数据挖掘互评作业二: 频繁模式与关联规则挖掘

1. 问题描述 本次作业中，将选择2个数据集进行分析与挖掘

1. 可选数据集 来源包括： SNAP(Stanford Large Network Dataset Collection): http://snap.stanford.edu/data/index.html Microsoft 资讯推荐: https://learn.microsoft.com/zh-cn/azure/open-datasets/dataset-microsoft-news?tabs=azureml-opendatasets YELP: https://www.yelp.com/dataset/download DBLP: https://dblp.uni-trier.de/xml/

2. 数据分析要求 数据获取与预处理； 频繁模式挖掘：可以是项集、序列和图。 模式命名：如论文-作者网络中合作模式、引用模式和发表模式等，不同的领域的频繁模式的含义也不尽相同，需自行确定模式的名称。 对挖掘结果进行分析； 可视化展示。

3. 提交的内容 数据集获取和预处理的代码 关联规则挖掘的代码 挖掘过程的报告：展示挖掘的过程、结果和你的分析 所选择的数据集在README中说明，数据文件不要上传到Github中

乐学平台提交注意事项： 仓库地址：https://github.com/DingDongCat/data-mining-homework-two 报告：附件，word，pdf，html格式都可以

一、针对Microsoft资讯推荐数据集的处理

1、数据获取与预处理

数据获取

运行 https://learn.microsoft.com/zh-cn/azure/open-datasets/dataset-microsoft-news?tabs=azureml-opendatasets 给出的数据获取代码

In [1]:
```
import os
import tempfile
import shutil
import urllib
import zipfile
import pandas as pd

# Temporary folder for data we need during execution of this notebook (we'll clean u
# at the end, we promise)
temp_dir = os.path.join(tempfile.gettempdir(), 'mind')
os.makedirs(temp_dir, exist_ok=True)

# The dataset is split into training and validation set, each with a large and small
# The format of the four files are the same.
# For demonstration purpose, we will use small version validation set only.
base_url = 'https://mind201910small.blob.core.windows.net/release'
training_small_url = f'{base_url}/MINDsmall_train.zip'
validation_small_url = f'{base_url}/MINDsmall_dev.zip'
```

```
training_large_url = f'{base_url}/MINDlarge_train.zip'
validation_large_url = f'{base_url}/MINDlarge_dev.zip'
```

In [2]:

```
def download_url(url,
                 destination_filename=None,
                 progress_updater=None,
                 force_download=False,
                 verbose=True):
    """
    Download a URL to a temporary file
    """
    if not verbose:
        progress_updater = None
    # This is not intended to guarantee uniqueness, we just know it happens to guaran
    # uniqueness for this application.
    if destination_filename is None:
        url_as_filename = url.replace('://', '_').replace('/', '_')
        destination_filename = \
            os.path.join(temp_dir,url_as_filename)
    if (not force_download) and (os.path.isfile(destination_filename)):
        if verbose:
            print('Bypassing download of already-downloaded file {}'.format(
                os.path.basename(url)))
        return destination_filename
    if verbose:
        print('Downloading file {} to {}'.format(os.path.basename(url),
                                                  destination_filename),
              end='')
    urllib.request.urlretrieve(url, destination_filename, progress_updater)
    assert (os.path.isfile(destination_filename))
    nBytes = os.path.getsize(destination_filename)
    if verbose:
        print('...done, {} bytes.'.format(nBytes))
    return destination_filename
```

In [3]:

```
# For demonstration purpose, we will use small version validation set only.
# This file is about 30MB.
zip_path = download_url(validation_small_url, verbose=True)
with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(temp_dir)

os.listdir(temp_dir)
```

```
Bypassing download of already-downloaded file MINDsmall_dev.zip
```

Out[3]:

```
['behaviors.tsv',
 'entity_embedding.vec',
 'https_mind201910small.blob.core.windows.net_release_MINDsmall_dev.zip',
 'news.tsv',
 'relation_embedding.vec']
```

In [4]:

```
# The behaviors.tsv file contains the impression logs and users' news click historie
# It has 5 columns divided by the tab symbol:
# - Impression ID. The ID of an impression.
# - User ID. The anonymous ID of a user.
# - Time. The impression time with format "MM/DD/YYYY HH:MM:SS AM/PM".
# - History. The news click history (ID list of clicked news) of this user before th
# - Impressions. List of news displayed in this impression and user's click behavior
behaviors_path = os.path.join(temp_dir, 'behaviors.tsv')
behaviors_table = pd.read_table(
    behaviors_path,
    header=None,
    names=['impression_id', 'user_id', 'time', 'history', 'impressions'])
behaviors_table
```

Out[4]:

	impression_id	user_id	time	history	impressions
0	1	U80234	11/15/2019 12:37:50 PM	N55189 N46039 N51741 N53234 N11276 N264 N40716...	N28682-0 N48740-0 N31958-1 N34130-0 N6916-0 N5...
1	2	U60458	11/15/2019 7:11:50 AM	N58715 N32109 N51180 N33438 N54827 N28488 N611...	N20036-0 N23513-1 N32536-0 N46976-0 N35216-0 N...
2	3	U44190	11/15/2019 9:55:12 AM	N56253 N1150 N55189 N16233 N61704 N51706 N5303...	N36779-0 N62365-0 N58098-0 N5472-0 N13408-0 N5...
3	4	U87380	11/15/2019 3:12:46 PM	N63554 N49153 N28678 N23232 N43369 N58518 N444...	N6950-0 N60215-0 N6074-0 N11930-0 N6916-0 N248...
4	5	U9444	11/15/2019 8:25:46 AM	N51692 N18285 N26015 N22679 N55556	N5940-1 N23513-0 N49285-0 N23355-0 N19990-0 N3...
...	...	...	...	...	...
73147	73148	U77536	11/15/2019 8:40:16 PM	N28691 N8845 N58434 N37120 N22185 N60033 N4702...	N496-0 N35159-0 N59856-0 N13270-0 N47213-0 N26...
73148	73149	U56193	11/15/2019 1:11:26 PM	N4705 N58782 N53531 N46492 N26026 N28088 N3109...	N49285-0 N31958-0 N55237-0 N42844-0 N29862-0 N...
73149	73150	U16799	11/15/2019 3:37:06 PM	N40826 N42078 N15670 N15295 N64536 N46845 N52294	N7043-0 N512-0 N60215-1 N45057-0 N496-0 N37055...
73150	73151	U8786	11/15/2019 8:29:26 AM	N3046 N356 N20483 N46107 N44598 N18693 N8254 N...	N23692-0 N19990-0 N20187-0 N5940-0 N13408-0 N3...
73151	73152	U68182	11/15/2019 11:54:34 AM	N20297 N53568 N4690 N60608 N43709 N43123 N1885...	N29862-0 N5472-0 N21679-1 N6400-0 N53572-0 N50...

