频繁模式与关联规则挖掘

1. 问题描述

将选择1个数据集进行频繁模式和关联规则挖掘。

2. 数据集

所选数据集：Wine Reviews

- winemag-data_first150k.csv

  包含10列和15万条葡萄酒评论

In [1]:

```python
#导入库
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

In [2]:

```python
#读取数据
path_15k = "../data/wine/winemag-data_first150k.csv"
data_15k = pd.read_csv(path_15k)
```

In [3]:

```python
data_15k.head()
```

Out[3]:

	Unnamed: 0	country	description	designation	points	price	province	region_1	region_2	variety
0	0	US	This tremendous 100% varietal wine hails from ...	Martha's Vineyard	96	235.0	California	Napa Valley	Napa	Cabernet Sauvignon
1	1	Spain	Ripe aromas of fig, blackberry and cassis are ...	Carodorum Selección Especial Reserva	96	110.0	Northern Spain	Toro	NaN	Tinta de Toro
2	2	US	Mac Watson honors the memory of a wine once ma...	Special Selected Late Harvest	96	90.0	California	Knights Valley	Sonoma	Sauvignon Blanc
3	3	US	This spent 20 months in 30% new French oak, an...	Reserve	96	65.0	Oregon	Willamette Valley	Willamette Valley	Pinot Noir

	Unnamed: 0	country	description	designation	points	price	province	region_1	region_2	variety
4	4	France	This is the top wine from La Bégude, named aft...	La Brûlade	95	66.0	Provence	Bandol	NaN	Provence red blend

3. 数据分析要求

3.1. 对数据集进行处理，转换成适合进行关联规则挖掘的形式

- 数据集中Unnamed:0，是评论的序号。description属性是对于葡萄酒的自然语言描述，二者在分析过程中不做考虑。

- country、province、region_1和region_2是对葡萄酒产地的位置信息，出于分析复杂性和这四个属性的数据缺失情况考虑， 这四个属性中只选择country进行数据挖掘。coutry属性有三个缺失值。所以要通过属性的相关关系，填补缺失值。根据designation属性，判断所属国家。

In [4]:

```
#根据空值的分布，定义一个从designation到country的转换字典
designation2country = {
    "Askitikos":"Greece",
    "Shah":"US",
    "Piedra Feliz":"Chile",
}
#处理country的空值
def country_nan_hander(data):
    for i in range(0,len(data)):
        tmp = data.iloc[i,1]
        if pd.isnull(tmp):
            designation = data.iloc[i,3]
            data.iloc[i,1] = designation2country[designation]
    return data
```

- price和points属性是数值， 对price进行离散化处理，此外points和price属性需要加上前缀， 方便区分频繁项生成结果。

In [5]:

```
def points_discretization(value):
    return "points-"+str(int(value/5))

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

- variety、winery、designation三个标称属性聚类数目过多（分别达到了632、14810、30622项） ， 出于计算复杂度的考虑， 在初步分析之后，单独选取选取variety中出现频数大于4000和winery中出现频数大于200的非空聚类进行分析。

- 初步分析过程中选取的属性包括designation、country、price、points，在之后的找出频繁模式调用mlxtend库来实现， 因此还需要将数据处理成相应的格式。

In [6]:
```
#处理country的空值
country_nan_hander(data_15k)

#过滤属性
data_15k = data_15k.drop(['Unnamed: 0','description','province','region_1','region_2','var
```

In [7]:
```
data_15k.head()
```

Out[7]:

	country	points	price
0	US	96	235.0
1	Spain	96	110.0
2	US	96	90.0
3	US	96	65.0
4	France	95	66.0

In [8]:
```
#离散化处理
data_15k.loc[:,'points'] = data_15k['points'].map(lambda x:points_discretization(x))
data_15k.loc[:,'price'] = data_15k['price'].map(lambda x:price_discretization(x))
```

In [9]:
```
#dataframe转换为列表
def deal(data):
    return data.to_list()
data_15k_arr = data_15k.apply(deal,axis=1).tolist()
```

In [10]:
```
#TransactionEncoder转换
from mlxtend.preprocessing import TransactionEncoder
te = TransactionEncoder()
tf = te.fit_transform(data_15k_arr)
new_df = pd.DataFrame(tf,columns=te.columns_)
```

3.2. 找出频繁模式

In [11]:
```
#mlsxtend库中apriori算法
from mlxtend.frequent_patterns import apriori
result = apriori(new_df, min_support=0.03, use_colnames=True, max_len=4).sort_values(by='s
```

