数据挖掘互评作业 2：频繁模式与关联规则挖掘

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Github 地址：https://github.com/Xiemixue/DataMining_MutualEvaluationAssignment_2

1 数据集处理

选择 Trending YouTube Video Statistics 数据集进行频繁模式和关联规则挖掘。这是 YouTube 热门视频统计信息的数据集，包括了 YouTube 上热门视频的类别、频道、标题、观众喜爱数等信息。数据集中包含不同国家的数据，这里我们仅选用美国的数据进行挖掘，包括 40949 条数据和 16 个属性，没有缺失值。

1.1 属性介绍

- 视频 id
- trending_date，登上热榜的时间
- title，视频标题
- channel_title，频道标题
- category_id，视频类别
- publish_time，发布时间
- tags，视频附加的标签
- views，观看数量
- likes，喜爱人数
- dislikes，不喜爱人数
- comment_count，评论数量
- thumbnail_link，缩略图链接
- comments_disable，是否禁止评论
- ratings_disabled，是否禁止评分
- video_error_or_removed，是否无法观看
- description，视频描述

1.2 属性选择

只选择一部分有意义的属性进行挖掘，这里选择 channel_title，category_id，tags，views，likes，dislikes，comment_count 属性。其中有些属性是数值属性，不好进行关联规则的挖掘，因此将这些属性转化为标称属性。

- 对于 category_id，这一属性用 id 代表类别，id 与类别的对应关系存储在 US_category_id.json 中，首先用实际类别替换 id.

[8]:
```
import pandas as pd
import numpy as np
import json as js
import Orange as og
import orangecontrib.associate.fpgrowth as oaf
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

data = pd.read_csv('archive/USvideos.csv', sep = ',')
with open('archive/US_category_id.json') as f:   # 读取 json 文件
    json_date = js.load(f)
    f.close()
id2cat = {}
for i in range(len(json_date['items'])):   # id 与类别对应
    id2cat[json_date['items'][i]['id']] =␣
 ↪json_date['items'][i]['snippet']['title']
for i in range(len(data)):    # 替换
    id = data.loc[i, 'category_id']
    data.loc[i, 'category_id'] = id2cat[str(id)]
print(data['category_id'])
```

```
0          People & Blogs
1           Entertainment
2                  Comedy
3           Entertainment
4           Entertainment
                …
40944      Pets & Animals
40945      People & Blogs
```

```
40946        Entertainment
40947     Film & Animation
40948               Gaming
Name: category_id, Length: 40949, dtype: object
```

- 对于 views，首先计算 views 的四分之一分位数和四分之三分位数。大于四分之三分位数的数据记为 “high view”，小于四分之一分位数的数据记为 “low view”，其余的记为 “medium view”。

[9]:
```python
arr = data['views']
one = arr.quantile(0.25)
three = arr.quantile(0.75)
view_level = []
for i in data['views']:
    if int(i) >= three:
        view_level.append('high view')
    elif int(i) <= one:
        view_level.append('low view')
    else:
        view_level.append('medium view')
print(view_level[:10])
```

```
['medium view', 'high view', 'high view', 'medium view', 'high view', 'low
view', 'high view', 'medium view', 'medium view', 'medium view']
```

- 对于 likes 和 dislikes，若 likes 的人数 >= dislikes 的人数，则标记这个视频为 “like”，否则为 “dislike”

[10]:
```python
like = []
for i in range(len(data)):
    if data.loc[i, 'likes'] >= data.loc[i, 'dislikes']:
        like.append('like')
    else:
        like.append('dislike')
print(like[0:10])
```

```
['like', 'like', 'like', 'like', 'like', 'like', 'like', 'like', 'like', 'like']
```

- 对于 comment_count，计算 $\frac{comment\_count}{views}$ 的四分之一分位数和四分之三分位数。如果一条数据的 $\frac{comment\_count}{views}$ 小于四分之一分位数，则记为 “low comment”，若大于四分之三分位数，则记为 “high comment”，其余的记为 “medium comment”

