# 网页浏览行为关联规则挖掘

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仓库地址：https://github.com/RIU-13/LRDataMining0327/Assignment2

# 数据集介绍

Anonymous Microsoft Web Data
该数据集记录了 38000 名随机选择的匿名用户对 www.microsoft.com 的使用情况，网站的一个域称为**vroot**

## 数据示例

1. 'A,1277,1,"NetShow for PowerPoint","/stream"'

A表示是属性行，1277是该域的ID，netshow for powerpoint是title，/stream是URL;

2. C,"10164",10164
   V,1123,1
   V,1009,1
   V,1052,1

   C表示是案例行，10164是一个使用者的案例的ID，V表示是这个案例的vote行；1123，1009,1052是某个使用者拜访的域属性ID，即表示用户10164拜访的域有1123,1009,1052

# 数据预处理: 清洗数据，处理缺失值，提取用户浏览记录。

根据数据集介绍可知本数据集不存在缺失值。

数据预处理过程如下，其中attr存储了各Vroot的属性，user存储了每个用户访问记录，userID存储了每个用户对应的ID，vis字典存储了各Vroot被访问的次数

```
import pandas as pd
import numpy as np
from mlxtend.preprocessing import TransactionEncoder#编码
from mlxtend.frequent_patterns import apriori#Apriori
from mlxtend.frequent_patterns import association_rules#导入关联规则包

fpath = "./anonymous-msweb.data"
attr = {}
vis={}
user = []
usrID = []
fp  =  open(fpath,"r")
fp.seek(0,0)
subline=""
canread = True
while  True:
    if canread:
        line  =  fp.readline()
    else:
        line = subline
    x = line.strip().split(',')
    if x[0] == 'A':#属性行
        lattr = []
        attr[x[1]]=x[3]
        vis[x[1]] = 0#将访问次数初始化为0
```

```
    elif x[0]=='C':
        luser=[]
        usrID.append(x[2])
        while True:
            subline = fp.readline()
            subx = subline.strip().split(',')
            if subx[0] == 'V':
                luser.append(subx[1])
                vis[subx[1]]+=1
                #print(luser)
            else:
                user.append(luser)

                canread = False
                break
    # If line is empty then end of file reached
    if  not  line  :
        break;

fp.close()
print("data has finished")
```

```
data has finished
```

# 数据探索性分析

分析最常被访问的页面、页面访问量分布。

```
max_p = max(zip(vis.values(), vis.keys()))
print("最常被访问的页面是%s,被访问次数是%d"%(attr[max_p[1]],max_p[0]))
dc = pd.DataFrame.from_dict(vis, orient='index',columns=['num'])
dc = dc.reset_index().rename(columns = {'index':'id'})
print("对访问次数的可能取值及频数分析如下：")
print(dc['num'].value_counts())
des = dc['num'].describe()
des_min = des['min']
des_q1 = des['25%']
des_median = des['50%']
des_q3 = des['75%']
des_max = des['max']
print("页面被访问次数的最小值为{},第一四分位数为{},中位数为{},第三四分位数为{},最大值为
{}".format(des_min,des_q1,des_median,des_q3,des_max))
```

```
最常被访问的页面是"Free Downloads",被访问次数是10836
对访问次数的可能取值及频数分析如下：
1       21
3       12
4       11
2       10
0        9
        ..
548      1
521      1
8463     1
1500     1
291      1
Name: num, Length: 168, dtype: int64
页面被访问次数的最小值为0.0,第一四分位数为8.25,中位数为43.5,第三四分位数为182.5,最大值为10836.0
```