73152 rows × 5 columns

In [5]:

```
# The news.tsv file contains the detailed information of news articles involved in tl
# It has 7 columns, which are divided by the tab symbol:
# - News ID
# - Category
# - Subcategory
# - Title
# - Abstract
# - URL
# - Title Entities (entities contained in the title of this news)
# - Abstract Entities (entities contained in the abstract of this news)
news_path = os.path.join(temp_dir, 'news.tsv')
news_table = pd.read_table(news_path,
              header=None,
              names=[
                  'id', 'category', 'subcategory', 'title', 'abstract', 'url',
                  'title_entities', 'abstract_entities'
              ])
news_table
```

Out[5]:

	id	category	subcategory	title	abstract	
0	N55528	lifestyle	lifestyleroyals	The Brands Queen Elizabeth, Prince Charles, an...	Shop the notebooks, jackets, and more that the...	https://assets.msn.com/labs/m
1	N18955	health	medical	Dispose of unwanted prescription drugs during ...	NaN	https://assets.msn.com/labs/n
2	N61837	news	newsworld	The Cost of Trump's Aid Freeze in the Trenches...	Lt. Ivan Molchanets peeked over a parapet of s...	https://assets.msn.com/labs/n
3	N53526	health	voices	I Was An NBA Wife. Here's How It Affected My M...	I felt like I was a fraud, and being an NBA wi...	https://assets.msn.com/labs/m
4	N38324	health	medical	How to Get Rid of Skin Tags, According to a De...	They seem harmless, but there's a very good re...	https://assets.msn.com/labs/n
...	...	...	...	...	...	
42411	N63550	lifestyle	lifestyleroyals	Why Kate & Meghan Were on Different Balconies ...	There's no scandal here. It's all about the or...	https://assets.msn.com/labs/m
42412	N30345	entertainment	entertainment-celebrity	See the stars at the 2019 Baby2Baby gala	Stars like Chrissy Teigen and Kate Hudson supp...	https://assets.msn.com/labs/m
42413	N30135	news	newsgoodnews	Tennessee judge holds lawyer's baby as he swea...	Tennessee Court of Appeals Judge Richard Dinki...	https://assets.msn.com/labs/r
42414	N44276	autos	autossports	Best Sports Car Deals for October	NaN	https://assets.msn.com/labs/i
42415	N39563	sports	more_sports	Shall we dance: Sports stars shake their leg	NaN	https://assets.msn.com/labs/m

In [6]:
```python
# The entity_embedding.vec file contains the 100-dimensional embeddings
# of the entities learned from the subgraph by TransE method.
# The first column is the ID of entity, and the other columns are the embedding vect
entity_embedding_path = os.path.join(temp_dir, 'entity_embedding.vec')
entity_embedding = pd.read_table(entity_embedding_path, header=None)
entity_embedding['vector'] = entity_embedding.iloc[:, 1:101].values.tolist()
entity_embedding = entity_embedding[[0,
                                     'vector']].rename(columns={0: "entity"})
entity_embedding
```

Out[6]:

	entity	vector
0	Q34433	[0.017808, -0.073256, 0.102521, -0.059926, -0....
1	Q41	[-0.063388, -0.181451, 0.057501, -0.091254, -0...
2	Q56037	[0.02155, -0.044888, -0.027872, -0.128843, 0.0...
3	Q1860	[0.060958, 0.069934, 0.015832, 0.079471, -0.02...
4	Q39631	[-0.093106, -0.052002, 0.020556, -0.020801, 0....
...	...	...
22888	Q278846	[0.042413, 0.021957, 0.072414, -0.068437, 0.02...
22889	Q54621949	[-0.018299, -0.048378, -0.021645, -0.079743, 0...
22890	Q42225228	[-0.051346, -0.028947, -0.07587, 0.017512, -0....
22891	Q54862508	[-0.052323, -0.078029, -0.060925, -0.052536, 0...
22892	Q42301562	[-0.00519, -0.047871, 0.009753, -0.0215, -4.9e...

22893 rows × 2 columns

In [7]:
```python
# The relation_embedding.vec file contains the 100-dimensional embeddings
# of the relations learned from the subgraph by TransE method.
# The first column is the ID of relation, and the other columns are the embedding vec
relation_embedding_path = os.path.join(temp_dir, 'relation_embedding.vec')
relation_embedding = pd.read_table(relation_embedding_path, header=None)
relation_embedding['vector'] = relation_embedding.iloc[:,
                                                       1:101].values.tolist()
relation_embedding = relation_embedding[[0, 'vector'
                                         ]].rename(columns={0: "relation"})
relation_embedding
```

Out[7]:

	relation	vector
0	P31	[-0.073467, -0.132227, 0.034173, -0.032769, 0....
1	P21	[-0.078436, 0.108589, -0.049429, -0.131355, 0....
2	P106	[-0.052137, 0.052444, -0.019886, -0.152309, 0....
3	P735	[-0.051398, 0.056219, 0.068029, -0.137717, -0....
4	P108	[0.091231, 0.022526, 0.059349, -0.141853, 0.03...
...	...	...
1086	P1897	[-0.019021, 0.001183, -0.009602, -0.040833, -0...
1087	P3776	[-0.018365, 0.028526, -0.025934, 0.032296, -0....
1088	P1194	[-0.026819, 0.003231, -0.011298, -0.015206, 0....
1089	P2502	[0.003554, -0.041121, -0.010559, -0.037862, -0...
1090	P6977	[-0.023617, -0.021648, 0.009369, -0.021757, 0....

1091 rows × 2 columns

数据预处理

将behaviors_table中的history按news_table中的类型替换为整数格式

In [8]:

```
behaviors_table = behaviors_table.dropna()
transaction = []
category = news_table['category'].unique().tolist()
print(category)
err_num = 0
for i in range(len(behaviors_table)):
    if i%1000 == 0:
        print(i,'/',len(behaviors_table))
# for i in range(10):
    try:
        news_list = behaviors_table['history'][i].split(' ')
        tmp_list = []
        for news_id in news_list:
            tmp_list.append(category.index(news_table['category'][news_table[news_ta
        transaction.append(tmp_list)
    except:
        err_num += 1
print('error count: ', err_num)
print(transaction[0:10])
```

```
['lifestyle', 'health', 'news', 'sports', 'weather', 'entertainment', 'foodanddrin
k', 'autos', 'travel', 'video', 'tv', 'finance', 'movies', 'music', 'kids', 'middlee
ast', 'games']
0 / 70938
1000 / 70938
2000 / 70938
3000 / 70938
4000 / 70938
5000 / 70938
6000 / 70938
7000 / 70938
8000 / 70938
9000 / 70938
10000 / 70938
11000 / 70938
12000 / 70938
13000 / 70938
14000 / 70938
15000 / 70938
16000 / 70938
17000 / 70938
18000 / 70938
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20000 / 70938
21000 / 70938
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56000 / 70938
57000 / 70938
58000 / 70938
59000 / 70938
60000 / 70938
```

```
61000 / 70938
62000 / 70938
63000 / 70938
64000 / 70938
65000 / 70938
66000 / 70938
67000 / 70938
68000 / 70938
69000 / 70938
70000 / 70938
error count:  2150
[[10, 2, 10, 2, 11, 7, 10, 12, 5, 2, 0, 2, 2, 1, 10], [2, 8, 11, 2, 2, 11, 13, 2, 1
1, 4, 11, 1, 0], [3, 2, 10, 2, 0, 3, 2, 5, 3], [8, 2, 3, 3, 8, 2, 10, 2, 3, 2, 10,
2, 12, 8, 9, 2, 3, 3, 2], [10, 3, 5, 3, 11], [3, 11, 3, 2, 2, 11, 6, 5, 3, 11, 7],
[10, 10, 2, 6, 11, 2, 11, 0, 6], [2, 3, 2, 2, 3, 3, 3, 2, 3, 2], [2, 3, 2, 2, 2, 2,
5, 2, 2], [2, 3, 11, 2, 2, 2, 2, 2, 1, 12]]
```