[11]:
```python
arr = data['comment_count']
one = arr.quantile(0.25)
three = arr.quantile(0.75)
comment_level = []
for i in data['comment_count']:
    if i >= three:
        comment_level.append('high comment')
    elif i <= one:
        comment_level.append('low comment')
    else:
        comment_level.append('medium comment')
print(comment_level[0:10])
```

```
['high comment', 'high comment', 'high comment', 'medium comment', 'high
comment', 'medium comment', 'medium comment', 'medium comment', 'low comment',
'medium comment']
```

- 之后将 views，likes，dislikes，comment_count 这四个属性替换为刚刚计算出的结果。

[12]:
```python
data = data.drop(['views', 'likes', 'dislikes', 'comment_count'], axis = 1)
data.insert(0, 'views', view_level)
data.insert(0, 'like', like)
data.insert(0, 'comment_count', comment_level)
# 删除不要的
data = data.drop(['video_id', 'trending_date', 'publish_time',␣
↪'video_error_or_removed', 'description', 'thumbnail_link', 'title',␣
↪'comments_disabled', 'ratings_disabled'], axis = 1)
print(data.head())
```

```
    comment_count  like         views          channel_title     category_id  \
0    high comment  like  medium view            CaseyNeistat  People & Blogs
1    high comment  like    high view         LastWeekTonight   Entertainment
2    high comment  like    high view            Rudy Mancuso          Comedy
3  medium comment  like  medium view  Good Mythical Morning   Entertainment
4    high comment  like    high view                nigahiga   Entertainment

                                                tags
0                                    SHANtell martin
1  last week tonight trump presidency|"last week …
```

```
2  racist superman|"rudy"|"mancuso"|"king"|"bach"…
3  rhett and link|"gmm"|"good mythical morning"|"…
4  ryan|"higa"|"higatv"|"nigahiga"|"i dare you"|"…
```

1.3 输入格式转换

因为 orangecontrib.associate.fpgrowth 包在进行频繁模式与关联规则挖掘时，要求输入的数据必须是整数类型的列表，因此需要将所有的字符串转化为整数。另外，由于 tags 属性是多个 tag 的组合，为了能区分出不同的 tag，还需将 tags 进行分割。

[13]:
```python
# 算法输入格式转换（转换后输出前 5 条为例）
id2str = {}   # 整数编码 —> 字符串
str2id = {}   # 字符串 -> 整数编码
id = 0
transaction = []
for i in range(len(data)):
    one = []
    for j in data.columns:
        # 拆分 tags
        if j == 'tags':
            str_arr = data.loc[i, j].split('|')
            for s in str_arr:
                if s in str2id:
                    one.append(str2id[s])
                else:
                    id2str[id] = s
                    str2id[s] = id
                    one.append(id)
                    id += 1
        else:
            if data.loc[i, j] in str2id:
                one.append(str2id[data.loc[i, j]])
            else:
                id2str[id] = data.loc[i, j]
                str2id[data.loc[i, j]] = id
                one.append(id)
                id += 1
```

```
    transaction.append(one)
print(transaction[:5])
```

```
[[0, 1, 2, 3, 4, 5], [0, 1, 6, 7, 8, 9, 10, 11, 12], [0, 1, 6, 13, 14, 15, 16,
17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36,
37], [38, 1, 2, 39, 8, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53,
54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66], [0, 1, 6, 67, 8, 68, 69,
70, 71, 72, 73, 74, 75, 76, 77, 64, 65, 78, 79]]
```