In [12]:
```
print(result.shape)
result[:20]
```

```
(52, 2)
```

Out[12]:

	support	itemsets
9	0.526887	(points-17)
7	0.413423	(US)
12	0.303419	(price-1)
10	0.299669	(points-18)
14	0.212986	(price-2)
37	0.201034	(price-1, points-17)

	support	itemsets
29	0.199788	(US, points-17)
4	0.155556	(Italy)
8	0.153694	(points-16)
3	0.139787	(France)
39	0.131604	(price-2, points-17)
30	0.128748	(US, points-18)
15	0.124554	(price-3)
13	0.118121	(price-10)
32	0.106460	(price-2, US)
31	0.101617	(price-1, US)
23	0.093964	(points-17, Italy)
16	0.082840	(price-4)
35	0.079454	(price-1, points-16)
33	0.076784	(US, price-3)

3.3. 导出关联规则，计算其支持度和置信度

从频繁项集中导出关联规则，并计算其支持度和置信度。这里使用mlxtend包中的association_rules方法，支持度阈值为0.03，置信度阈值设为0.4，方法默认状态下会计算关联规则的计算支持度、置信度和提升度。

In [13]:

```
from mlxtend.frequent_patterns import association_rules
rules =  association_rules(result,metric ='confidence',min_threshold = 0.4)
rules = rules.drop(['leverage','conviction'],axis = 1)
print(rules.shape)
rules
```

```
(28, 7)
```

Out[13]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift
0	(price-1)	(points-17)	0.303419	0.526887	0.201034	0.662561	1.257503
1	(US)	(points-17)	0.413423	0.526887	0.199788	0.483253	0.917185
2	(price-2)	(points-17)	0.212986	0.526887	0.131604	0.617900	1.172737
3	(points-18)	(US)	0.299669	0.413423	0.128748	0.429636	1.039215
4	(price-2)	(US)	0.212986	0.413423	0.106460	0.499844	1.209038
5	(Italy)	(points-17)	0.155556	0.526887	0.093964	0.604055	1.146461
6	(points-16)	(price-1)	0.153694	0.303419	0.079454	0.516963	1.703795
7	(price-3)	(US)	0.124554	0.413423	0.076784	0.616469	1.491132
8	(points-16)	(US)	0.153694	0.413423	0.076048	0.494805	1.196849
9	(France)	(points-17)	0.139787	0.526887	0.066998	0.479287	0.909659
10	(price-3)	(points-17)	0.124554	0.526887	0.062327	0.500399	0.949728
11	(price-2, US)	(points-17)	0.106460	0.526887	0.060757	0.570700	1.083154

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift
12	(price-2, points-17)	(US)	0.131604	0.413423	0.060757	0.461662	1.116682
13	(price-1, US)	(points-17)	0.101617	0.526887	0.058424	0.574949	1.091220
14	(price-10)	(points-18)	0.118121	0.299669	0.051898	0.439365	1.466169
15	(price-3)	(points-18)	0.124554	0.299669	0.049990	0.401351	1.339316
16	(price-10)	(France)	0.118121	0.139787	0.049930	0.422706	3.023936
17	(price-4)	(US)	0.082840	0.413423	0.049692	0.599856	1.450948
18	(price-10)	(points-17)	0.118121	0.526887	0.049102	0.415694	0.788964
19	(price-4)	(points-18)	0.082840	0.299669	0.043855	0.529393	1.766594
20	(US, price-3)	(points-17)	0.076784	0.526887	0.038064	0.495729	0.940864
21	(price-3, points-17)	(US)	0.062327	0.413423	0.038064	0.610715	1.477215
22	(price-1, points-16)	(US)	0.079454	0.413423	0.033936	0.427118	1.033125
23	(points-16, US)	(price-1)	0.076048	0.303419	0.033936	0.446245	1.470723
24	(price-1, Italy)	(points-17)	0.039422	0.526887	0.033426	0.847899	1.609263
25	(price-4)	(points-17)	0.082840	0.526887	0.033380	0.402943	0.764763
26	(Spain)	(points-17)	0.054780	0.526887	0.030504	0.556846	1.056860
27	(price-5)	(points-18)	0.049990	0.299669	0.030405	0.608217	2.029632