2、频繁模式与关联规则挖掘

使用orangecontrib.associate.fpgrowth包进行频繁模式挖掘。首先使用默认的0.2作为频繁模式的相对支持度支持度阈值。

In [24]:
```python
import orangecontrib.associate.fpgrowth as oaf

items = list(oaf.frequent_itemsets(transaction, 0.5))
for i in items:
    print(i)
```

```
(frozenset({0}), 49167)
(frozenset({2}), 61406)
(frozenset({0, 2}), 45533)
(frozenset({3}), 47444)
(frozenset({0, 3}), 35535)
(frozenset({2, 3}), 43907)
(frozenset({10}), 45719)
(frozenset({0, 10}), 36972)
(frozenset({2, 10}), 42526)
(frozenset({0, 2, 10}), 35192)
(frozenset({11}), 42614)
(frozenset({2, 11}), 40412)
```

frozenset是项集，后面的数字是这个项集的绝对支持度。为了更好地显示频繁项集，下面将数字重新转化为原始的字符串，同时计算相对支持度。

In [25]:
```python
for i in items:
    freq_set = []
    abs_sup = i[1]
    for j in i[0]:
        freq_set.append(category[j])
    print(freq_set, abs_sup, round(float(abs_sup) / len(behaviors_table), 2))
```

```
['lifestyle'] 49167 0.69
['news'] 61406 0.87
['lifestyle', 'news'] 45533 0.64
['sports'] 47444 0.67
['lifestyle', 'sports'] 35535 0.5
['news', 'sports'] 43907 0.62
['tv'] 45719 0.64
['lifestyle', 'tv'] 36972 0.52
['news', 'tv'] 42526 0.6
['lifestyle', 'news', 'tv'] 35192 0.5
['finance'] 42614 0.6
['news', 'finance'] 40412 0.57
```

在计算出频繁项集的基础上，计算关联规则，置信度阈值选择为0.5，结果转化为原始字符串输出.

In [29]:
```
items = list(oaf.frequent_itemsets(transaction, 0.5))
rules = list(oaf.association_rules(dict(items), 0.5))
for i in rules:
    antecedent = []
    consequent = []
    for j in i[0]:
        antecedent.append(category[j])
    for j in i[1]:
        consequent.append(category[j])
    print(antecedent, "->", consequent, i[2], round(i[3],2))
print(len(rules))
```

```
['news', 'tv'] -> ['lifestyle'] 35192 0.83
['lifestyle', 'tv'] -> ['news'] 35192 0.95
['tv'] -> ['lifestyle', 'news'] 35192 0.77
['lifestyle', 'news'] -> ['tv'] 35192 0.77
['news'] -> ['lifestyle', 'tv'] 35192 0.57
['lifestyle'] -> ['tv', 'news'] 35192 0.72
['news'] -> ['lifestyle'] 45533 0.74
['lifestyle'] -> ['news'] 45533 0.93
['sports'] -> ['lifestyle'] 35535 0.75
['lifestyle'] -> ['sports'] 35535 0.72
['sports'] -> ['news'] 43907 0.93
['news'] -> ['sports'] 43907 0.72
['tv'] -> ['lifestyle'] 36972 0.81
['lifestyle'] -> ['tv'] 36972 0.75
['tv'] -> ['news'] 42526 0.93
['news'] -> ['tv'] 42526 0.69
['finance'] -> ['news'] 40412 0.95
['news'] -> ['finance'] 40412 0.66
18
```

3.关联规则的评价

使用Lift和Kulc两种评价指标评价关联规则。

In [30]:
```
measure = list(oaf.rules_stats(oaf.association_rules(dict(items), 0.5), dict(oaf.fre
for i in measure:
    antecedent = []
    consequent = []
    for j in i[0]:
        antecedent.append(category[j])
    for j in i[1]:
        consequent.append(category[j])
    print(antecedent, "->", consequent, round(i[6], 2))
```

```
['news', 'tv'] -> ['lifestyle'] 1.19
['lifestyle', 'tv'] -> ['news'] 1.1
['tv'] -> ['lifestyle', 'news'] 1.2
['lifestyle', 'news'] -> ['tv'] 1.2
['news'] -> ['lifestyle', 'tv'] 1.1
['lifestyle'] -> ['tv', 'news'] 1.19
['news'] -> ['lifestyle'] 1.07
['lifestyle'] -> ['news'] 1.07
['sports'] -> ['lifestyle'] 1.08
['lifestyle'] -> ['sports'] 1.08
['sports'] -> ['news'] 1.07
['news'] -> ['sports'] 1.07
['tv'] -> ['lifestyle'] 1.17
['lifestyle'] -> ['tv'] 1.17
['tv'] -> ['news'] 1.07
['news'] -> ['tv'] 1.07
['finance'] -> ['news'] 1.1
['news'] -> ['finance'] 1.1
```

In [31]:

```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(category[k])
            for k in rules[i][1]:
                consequent.append(category[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] + rule
            visit[j] = True
```

```
Kulc( ['news', 'tv'] ['lifestyle'] ) =  0.77
Kulc( ['lifestyle', 'tv'] ['news'] ) =  0.76
Kulc( ['tv'] ['lifestyle', 'news'] ) =  0.77
Kulc( ['news'] ['lifestyle'] ) =  0.83
Kulc( ['sports'] ['lifestyle'] ) =  0.74
Kulc( ['sports'] ['news'] ) =  0.82
Kulc( ['tv'] ['lifestyle'] ) =  0.78
Kulc( ['tv'] ['news'] ) =  0.81
Kulc( ['finance'] ['news'] ) =  0.8
```

4.挖掘结果的分析

lift可以用于衡量关联规则中两个项目的相关度， lift(A,B)>1说明A与B正相关， lift(A,B)=1说明A与B相互独立， lift(A,B)<1说明A与B负相关。所有的18条关联规则中，lift值均大于1。