# 关联规则挖掘和结果评估:

使用Apriori算法，根据用户浏览记录计算频繁项集和关联规则。使用mlxtend包中的association_rules方法，设置支持度阈值和置信度阈值后，会默认计算关联规则的支持度、置信度和提升度。

```
print("start analysis")
te = TransactionEncoder()
#进行 one-hot 编码

tf = te.fit_transform(user)
df = pd.DataFrame(tf,columns=te.columns_)
freq = apriori(df, min_support=0.05, use_colnames=True).sort_values(by='support',
ascending=False)
print("当阈值设置为0.05时的频繁项集如下：")
print(freq)
```

```
start analysis
当阈值设置为0.05时的频繁项集如下：
     support      itemsets
3   0.331265        (1008)
9   0.286845        (1034)
2   0.258720        (1004)
6   0.162942        (1018)
18  0.160802  (1008, 1034)
5   0.156155        (1017)
4   0.141481        (1009)
0   0.136070        (1001)
8   0.098438        (1026)
1   0.090734        (1003)
15  0.077925  (1008, 1009)
17  0.073064  (1008, 1018)
7   0.064902        (1025)
16  0.061233  (1008, 1017)
13  0.060438  (1008, 1004)
12  0.059430  (1001, 1018)
11  0.055211  (1001, 1003)
10  0.054752        (1035)
14  0.053285  (1004, 1034)
```

```
rules =  association_rules(freq,metric ='confidence',min_threshold = 0.4)
rules = rules.drop(['leverage','conviction'],axis = 1)
print("支持度阈值为0.03，置信度阈值设为0.4时，关联规则及其支持度、置信度和提升度如下：")
print(rules)
```

```
支持度阈值为0.03，置信度阈值设为0.4时，关联规则及其支持度、置信度和提升度如下：
  antecedents consequents  antecedent support  consequent support   support  \
0      (1008)      (1034)            0.331265            0.286845  0.160802
1      (1034)      (1008)            0.286845            0.331265  0.160802
2      (1009)      (1008)            0.141481            0.331265  0.077925
3      (1018)      (1008)            0.162942            0.331265  0.073064
4      (1001)      (1018)            0.136070            0.162942  0.059430
5      (1001)      (1003)            0.136070            0.090734  0.055211
6      (1003)      (1001)            0.090734            0.136070  0.055211

   confidence      lift  zhangs_metric
```

```
0     0.485419  1.692267       0.611717
1     0.560588  1.692267       0.573616
2     0.550778  1.662652       0.464231
3     0.448405  1.353616       0.312091
4     0.436756  2.680435       0.725668
5     0.405752  4.471879       0.898662
6     0.608491  4.471879       0.853854
```

```
for index, row in rules.iterrows():
    #print(row)
    t1 = next(iter(row['antecedents']))
    t2 = next(iter(row['consequents']))
    print("%s ⇒ %s (支持度是 = %f, 置信度是 = %f )"%
(attr[t1],attr[t2],row['support'],row['confidence']))
```

```
"Free Downloads" ⇒ "Internet Explorer" (支持度是 = 0.160802, 置信度是 = 0.485419 )
"Internet Explorer" ⇒ "Free Downloads" (支持度是 = 0.160802, 置信度是 = 0.560588 )
"Windows Family of OSs" ⇒ "Free Downloads" (支持度是 = 0.077925, 置信度是 = 0.550778 )
"isapi" ⇒ "Free Downloads" (支持度是 = 0.073064, 置信度是 = 0.448405 )
"Support Desktop" ⇒ "isapi" (支持度是 = 0.059430, 置信度是 = 0.436756 )
"Support Desktop" ⇒ "Knowledge Base" (支持度是 = 0.055211, 置信度是 = 0.405752 )
"Knowledge Base" ⇒ "Support Desktop" (支持度是 = 0.055211, 置信度是 = 0.608491 )
```