2 频繁模型挖掘

使用 orangecontrib.associate.fpgrowth 包进行频繁模式挖掘。
相对支持度：

$$Sup(X) = \frac{Sum(X)}{N}$$

- 首先使用默认的 0.2 作为频繁模式的相对支持度阈值：

[17]:
```
items = list(oaf.frequent_itemsets(transaction))
for i in items:
    freq_set = []
    abs_sup = i[1]
    for j in i[0]:
        freq_set.append(id2str[j])
    print(freq_set, abs_sup, round(float(abs_sup) / len(data), 2))
```

```
['high comment'] 10239 0.25
['like'] 40373 0.99
['high comment', 'like'] 10141 0.25
['medium view'] 20472 0.5
['like', 'medium view'] 20263 0.49
['high view'] 10238 0.25
['like', 'high view'] 10205 0.25
['Entertainment'] 9964 0.24
['Entertainment', 'like'] 9808 0.24
['medium comment'] 20460 0.5
['like', 'medium comment'] 20256 0.49
['medium view', 'medium comment'] 15081 0.37
['like', 'medium view', 'medium comment'] 14974 0.37
```

```
['low view'] 10239 0.25
['low view', 'like'] 9905 0.24
['low comment'] 10250 0.25
['low comment', 'like'] 9976 0.24
```

- 改用 0.3 作为相对支持度阈值，再次计算频繁项集：

[18]:
```python
items = list(oaf.frequent_itemsets(transaction, 0.3))
for i in items:
    freq_set = []
    abs_sup = i[1]
    for j in i[0]:
        freq_set.append(id2str[j])
    print(freq_set, abs_sup, round(float(abs_sup) / len(data), 2))
```

```
['like'] 40373 0.99
['medium view'] 20472 0.5
['like', 'medium view'] 20263 0.49
['medium comment'] 20460 0.5
['like', 'medium comment'] 20256 0.49
['medium view', 'medium comment'] 15081 0.37
['like', 'medium view', 'medium comment'] 14974 0.37
```

3 关联规则挖掘

在相对支持度阈值设定为 0.2 时计算得出的频繁项集基础上，计算关联规则，置信度阈值选择为 0.2。结果转化为原始字符串输出，置信度保留两位小数。
置信度：

$$Conf(X \Rightarrow Y) = \frac{Sup(X \bigcup Y)}{Sup(X)}$$

[19]:
```python
# 关联规则
items = list(oaf.frequent_itemsets(transaction, 0.2))
rules = list(oaf.association_rules(dict(items), 0.2))
for i in rules:
    antecedent = []
    consequent = []
    for j in i[0]:
        antecedent.append(id2str[j])
```

```python
    for j in i[1]:
        consequent.append(id2str[j])
    print(antecedent, "->", consequent, i[2], round(i[3],2))
print(len(rules))
```

```
['medium view', 'medium comment'] -> ['like'] 14974 0.99
['like', 'medium comment'] -> ['medium view'] 14974 0.74
['medium comment'] -> ['like', 'medium view'] 14974 0.73
['like', 'medium view'] -> ['medium comment'] 14974 0.74
['medium view'] -> ['like', 'medium comment'] 14974 0.73
['like'] -> ['medium view', 'medium comment'] 14974 0.37
['like'] -> ['high comment'] 10141 0.25
['high comment'] -> ['like'] 10141 0.99
['medium view'] -> ['like'] 20263 0.99
['like'] -> ['medium view'] 20263 0.5
['high view'] -> ['like'] 10205 1.0
['like'] -> ['high view'] 10205 0.25
['like'] -> ['Entertainment'] 9808 0.24
['Entertainment'] -> ['like'] 9808 0.98
['medium comment'] -> ['like'] 20256 0.99
['like'] -> ['medium comment'] 20256 0.5
['medium comment'] -> ['medium view'] 15081 0.74
['medium view'] -> ['medium comment'] 15081 0.74
['like'] -> ['low view'] 9905 0.25
['low view'] -> ['like'] 9905 0.97
['like'] -> ['low comment'] 9976 0.25
['low comment'] -> ['like'] 9976 0.97
```

22

共得到 22 条关联规则，后面将对这些规则进行分析。

4 关联规则的评价

虽然已经得到了频繁项集的支持度、关联规则的置信度，但是由于数据的分布不均，这些关联规则可能不准确。因此使用 Lift 和 Kulc 两种评价指标评价关联规则。

4.1 Lift 的计算

提升度（Lift）用于判断规则 $X \Rightarrow Y$ 中的 X 和 Y 是否独立。如果独立，那么这个规则是无效的；如果该值等于 1，说明两个条件没有任何关联；如果小于 1，说明 X 和 Y 是负相关的关系，意味着一个出现可能导致另一个不出现；如果大于 1，表明 X 和 Y 是正相关关系。

$$Lift(X \Rightarrow Y) = \frac{Sup(X \bigcup Y)}{Sup(X) \times Sup(Y)} = \frac{Conf(X \Rightarrow Y)}{Sup(Y)}$$