在所有计算出的关联规则的Kulc值中，以下三个Kulc值较大：

Kulc(['news'] ['lifestyle']) = 0.83

Kulc(['sports'] ['news']) = 0.82

Kulc(['tv'] ['news']) = 0.81

因此可以得到以下结论：

1、对新闻相关内容感兴趣的观众对生活方式相关内容同样感兴趣

2、对体育相关内容感兴趣的观众对新闻相关内容同样感兴趣

3、对电视节目相关内容感兴趣的观众对新闻相关内容同样感兴趣

在关联规则中，有两条的置信度很高：

['lifestyle', 'tv'] -> ['news'] 35192 0.95

['finance'] -> ['news'] 40412 0.95

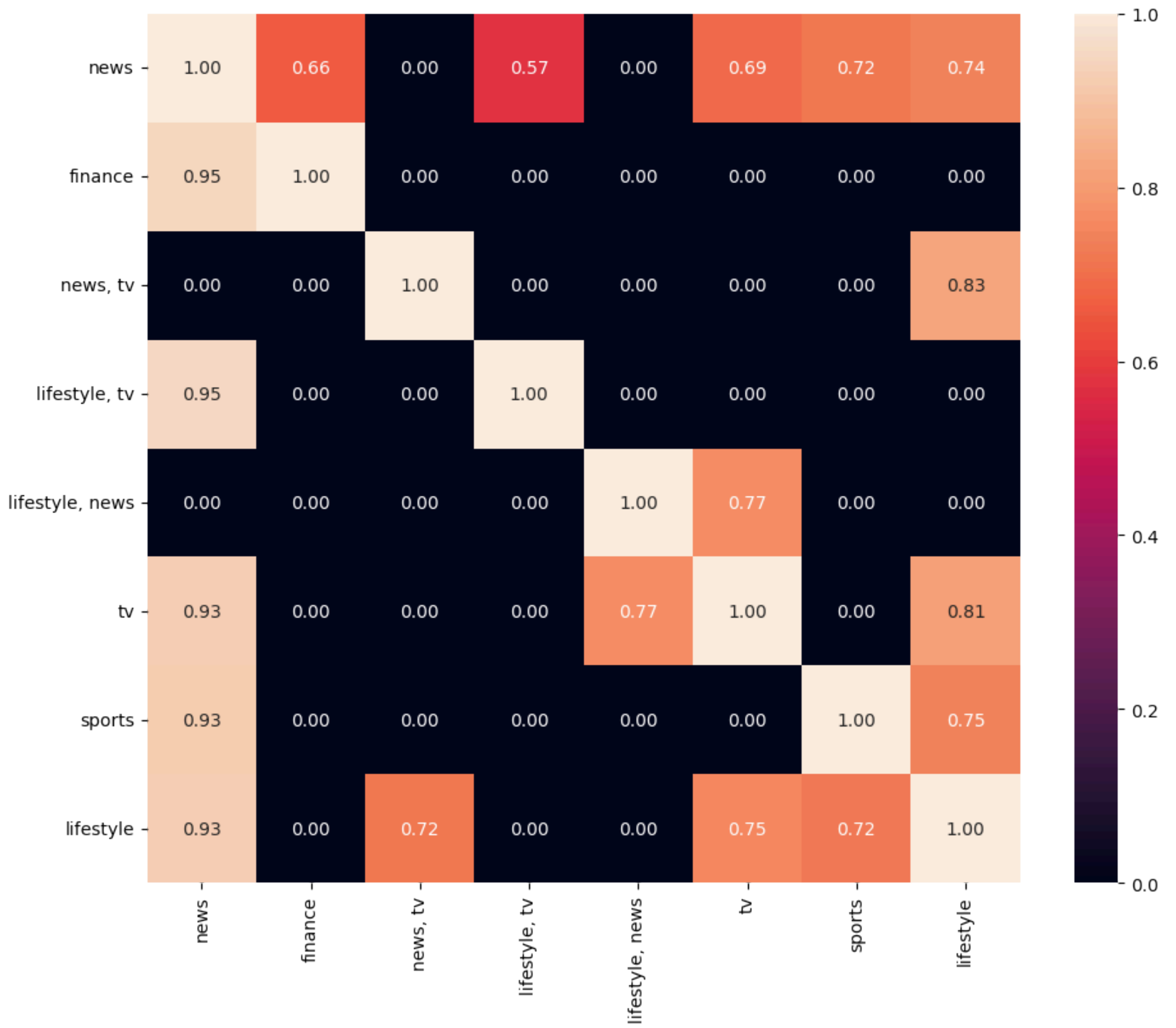
5.可视化展示

绘制关联规则的置信度、Lift和Kulc相关性热图

横纵坐标是关联规则中包含的项，热图中每个点的数据是两项的置信度、Lift值或Kulc值

In [36]:
```
import matplotlib.pyplot as plt
import seaborn as sns
# 利用置信度绘制热图
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])
                    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 += category[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 = []
```

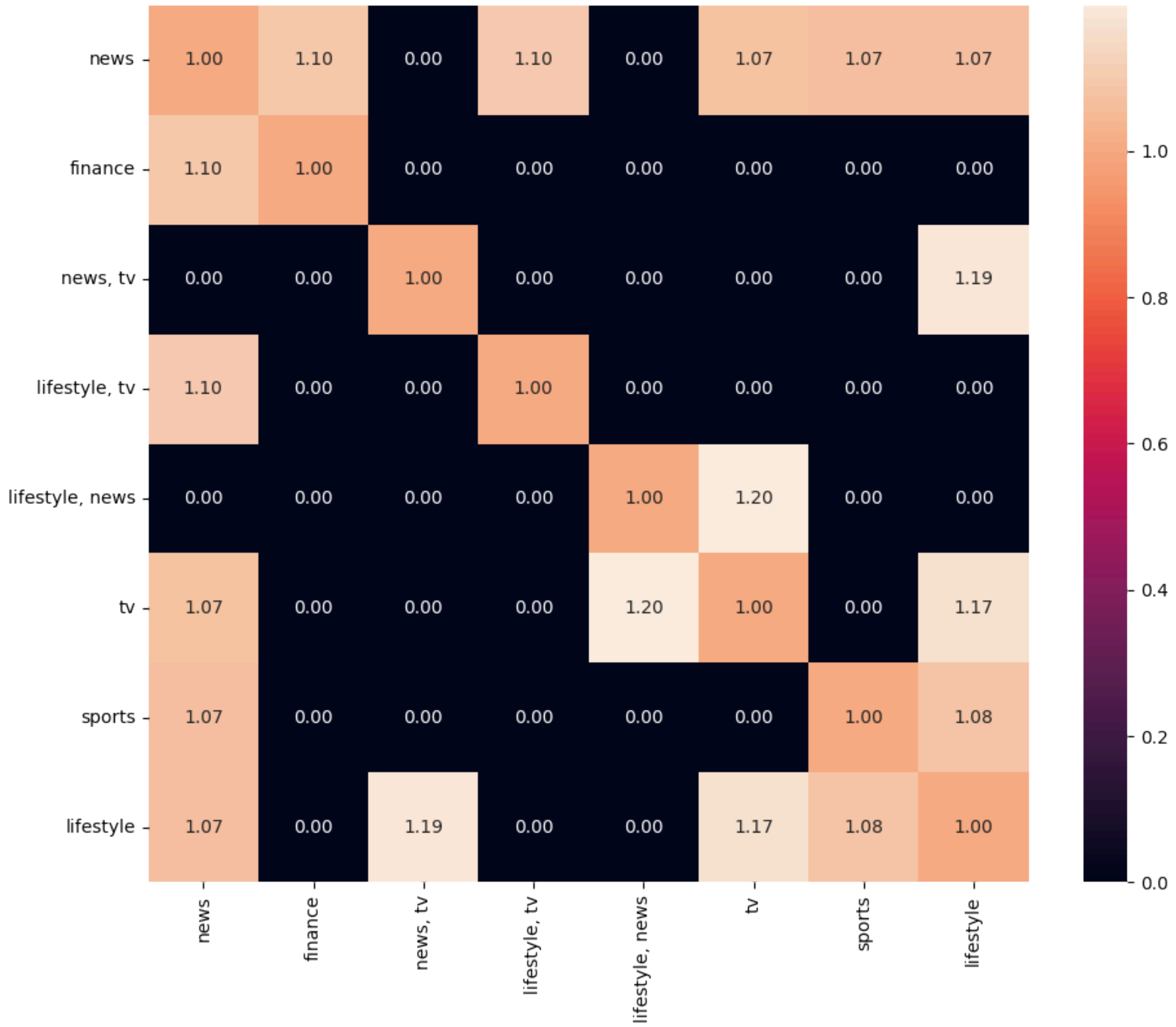
```
for i in rules_column:
    one = ""
    for j in range(len(i)):
        one += category[list(i)[j]]
        if j < len(i) - 1:
            one += ", "
    rules_column_list.append(one)

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



In [37]:

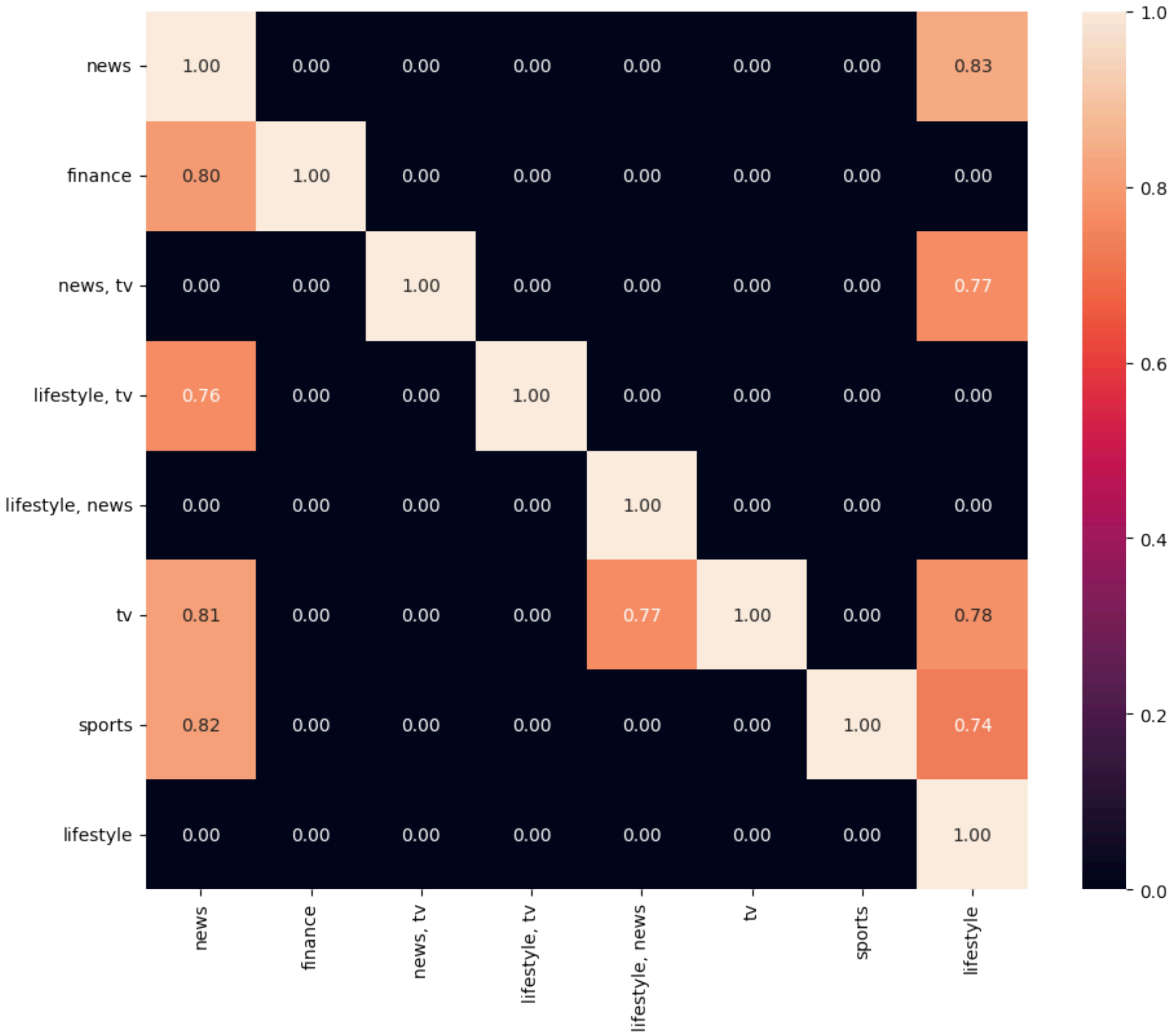
```
# 使用Lift值绘制热图
# 计算lift矩阵
lift_matrix = []
for i in rules_column:
    one = []
    for j in rules_column:
        if i == j:
            one.append(1)
        else:
            flag = False
            for k in range(len(measure)):
                if measure[k][0] == i and measure[k][1] == j:
                    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_colum
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = lift_pd, annot = True, fmt = ".2f")
plt.show()
```



In [38]:

```
# 使用Kulc值绘制热图
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_colum
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = kulc_pd, annot = True, fmt = ".2f")
plt.show()
```



二、针对YELP数据集的处理

1、数据获取与预处理

In [1]:
```
# import json
# file = open("yelp_academic_dataset_business.json", 'r', encoding='utf-8')
# papers = []
# for line in file.readlines():
#     dic = json.loads(line)
#     papers.append(dic)


# print(len(papers))
# print(papers[0])
# print(papers[1])

import pandas as pd

df = pd.read_json('yelp_academic_dataset_business.json',lines=True)

df
```

Out[1]:

	business_id	name	address	city	state	postal_code	latitu
0	Pns2l4eNsfO8kk83dixA6A	Abby Rappoport, LAC, CMQ	1616 Chapala St, Ste 2	Santa Barbara	CA	93101	34.426
1	mpf3x-BjTdTEA3yCZrAYPw	The UPS Store	87 Grasso Plaza Shopping Center	Affton	MO	63123	38.551
2	tUFrWirKiKi_TAnsVWINQQ	Target	5255 E Broadway Blvd	Tucson	AZ	85711	32.223
3	MTSW4McQd7CbVtyjqoe9mw	St Honore Pastries	935 Race St	Philadelphia	PA	19107	39.955
4	mWMc6_wTdE0EUBKIGXDVfA	Perkiomen Valley Brewery	101 Walnut St	Green Lane	PA	18054	40.338
...	...	...	...	...	...	...	
150341	IUQopTMmYQG-qRtBk-8QnA	Binh's Nails	3388 Gateway Blvd	Edmonton	AB	T6J 5H2	53.468
150342	c8GjPIOTGVmIemT7j5_SyQ	Wild Birds Unlimited	2813 Bransford Ave	Nashville	TN	37204	36.115
150343	_QAMST-NrQobXduilWEqSw	Claire's Boutique	6020 E 82nd St, Ste 46	Indianapolis	IN	46250	39.908
150344	mtGm22y5c2UHNXDFAjaPNw	Cyclery & Fitness Center	2472 Troy Rd	Edwardsville	IL	62025	38.782
150345	jV_XOycEzSlTx-65W906pg	Sic Ink	238 Apollo Beach Blvd	Apollo beach	FL	33572	27.771

150346 rows × 14 columns

数据预处理

将categories替换和stars为整数格式

In [22]:

```python
df = df.dropna()
id2str = []
str2id = {}
id = 0
transaction = []
for i,row in df.iterrows():
#     print(i, row)
    one = []
    cate = df['categories'][i].split(', ')
    for j in cate:
        if j in str2id:
            one.append(str2id[j])
        else:
            id2str.append(j)
            str2id[j] = len(id2str)
            one.append(str2id[j])
    if df['stars'][i] in str2id:
        one.append(str2id[str(df['stars'][i])])
    else:
        id2str.append(str(df['stars'][i]))
        str2id[str(df['stars'][i])] = len(id2str)
        one.append(str2id[str(df['stars'][i])])
    transaction.append(one)
print(transaction[0:10])
id2str
```

