = 0.574949 )
```

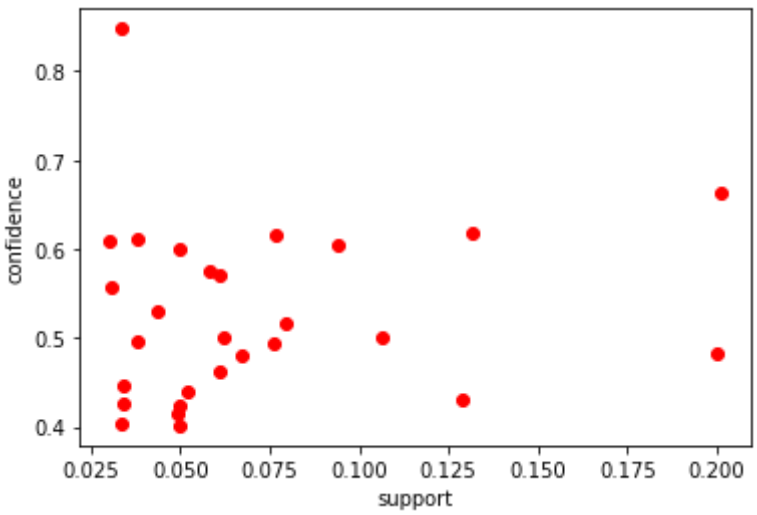
根据规则挖掘结果，可以发现以下信息：

- 法国的葡萄酒价格较高（由1可得）
- 葡萄酒价格和评分成正相关（由2，3，4，7，9，10，13可得）
- 美国的葡萄酒价格分布较为广泛（由5，6，8，12，15，16可得）

In [ ]:

```
# 5.可视化展示
# ------------------------------------------------
import  matplotlib.pyplot as plt

# 支持度与置信度关联关系展示
plt.xlabel('support')
plt.ylabel('confidence')
for i in range(rules.shape[0]):
    plt.scatter(rules.support[i],rules.confidence[i],c='r')
```



In [ ]:

```
# 支持度与lift关联关系展示
plt.xlabel('support')
plt.ylabel('lift')
```

```
for i in range(rules.shape[0]):
    plt.scatter(rules.support[i],rules.lift[i],c='r')
```