[20]:
```python
measure = list(oaf.rules_stats(oaf.association_rules(dict(items), 0.2),␣
↪dict(oaf.frequent_itemsets(transaction, 0.2)), len(data)))
for i in measure:
    antecedent = []
    consequent = []
    for j in i[0]:
        antecedent.append(id2str[j])
    for j in i[1]:
        consequent.append(id2str[j])
    print(antecedent, "->", consequent, round(i[6], 2))
```

```
['medium view', 'medium comment'] -> ['like'] 1.01
['like', 'medium comment'] -> ['medium view'] 1.48
['medium comment'] -> ['like', 'medium view'] 1.48
['like', 'medium view'] -> ['medium comment'] 1.48
['medium view'] -> ['like', 'medium comment'] 1.48
['like'] -> ['medium view', 'medium comment'] 1.01
['like'] -> ['high comment'] 1.0
['high comment'] -> ['like'] 1.0
['medium view'] -> ['like'] 1.0
['like'] -> ['medium view'] 1.0
['high view'] -> ['like'] 1.01
['like'] -> ['high view'] 1.01
['like'] -> ['Entertainment'] 1.0
['Entertainment'] -> ['like'] 1.0
['medium comment'] -> ['like'] 1.0
['like'] -> ['medium comment'] 1.0
['medium comment'] -> ['medium view'] 1.47
['medium view'] -> ['medium comment'] 1.47
['like'] -> ['low view'] 0.98
```

```
['low view'] -> ['like'] 0.98
['like'] -> ['low comment'] 0.99
['low comment'] -> ['like'] 0.99
```

4.2 Kulczynski (Kulc) 的计算

根据 Kulc 的计算公式：$Kulc(X,Y) = \frac{1}{2} \times (\frac{Sup(X \cup Y)}{Sup(X)} + \frac{Sup(X \cup Y)}{Sup(Y)})$，即 $X \Rightarrow Y$Y 的规则与 $Y \Rightarrow X$ 的规则的置信度的平均值。观察到所有找出的关联规则都包含对应的反向的规则，即 $\forall X \Rightarrow Y \in rules, Y \Rightarrow X \in rules$，因此直接在现有的关联规则中计算 Kulc.

[21]:
```python
# 计算 Kulc
kulc = []
visit = [False for i in range(len(rules))]
for i in range(len(rules)):
    if visit[i] == True:
        continue
    visit[i] = True
    for j in range(len(rules)):
        if visit[j] == True:
            continue
        if rules[j][0] == rules[i][1] and rules[j][1] == rules[i][0]:
            one = []
            antecedent = []
            consequent = []
            for k in rules[i][0]:
                antecedent.append(id2str[k])
            for k in rules[i][1]:
                consequent.append(id2str[k])
            one.append(rules[i][0])
            one.append(rules[i][1])
            one.append((rules[i][3] + rules[j][3])/2)
            kulc.append(one)
            print('Kulc(', antecedent, consequent, ') = ', round((rules[i][3] +␣
 ↪rules[j][3])/2, 2))
            visit[j] = True
```

```
Kulc( ['medium view', 'medium comment'] ['like'] ) =  0.68
Kulc( ['like', 'medium comment'] ['medium view'] ) =  0.74
```

```
Kulc( ['medium comment'] ['like', 'medium view'] ) =  0.74
Kulc( ['like'] ['high comment'] ) =  0.62
Kulc( ['medium view'] ['like'] ) =  0.75
Kulc( ['high view'] ['like'] ) =  0.62
Kulc( ['like'] ['Entertainment'] ) =  0.61
Kulc( ['medium comment'] ['like'] ) =  0.75
Kulc( ['medium comment'] ['medium view'] ) =  0.74
Kulc( ['like'] ['low view'] ) =  0.61
Kulc( ['like'] ['low comment'] ) =  0.61
```