```
[[1, 2, 3, 4, 5, 6], [7, 8, 9, 10, 11, 12, 13], [14, 15, 16, 17, 18, 19], [20, 21, 1
5, 22], [23, 24, 25, 15, 26, 14, 27], [28, 9, 29, 8, 30, 31, 32], [26, 24, 23, 14, 1
5, 33], [7, 8, 9, 34], [35, 15, 14, 36, 37], [38, 14, 39, 40, 41]]
```

Out[22]:
```
['Shipping Centers',
 'Local Services',
 'Notaries',
 'Mailbox Centers',
 'Printing Services',
 '3.0',
 'Department Stores',
 'Shopping',
 'Fashion',
 'Home & Garden',
 'Electronics',
 'Furniture Stores',
 '3.5',
 'Restaurants',
 'Food',
 'Bubble Tea',
 'Coffee & Tea',
 'Bakeries',
 '4.0',
 'Brewpubs',
 'Breweries',
 '4.5',
 'Burgers',
 'Fast Food',
 'Sandwiches',
 'Ice Cream & Frozen Yogurt',
 '2.0',
 'Sporting Goods',
 'Shoe Stores',
 'Sports Wear',
 'Accessories',
 '2.5',
 '1.5',
 '3.5',
 'Vietnamese',
 'Food Trucks',
 '4.0',
 'American (Traditional)',
 'Diners',
 'Breakfast & Brunch',
 '2.5',
 'General Dentistry',
 'Dentists',
 'Health & Medical',
 'Cosmetic Dentists',
 '5.0',
 'Delis',
 'Italian',
 '4.5',
 'Sushi Bars',
 'Japanese',
 '4.0',
 'Automotive',
 'Auto Parts & Supplies',
 'Auto Customization',
 '4.5',
 'Vape Shops',
 'Tobacco Shops',
 'Personal Shopping',
 'Vitamins & Supplements',
 '4.0',
 'Korean',
 '4.5',
 'Cafes',
```

'Bars’,
'Wine Bars’,
'Nightlife’,
'4.0’,
'Books’,
'Mags’,
'Music & Video’,
'Bookstores’,
'4.0’,
'Steakhouses’,
'Asian Fusion’,
'4.0’,
'2.5’,
″Women's Clothing″,
″Children's Clothing″,
″Men's Clothing″,
'Adult’,
'3.0’,
'Seafood’,
'4.0’,
'Cocktail Bars’,
'4.0’,
'Pizza’,
'Chicken Wings’,
'3.5’,
'Trampoline Parks’,
'Active Life’,
'5.0’,
'Salad’,
'Soup’,
'3.0’,
'Dance Wear’,
'Arts & Entertainment’,
'Social Clubs’,
'Performing Arts’,
'4.5’,
'3.5’,
'Eatertainment’,
'3.5’,
'Mobile Phones’,
'Telecommunications’,
'Mobile Phone Accessories’,
'IT Services & Computer Repair’,
'2.0’,
'Museums’,
'Kids Activities’,
'Education’,
'Playgrounds’,
″Children's Museums″,
'4.5’,
'Musicians’,
'DJs’,
'Karaoke’,
'Event Planning & Services’,
'5.0’,
'Hair Salons’,
'Hair Extensions’,
'Beauty & Spas’,
'Wigs’,
'1.5’,
'Specialty Food’,
'Pasta Shops’,
'3.0’,
'Laser Hair Removal’,

'Doctors',
'Hair Removal',
'Chiropractors',
'Weight Loss Centers',
'Sports Medicine',
'Medical Spas',
'Skin Care',
'4.0',
'Candle Stores',
'Home Decor',
'2.5',
'Chinese',
'3.0',
'Music Venues',
'Internet Service Providers',
'Jazz & Blues',
'Professional Services',
'Internet Cafes',
'4.0',
'Caterers',
'3.5',
'5.0',
'Fitness & Instruction',
'Trainers',
'Gyms',
'Yoga',
'3.0',
'Health Markets',
'4.0',
'Pets',
'Pet Adoption',
'5.0',
'Juice Bars & Smoothies',
'3.0',
'Ophthalmologists',
'Eyewear & Opticians',
'Optometrists',
'2.5',
'American (New)',
'4.0',
'4.0',
'2.5',
'Sports Bars',
'3.5',
'Hotels & Travel',
'Tours',
'Local Flavor',
'4.0',
'Appliances & Repair',
'5.0',
'Chocolatiers & Shops',
'Candy Stores',
'4.0',
'Baby Gear & Furniture',
'1.5',
'Personal Care Services',
'Massage',
'Nail Salons',
'4.5',
'Beer Bar',
'4.5',
'Grocery',
'2.5',
'Tabletop Games',

'4.5’,
'Lounges’,
'Wraps’,
'4.5’,
'Beer’,
'Wine & Spirits’,
'4.5’,
'Gas Stations’,
'Convenience Stores’,
'3.0’,
'Keys & Locksmiths’,
'Home Services’,
'4.5’,
'4.0’,
'Pubs’,
'Gastropubs’,
'Venues & Event Spaces’,
'4.5’,
'Fruits & Veggies’,
'4.5’,
'4.5’,
'Antiques’,
'4.5’,
'Towing’,
'Body Shops’,
'4.5’,
'5.0’,
'5.0’,
'Masonry/Concrete’,
'Gardeners’,
'Lawn Services’,
'Tree Services’,
'Landscape Architects’,
'Contractors’,
'Landscaping’,
'3.5’,
'Party & Event Planning’,
'3.5’,
'4.5’,
'4.5’,
'3.5’,
'Physical Therapy’,
'5.0’,
'Jewelry’,
'3.5’,
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'Cajun/Creole’,
'4.0’,
'Couriers & Delivery Services’,
'3.0’,
'French’,
'Moroccan’,
'Mediterranean’,
'4.0’,
'Flooring’,
'Handyman’,
'4.0’,
'Pest Control’,
'4.5’,
'Auction Houses’,
'1.5’,
'4.0’,
'3.5’,
'Beer Gardens’,

'Wine Tours',
'Beer Tours',
'4.5',
'3.0',
'Drugstores',
'Discount Store',
'2.0',
'4.5',
'Public Services & Government',
'Libraries',
'3.5',
'3.0',
'Flowers & Gifts',
'Embroidery & Crochet',
'Uniforms',
'Arts & Crafts',
'Gift Shops',
'4.5',
'Parenting Classes',
'Maternity Wear',
'Specialty Schools',
'Laundry Services',
'Child Care & Day Care',
'5.0',
'3.0',
'2.5',
'Glass & Mirrors',
'Door Sales/Installation',
'5.0',
'Hardware Stores',
'Hot Tub & Pool',
'Pool & Hot Tub Service',
'2.5',
'Tires',
'Auto Repair',
'Oil Change Stations',
'1.5',
'Medical Centers',
'Diagnostic Services',
'Orthopedists',
'Spine Surgeons',
'Diagnostic Imaging',
'3.0',
'3.0',
'3.5',
'3.5',
'Custom Cakes',
'Desserts',
'Cupcakes',
'3.0',
'1.5',
'4.5',
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'Organic Stores',
'3.5',
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'Patisserie/Cake Shop',
'4.0',
'Live/Raw Food',
'4.0',
'Real Estate',
'Real Estate Agents',

```
'5.0',
'Buses',
'Transportation',
'Bus Tours',
'Travel Agents',
'Travel Services',
'Airport Shuttles',
'Public Transportation',
'4.5',
'Filipino',
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'4.5',
'4.5',
'Toy Stores',
'Hobby Shops',
'Comic Books',
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'3.0',
'Painters',
'Decks & Railing',
'Pressure Washers',
'4.5',
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'1.5',
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'Art Supplies',
'3.5',
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'Barbeque',
'3.5',
'Urgent Care',
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'Basketball Courts',
'Stadiums & Arenas',
'Professional Sports Teams',
'5.0',
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'Tattoo',
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'Music & DVDs',
'Video Game Stores',
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'Eyelash Service',
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'Life Coach',
'Meditation Centers',
'Nutritionists',
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'Office Cleaning',
'Window Washing',
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'Hair Stylists',
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```