以上列出的为支持度阈值设置为0.03，置信度阈值设置为0.4时的强关联规则。

# 规则评价

这里使用提升度Lift和全置信度allconf。提升度Lift已经在上面的计算过程中展示了，下面将计算全置信度：

```
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)
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

| | antecedents | consequents | support | confidence | lift | zhangs_metric | allconf |
|---|---|---|---|---|---|---|---|
| **0** | (1008) | (1034) | 0.160802 | 0.485419 | 1.692267 | 0.611717 | 0.485419 |
| **1** | (1034) | (1008) | 0.160802 | 0.560588 | 1.692267 | 0.573616 | 0.485419 |
| **2** | (1009) | (1008) | 0.077925 | 0.550778 | 1.662652 | 0.464231 | 0.235234 |
| **3** | (1018) | (1008) | 0.073064 | 0.448405 | 1.353616 | 0.312091 | 0.220561 |

| | antecedents | consequents | support | confidence | lift | zhangs_metric | allconf |
|---|---|---|---|---|---|---|---|
| 4 | (1001) | (1018) | 0.059430 | 0.436756 | 2.680435 | 0.725668 | 0.364728 |
| 5 | (1001) | (1003) | 0.055211 | 0.405752 | 4.471879 | 0.898662 | 0.405752 |
| 6 | (1003) | (1001) | 0.055211 | 0.608491 | 4.471879 | 0.853854 | 0.405752 |

# 结果分析与应用

分析得到的关联规则，为网站提供导航结构优化建议，以提升用户体验

可以将（Internet Explorer，/ie）的Vroot和（Free Downloads,"/msdownload"）相互关联；

将（Support Desktop，/support）和（Knowledge Base，/kb）相互关联；

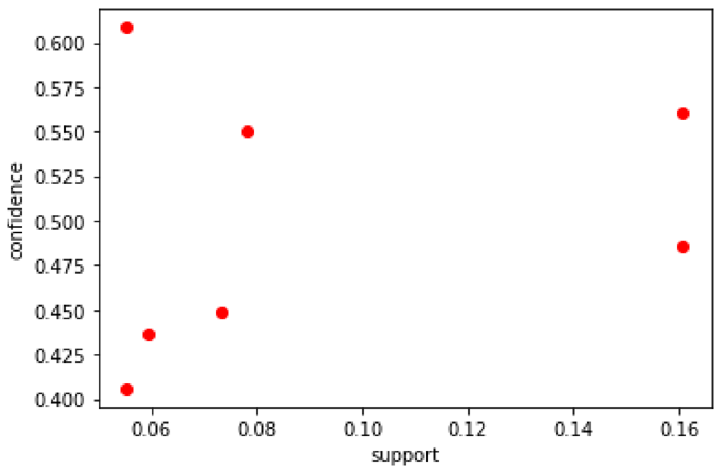
实现以下导航：（Support Desktop，/support）=>（isapi，/isapi）=>（Free Downloads，/msdownload）

都将提升用户体验

# 可视化

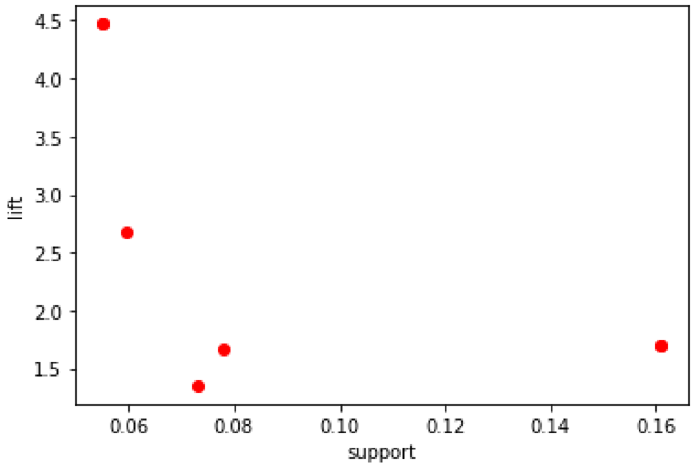
## 置信度-支持度散点图

```
from matplotlib import pyplot as plt
plt.xlabel('support')
plt.ylabel('confidence')
for i in range(rules.shape[0]):
    plt.scatter(rules.support[i],rules.confidence[i],c='r')
```




## 支持度-提升度散点图

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



4.5
4.0
3.5
3.0
2.5
2.0
1.5
lift
0.06
0.08
0.10
0.12
0.14
0.16
support