5 挖掘结果分析

在所有的 22 条关联规则中，lift 值大于 1 的只有 6 条（有两条的 lift = 1.01，这里近似认为其等于 1），分别是：
['like'， 'medium comment'] -> ['medium view'] 1.48
['medium comment'] -> ['like'， 'medium view'] 1.48
['like'， 'medium view'] -> ['medium comment'] 1.48
['medium view'] -> ['like'， 'medium comment'] 1.48
['medium comment'] -> ['medium view'] 1.47
['medium view'] -> ['medium comment'] 1.47
再来看看这 6 条规则的 Kulc 值：
Kulc(['like'， 'medium comment'] ['medium view']) = 0.74 Kulc(['medium comment'] ['like'， 'medium view']) = 0.74 Kulc(['medium comment'] ['medium view']) = 0.74
在所有计算出的关联规则的 Kulc 值中，这三个 Kulc 值属于比较大的。因此可以认为这 6 条关联规则是可以接受的。可以得到结论：1. 观众喜爱的，且评论数量中等的，会有中等的观看量 2. 观众喜爱的，且观看量中等的，会有中等的评论量 3. 中等的观看量的视频会有中等评论量以上三条结论，反过来也成立。
在关联规则中，有一条的置信度很高：
['low view'] -> ['like'] 9905 0.97
这条规则说明观看量少的，观众会喜爱，这与我们的尝试不符。这条规则的 Lift 值为 0.98，说明这两项实际上是负相关的，但是 Kulc 值为 0.606，是所有 Kulc 值中最小的。说明这条关联规则是具有误导性的，推测原因可能是因为 "like" 项或 "low view" 项出现次数太多。

[23]:
```python
# "like" 数量和 "low view" 数量
like_cnt = 0
```

```
low_view_cnt = 0
for i in data['like']:
    if i == 'like':
        like_cnt += 1
for i in data['views']:
    if i == 'low view':
        low_view_cnt += 1
print("like 项数量 ={}, low view 项数量 ={}".format(like_cnt, low_view_cnt))
```

```
like 项数量 =40373, low view 项数量 =10239
```

可以看见，在 40949 条数据中，有 40373 项 “like”，占到了 98.6%。因此导致出现了有误导性的关于 “like” 的关联规则。

6 可视化展示

使用 matplotlib 绘制关联规则的置信度、Lift 和 Kulc 相关性热力图。

热力图的横纵坐标是关联规则中包含的项（共 11 项），热力图中每个点的数据是两项的置信度、Lift 值或 Kulc 值，若这两项不包括在关联规则中，则对应的值记为 0.