'Dog Parks',
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'Windshield Installation & Repair',
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'Bagels',
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'Hiking',

'Mountain Biking',
'ATV Rentals/Tours',
'RV Rental',
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'Hawaiian',
'Street Vendors',
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'Mattresses',
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'Tapas/Small Plates',
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'Walking Tours',
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'Eyebrow Services',
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'Costumes',
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'Pakistani',
'Indian',
'Halal',
'4.0',
'Greek',
'Food Stands',
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'Sewing & Alterations',
'Dry Cleaning & Laundry',
'3.5',
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'Car Wash',
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'Seafood Markets',
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'Movers',
'Self Storage',
'Truck Rental',
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'4.0',
'3.5',
'Hot Dogs',
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'4.0',
'4.0',
'Auto Detailing',
'2.5',
'4.0',
'Musical Instruments & Teachers',
'4.0',
'4.0',
'3.0',
'4.0',
'4.0',
'4.5',
'2.5',
'Community Service/Non-Profit',
'Family Practice',
'Counseling & Mental Health',
'3.0',
'4.5',
'Bowling',
'3.5',
'4.0',
```

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'Cabinetry',
'Kitchen & Bath',
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'3.5',
'Building Supplies',
'Interior Design',
'4.5',
'Military Surplus',
'3.0',
'Buffets',
'4.0',
'4.0',
'Medical Supplies',
'Laser Eye Surgery/Lasik',
'4.0',
'5.0',
'Hair Loss Centers',
'4.0',
'4.5',
'Walk-in Clinics',
'2.5',
'Empanadas',
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'Pet Stores',

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'Parasailing’,
'Beaches’,
'Boating’,
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'Heating & Air Conditioning/HVAC’,
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'Whiskey Bars’,
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'5.0’,
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'2.5’,
'4.5’,
'2.5’,
'3.5’,
'1.5’,
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'3.0’,
'3.5’,
'Ramen’,
'3.0’,
'3.0’,
'2.5’,
'3.5’,
'4.5’,
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'Cannabis Clinics’,
'Cannabis Dispensaries’,
'4.0’,
'3.5’,
'4.5’,
'4.5’,
'Home Window Tinting’,
'Car Window Tinting’,
'Vehicle Wraps’,
'4.5’,
'1.5’,
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'5.0’,
'4.0’,
'4.0’,

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'Arcades',
'Recreation Centers',
'Art Schools',
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'4.5',
'Car Stereo Installation',
'3.0',
'5.0',
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'Dry Cleaning',
'5.0',
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'4.0',
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'Permanent Makeup',
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'Traditional Chinese Medicine',
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'Noodles',
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'Formal Wear',
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'3.0',
'4.0',
'Pediatric Dentists',
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'5.0',

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'Massage Therapy',
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'3.0',
'2.5',
'4.0',
'Cheesesteaks',
'4.0',
'Garage Door Services',
'5.0',
'4.0',
'African',
'4.0',
'3.5',
'3.0',
'4.5',
'2.5',
'Florists',
'4.0',
'University Housing',
'Property Management',
'1.0',
'4.0',
'Furniture Assembly',
'Pool & Billiards',
'Furniture Repair',
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'Party Equipment Rentals',
'4.0',
'2.0',
'3.5',
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'Kebab',
'Turkish',
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'3.5',
'Amusement Parks',
'Laser Tag',
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'5.0',
'4.0',
'4.0',
'Race Tracks',
'Mini Golf',

```
'Go Karts',
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'Community Centers',
'Day Camps',
'Summer Camps',
'3.5',
'3.5',
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'Patio Coverings',
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'Paint & Sip',
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'2.0',
'Signmaking',
'3.5',
'4.0',
'1.5',
'Guns & Ammo',
'3.5',
'4.5',
'Tea Rooms',
'4.0',
'2.0',
'4.0',
'Middle Eastern',
'Lebanese',
'4.0',
'4.5',
'Pilates',
'Barre Classes',
...]
```

2、频繁模式与关联规则挖掘

使用orangecontrib.associate.fpgrowth包进行频繁模式挖掘。由于关联项集过小因此降低了置信度阈值。

In [27]:

```
import orangecontrib.associate.fpgrowth as oaf
items_thr = 0.05
rules_thr = 0.05
items = list(oaf.frequent_itemsets(transaction, items_thr))
for i in items:
    print(i)
```

```
(frozenset({2}), 9351)
(frozenset({8}), 21053)
(frozenset({14}), 44676)
(frozenset({15}), 23910)
(frozenset({14, 15}), 13816)
(frozenset({17}), 6186)
(frozenset({17, 15}), 6186)
(frozenset({24}), 5959)
(frozenset({24, 14}), 5959)
(frozenset({25}), 7623)
(frozenset({25, 14}), 7623)
(frozenset({38}), 7419)
(frozenset({38, 14}), 7419)
(frozenset({44}), 9821)
(frozenset({53}), 8083)
(frozenset({65}), 9882)
(frozenset({65, 14}), 7713)
(frozenset({67}), 10777)
(frozenset({67, 14}), 8036)
(frozenset({65, 67}), 9882)
(frozenset({65, 67, 14}), 7713)
(frozenset({87}), 6026)
(frozenset({14, 87}), 6026)
(frozenset({118}), 8137)
(frozenset({122}), 12038)
(frozenset({204}), 11760)
```

In [28]:

```
items = list(oaf.frequent_itemsets(transaction, items_thr))
rules = list(oaf.association_rules(dict(items), rules_thr))
for i in rules:
    antecedent = []
    consequent = []
    for j in i[0]:
        antecedent.append(id2str[j])
    for j in i[1]:
        consequent.append(id2str[j])
    print(antecedent, "->", consequent, i[2], round(i[3],2))
print(len(rules))
```

```
['4.0', 'Food'] -> ['Wine Bars'] 7713 0.96
['4.0'] -> ['Wine Bars', 'Food'] 7713 0.72
['Wine Bars', 'Food'] -> ['4.0'] 7713 1.0
['Food'] -> ['Wine Bars', '4.0'] 7713 0.17
['Wine Bars'] -> ['4.0', 'Food'] 7713 0.78
['Wine Bars', '4.0'] -> ['Food'] 7713 0.78
['Bubble Tea'] -> ['Food'] 13816 0.58
['Food'] -> ['Bubble Tea'] 13816 0.31
['Bubble Tea'] -> ['Bakeries'] 6186 0.26
['Bakeries'] -> ['Bubble Tea'] 6186 1.0
['Food'] -> ['Sandwiches'] 5959 0.13
['Sandwiches'] -> ['Food'] 5959 1.0
['Food'] -> ['Ice Cream & Frozen Yogurt'] 7623 0.17
['Ice Cream & Frozen Yogurt'] -> ['Food'] 7623 1.0
['Food'] -> ['Diners'] 7419 0.17
['Diners'] -> ['Food'] 7419 1.0
['Food'] -> ['Wine Bars'] 7713 0.17
['Wine Bars'] -> ['Food'] 7713 0.78
['Food'] -> ['4.0'] 8036 0.18
['4.0'] -> ['Food'] 8036 0.75
['4.0'] -> ['Wine Bars'] 9882 0.92
['Wine Bars'] -> ['4.0'] 9882 1.0
['Chicken Wings'] -> ['Food'] 6026 1.0
['Food'] -> ['Chicken Wings'] 6026 0.13
24
```

3.关联规则的评价

使用Lift和Kulc两种评价指标评价关联规则。

In [29]:

```
measure = list(oaf.rules_stats(oaf.association_rules(dict(items), items_thr), dict(o
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))
```