In [14]:

```
#导出的各项关联规则
for index, row in rules.iterrows():
    #print(row)
    t1 = tuple(row['antecedents'])
    t2 = tuple(row['consequents'])
    print("%s ⇒ %s (suupport = %f, confidence = %f )"%(t1,t2,row['support'],row['confidenc
```

```
('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 )
('price-2', 'US') ⇒ ('points-17',) (suupport = 0.060757, confidence = 0.570700 )
('price-2', 'points-17') ⇒ ('US',) (suupport = 0.060757, confidence = 0.461662 )
('price-1', 'US') ⇒ ('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 )
('US', 'price-3') ⇒ ('points-17',) (suupport = 0.038064, confidence = 0.495729 )
('price-3', 'points-17') ⇒ ('US',) (suupport = 0.038064, confidence = 0.610715 )
('price-1', 'points-16') ⇒ ('US',) (suupport = 0.033936, confidence = 0.427118 )
('points-16', 'US') ⇒ ('price-1',) (suupport = 0.033936, confidence = 0.446245 )
```

```
('price-1', 'Italy') ⇒ ('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 )
```

3.4. 规则进行评价

对规则进行评价，使用提升度Lift和全置信度allconf。提升度Lift已经在上述导出关联规则的过程中被计算出来了，如下计算全置信度。

In [15]:

```python
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)#.sort_values
```

Out[15]:

	antecedents	consequents	support	confidence	lift	allconf
0	(price-1)	(points-17)	0.201034	0.662561	1.257503	0.381550
1	(US)	(points-17)	0.199788	0.483253	0.917185	0.379186
2	(price-2)	(points-17)	0.131604	0.617900	1.172737	0.249777
3	(points-18)	(US)	0.128748	0.429636	1.039215	0.311420
4	(price-2)	(US)	0.106460	0.499844	1.209038	0.257508
5	(Italy)	(points-17)	0.093964	0.604055	1.146461	0.178338
6	(points-16)	(price-1)	0.079454	0.516963	1.703795	0.261863
7	(price-3)	(US)	0.076784	0.616469	1.491132	0.185727
8	(points-16)	(US)	0.076048	0.494805	1.196849	0.183948
9	(France)	(points-17)	0.066998	0.479287	0.909659	0.127158
10	(price-3)	(points-17)	0.062327	0.500399	0.949728	0.118293
11	(price-2, US)	(points-17)	0.060757	0.570700	1.083154	0.115313
12	(price-2, points-17)	(US)	0.060757	0.461662	1.116682	0.146960
13	(price-1, US)	(points-17)	0.058424	0.574949	1.091220	0.110886
14	(price-10)	(points-18)	0.051898	0.439365	1.466169	0.173185
15	(price-3)	(points-18)	0.049990	0.401351	1.339316	0.166818
16	(price-10)	(France)	0.049930	0.422706	3.023936	0.357190
17	(price-4)	(US)	0.049692	0.599856	1.450948	0.120196
18	(price-10)	(points-17)	0.049102	0.415694	0.788964	0.093193
19	(price-4)	(points-18)	0.043855	0.529393	1.766594	0.146344
20	(US, price-3)	(points-17)	0.038064	0.495729	0.940864	0.072243
21	(price-3, points-17)	(US)	0.038064	0.610715	1.477215	0.092070
22	(price-1, points-16)	(US)	0.033936	0.427118	1.033125	0.082086
23	(points-16, US)	(price-1)	0.033936	0.446245	1.470723	0.111846
24	(price-1, Italy)	(points-17)	0.033426	0.847899	1.609263	0.063441
25	(price-4)	(points-17)	0.033380	0.402943	0.764763	0.063353

	antecedents	consequents	support	confidence	lift	allconf
26	(Spain)	(points-17)	0.030504	0.556846	1.056860	0.057895
27	(price-5)	(points-18)	0.030405	0.608217	2.029632	0.101461

In [16]:

```
#过滤allconf小于0.1的规则，按照lift从大到小排序取前16项，得到用于分析的关联规则。
final_rules = rules.iloc[:]
from sklearn.preprocessing import LabelEncoder
for index, row in final_rules.iterrows():
    #print(row)
    if row['allconf'] < 0.1:
        final_rules.drop(index=index,inplace=True)
final_rules = final_rules.sort_values(by=['lift'], ascending=False)[:16]
final_rules
```

Out[16]:

	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
23	(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
12	(price-2, points-17)	(US)	0.131604	0.413423	0.060757	0.461662	1.116682	0.146960
13	(price-1, US)	(points-17)	0.101617	0.526887	0.058424	0.574949	1.091220	0.110886