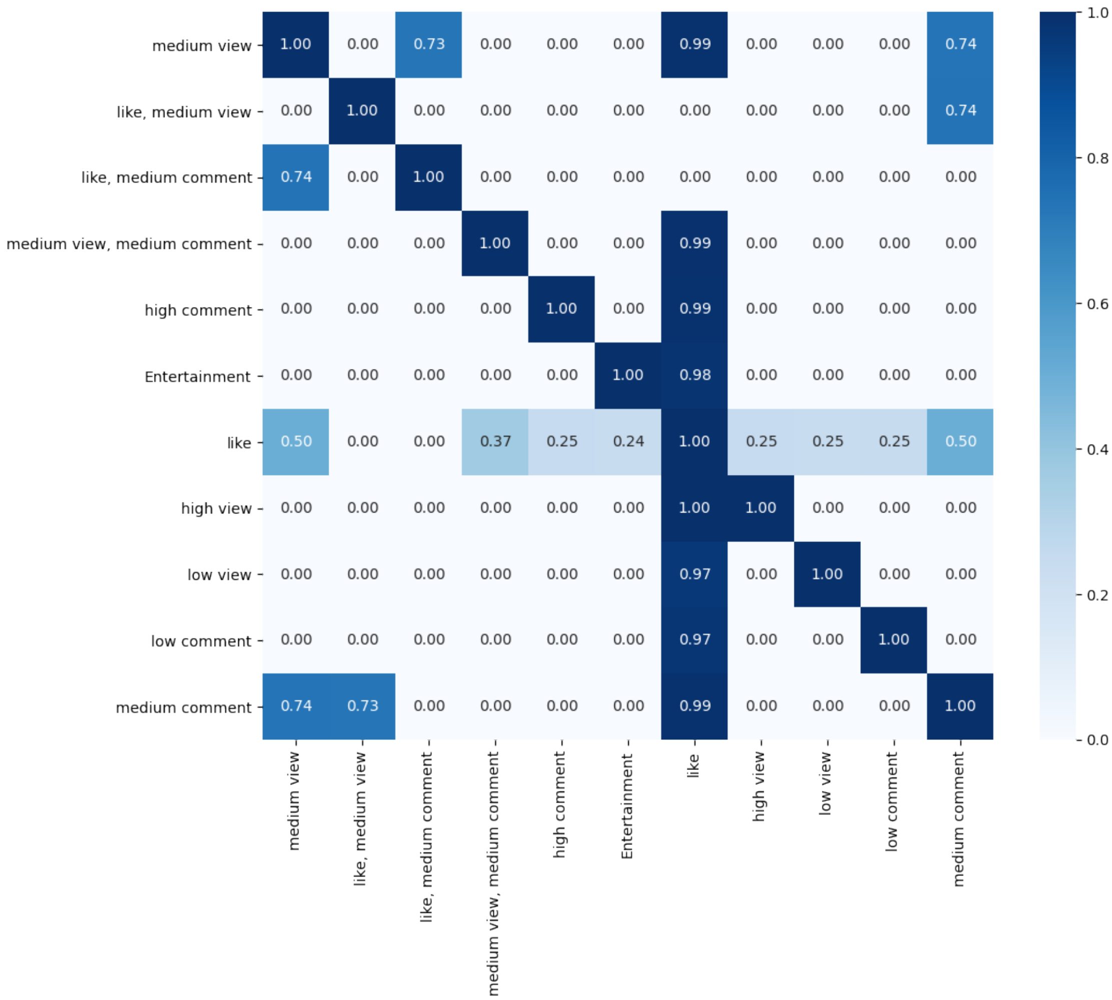
- 利用置信度绘制热力图。

[29]:
```
# 可视化
conf_matrix = []
rules_column = set()

for i in range(len(measure)):
    rules_column.add(measure[i][0])
# 计算置信度矩阵
for i in rules_column:
    one = []
    for j in rules_column:
        if i == j:
            one.append(1)
        else:
            flag = False
            for k in range(len(rules)):
                if rules[k][0] == i and rules[k][1] == j:
                    one.append(rules[k][3])
```

```python
                    flag = True
            if flag == False:
                one.append(0)
    conf_matrix.append(one)
# 改 columns 名字
rules_column_list = []
for i in rules_column:
    one = ""
    for j in range(len(i)):
        one += id2str[j]
        if j < len(i) - 1:
            one += ", "
    rules_column_list.append(one)
# 绘制热图的数据
rules_column = list(rules_column)
rules_column_list = []
for i in rules_column:
    one = ""
    for j in range(len(i)):
        one += id2str[list(i)[j]]
        if j < len(i) - 1:
            one += ", "
    rules_column_list.append(one)

conf_pd = pd.DataFrame(conf_matrix, columns = rules_column_list, index =␣
 ↪rules_column_list)
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = conf_pd, annot = True, fmt = ".2f", cmap = "Blues")
plt.show()
```

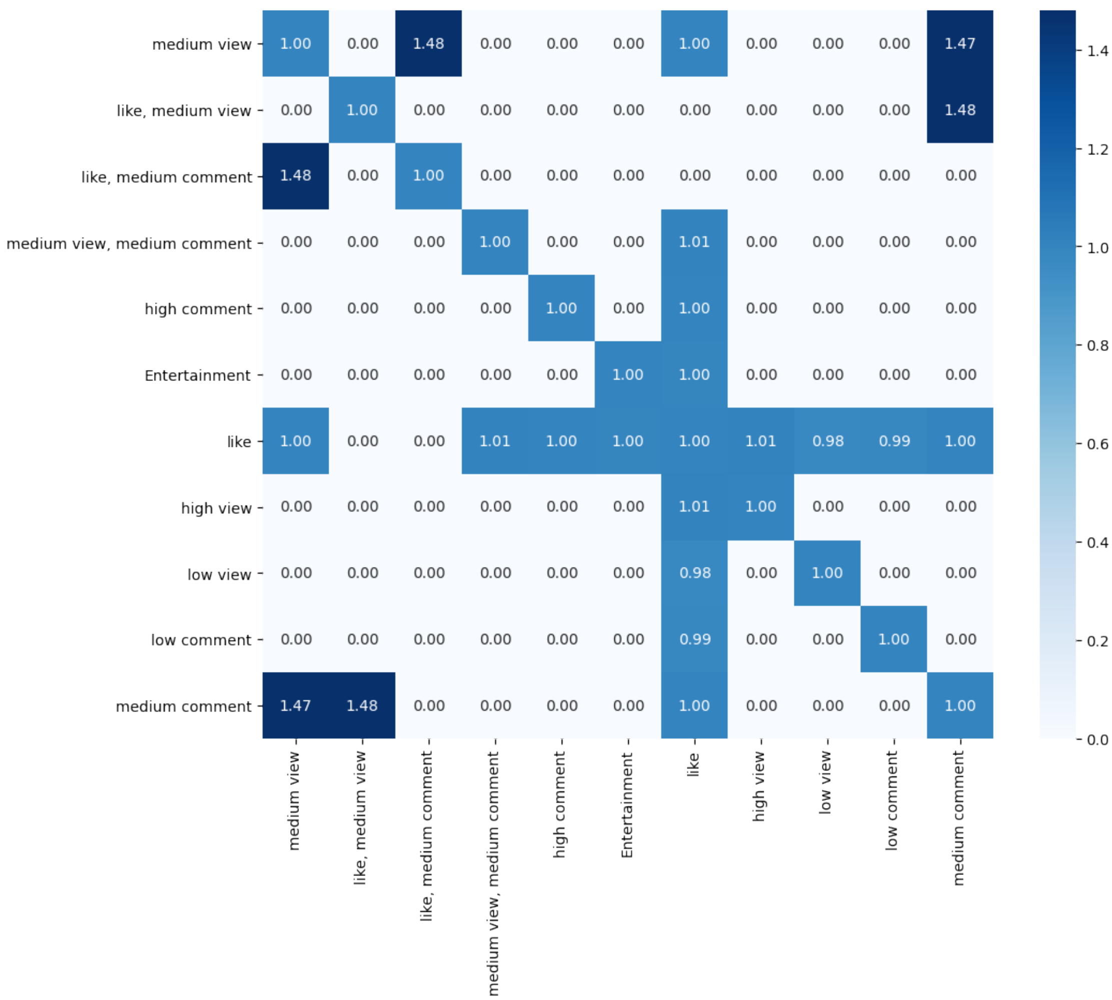


- 利用 Lift 值绘制热力图

[30]:
```python
# 计算 lift 矩阵
lift_matrix = []
for i in rules_column:
    one = []
    for j in rules_column:
        if i == j:
            one.append(1)
        else:
            flag = False
            for k in range(len(measure)):
                if measure[k][0] == i and measure[k][1] == j:
```

```python
                    one.append(measure[k][6])
                    flag = True
            if flag == False:
                one.append(0)
    lift_matrix.append(one)

lift_pd = pd.DataFrame(lift_matrix, columns = rules_column_list, index =␣
↪rules_column_list)
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = lift_pd, annot = True, fmt = ".2f", cmap = "Blues")
plt.show()
```