3.5. 结果分析与可视化展示

In [17]:

```
#最后生成的规则
i = 1
for index, row in final_rules.iterrows():
    t1 = tuple(row['antecedents'])
    t2 = tuple(row['consequents'])
    print("%d : %s ⇒ %s (suupport = %f, confidence = %f )"%(i,t1,t2,row['support'],row['co
    i = i + 1
```

```
1 : ('price-10',) ⇒ ('France',) (suupport = 0.049930, confidence = 0.422706 )
2 : ('price-5',) ⇒ ('points-18',) (suupport = 0.030405, confidence = 0.608217 )
3 : ('price-4',) ⇒ ('points-18',) (suupport = 0.043855, confidence = 0.529393 )
```

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

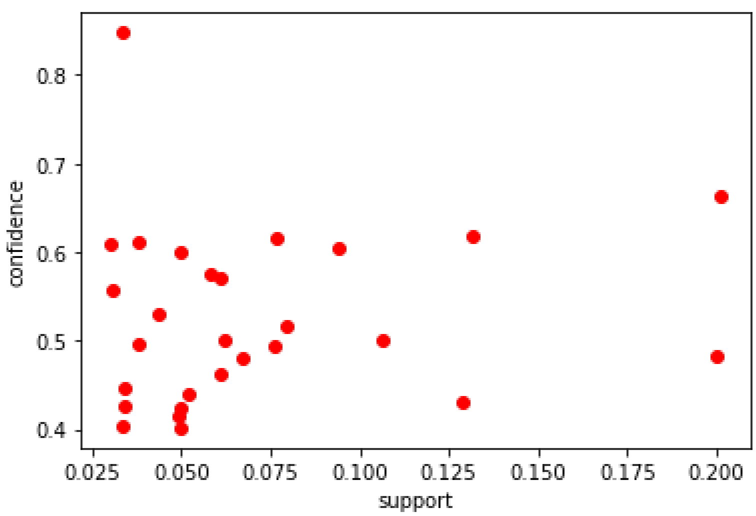
- 在price和points的数值越大代表价格越高、分数越高。根据规则2，3，4，7，9，10，13可以看出，价格对葡萄酒的评分存在一定的影响， 价格比较低（price-1和price-2， 对应价格区间为10-29）的葡萄酒的评分更多地集中在16和17的评分档位（对应百分制评分的80-89）。而价格相对较高的葡萄酒（price-3到price-10，价格为30以上的）评分集中在18的评分档位（对应百分制评分的90-95），而且当价格高于price-40（price>40） 档位后，评分并不会升高。

- 从('price-4',) -> ('US',) ('price-2',) -> ('US',) ('price-16',) -> ('US',) ('price-1', 'US')的规则可以看出，来自美国的葡萄酒的价格分布比较广泛。

- 从('price-10',) -> ('France',),('Italy',) -> ('points-17',)的规则可以看出，法国的葡萄酒的价格较高（price超过100）， 来自意大利的葡萄酒评分居中（points位于85-90之间） 。

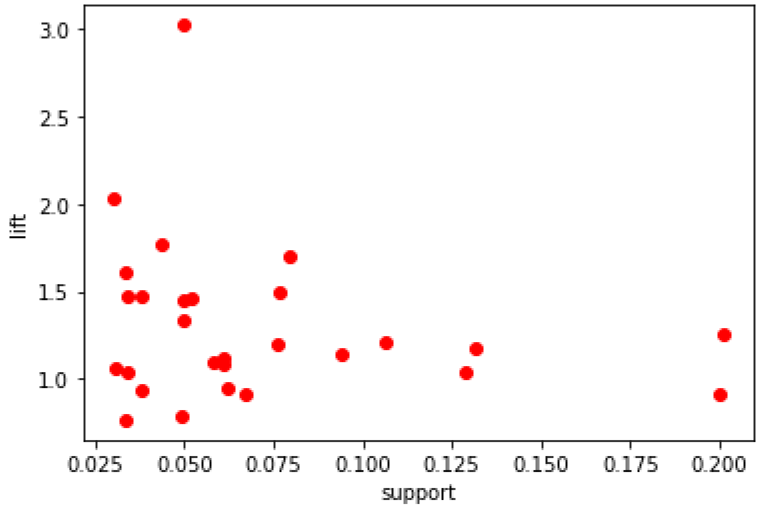
In [18]:

```python
#rules规则的散点图
plt.xlabel('support')
plt.ylabel('confidence')
for i in range(rules.shape[0]):
    plt.scatter(rules.support[i],rules.confidence[i],c='r')
```



In [19]:

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


3.0
2.5
2.0
1.5
1.0
lift
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
support