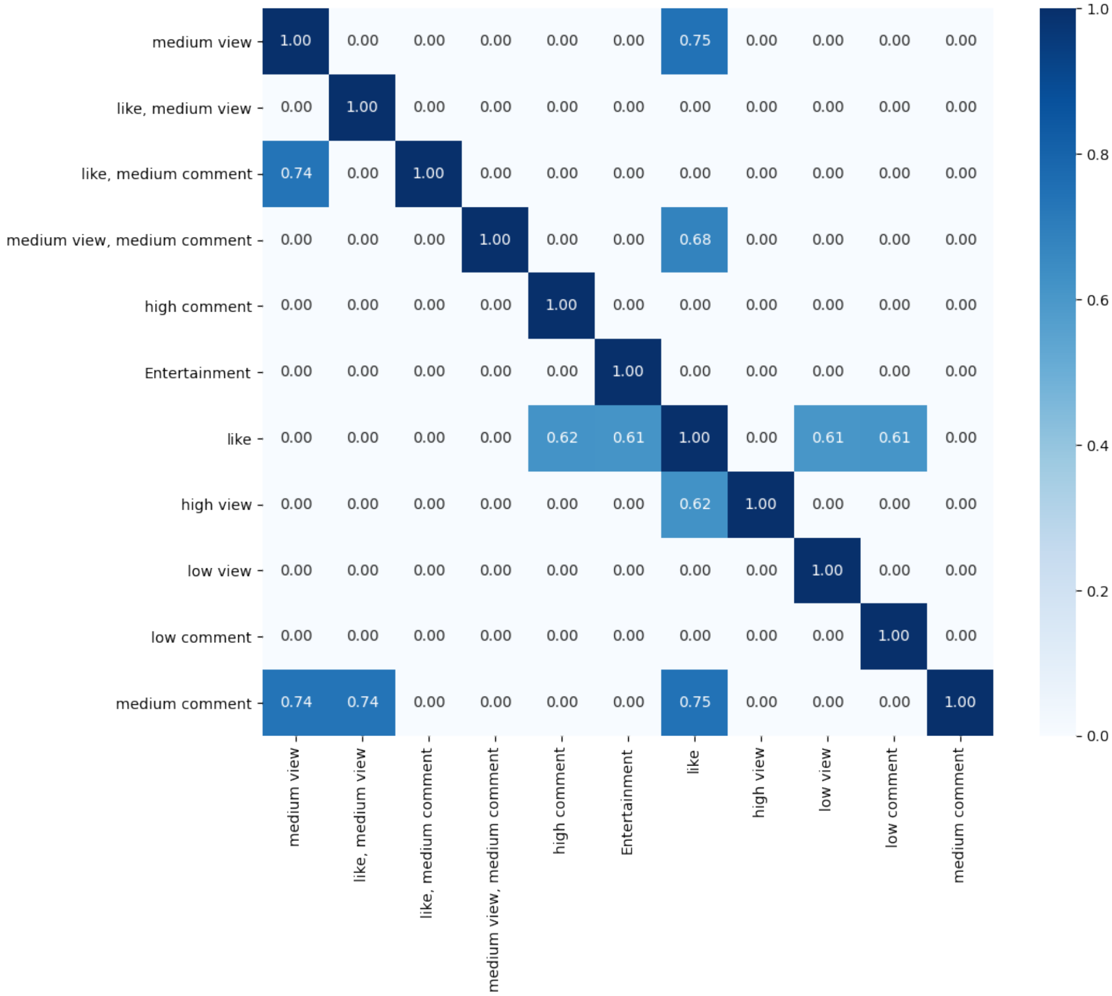


- 利用 Kulc 值绘制热力图

[31]:

```python
kulc_matrix = []
# 计算 kulc 矩阵
for i in rules_column:
    one = []
    for j in rules_column:
        if i == j:
            one.append(1)
        else:
            flag = False
            for k in range(len(kulc)):
                if kulc[k][0] == i and kulc[k][1] == j:
                    one.append(kulc[k][2])
                    flag = True
            if flag == False:
                one.append(0)
    kulc_matrix.append(one)

kulc_pd = pd.DataFrame(kulc_matrix, columns = rules_column_list, index =␣
 ↪rules_column_list)
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = kulc_pd, annot = True, fmt = ".2f", cmap = "Blues")
plt.show()
```



medium view
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Entertainment
like
high view
low view
low comment
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