```
['4.0', 'Food'] -> ['Wine Bars'] 11.42
['4.0'] -> ['Wine Bars', 'Food'] 10.91
['Wine Bars', 'Food'] -> ['4.0'] 10.91
['Food'] -> ['Wine Bars', '4.0'] 2.05
['Wine Bars'] -> ['4.0', 'Food'] 11.42
['Wine Bars', '4.0'] -> ['Food'] 2.05
['Bubble Tea'] -> ['Food'] 1.52
['Food'] -> ['Bubble Tea'] 1.52
['Bubble Tea'] -> ['Bakeries'] 4.92
['Bakeries'] -> ['Bubble Tea'] 4.92
['Food'] -> ['Sandwiches'] 2.63
['Sandwiches'] -> ['Food'] 2.63
['Food'] -> ['Ice Cream & Frozen Yogurt'] 2.63
['Ice Cream & Frozen Yogurt'] -> ['Food'] 2.63
['Food'] -> ['Diners'] 2.63
['Diners'] -> ['Food'] 2.63
['Food'] -> ['Wine Bars'] 2.05
['Wine Bars'] -> ['Food'] 2.05
['Food'] -> ['4.0'] 1.96
['4.0'] -> ['Food'] 1.96
['4.0'] -> ['Wine Bars'] 10.91
['Wine Bars'] -> ['4.0'] 10.91
['Chicken Wings'] -> ['Food'] 2.63
['Food'] -> ['Chicken Wings'] 2.63
```

In [30]:

```
# 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] + rule
            visit[j] = True
```

```
Kulc( ['4.0', 'Food'] ['Wine Bars'] ) =  0.87
Kulc( ['4.0'] ['Wine Bars', 'Food'] ) =  0.86
Kulc( ['Food'] ['Wine Bars', '4.0'] ) =  0.48
Kulc( ['Bubble Tea'] ['Food'] ) =  0.44
Kulc( ['Bubble Tea'] ['Bakeries'] ) =  0.63
Kulc( ['Food'] ['Sandwiches'] ) =  0.57
Kulc( ['Food'] ['Ice Cream & Frozen Yogurt'] ) =  0.59
Kulc( ['Food'] ['Diners'] ) =  0.58
Kulc( ['Food'] ['Wine Bars'] ) =  0.48
Kulc( ['Food'] ['4.0'] ) =  0.46
Kulc( ['4.0'] ['Wine Bars'] ) =  0.96
Kulc( ['Chicken Wings'] ['Food'] ) =  0.57
```

4.挖掘结果的分析

所有的24条关联规则中，lift值均大于1。

在所有计算出的关联规则的Kulc值中，以下三个Kulc值较大：

Kulc(['4.0'] ['Wine Bars']) = 0.96

Kulc(['4.0', 'Food'] ['Wine Bars']) = 0.87

Kulc(['4.0'] ['Wine Bars', 'Food']) = 0.86

因此可以得到以下结论：

Wine Bars 通常提供食物且评星在4星

在关联规则中，以下几条的置信度很高，达到了1.0：

['Wine Bars', 'Food'] -> ['4.0'] 7713 1.0

['Bakeries'] -> ['Bubble Tea'] 6186 1.0

['Sandwiches'] -> ['Food'] 5959 1.0

['Diners'] -> ['Food'] 7419 1.0

['Wine Bars'] -> ['4.0'] 9882 1.0

['Chicken Wings'] -> ['Food'] 6026 1.0

5.可视化展示

绘制关联规则的置信度、Lift和Kulc相关性热图

横纵坐标是关联规则中包含的项，热图中每个点的数据是两项的置信度、Lift值或Kulc值

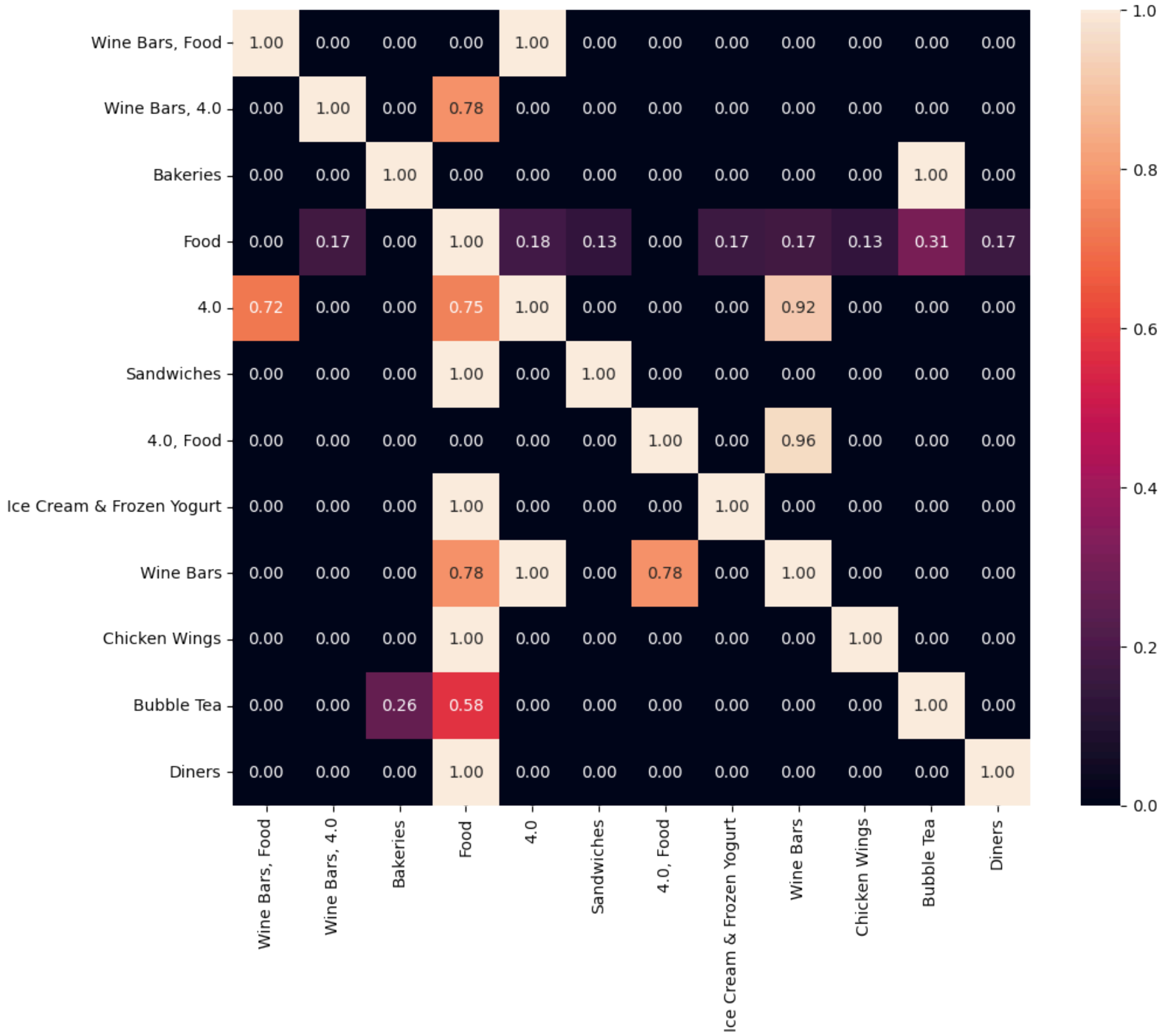
In [32]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# 利用置信度绘制热图
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])
                    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)

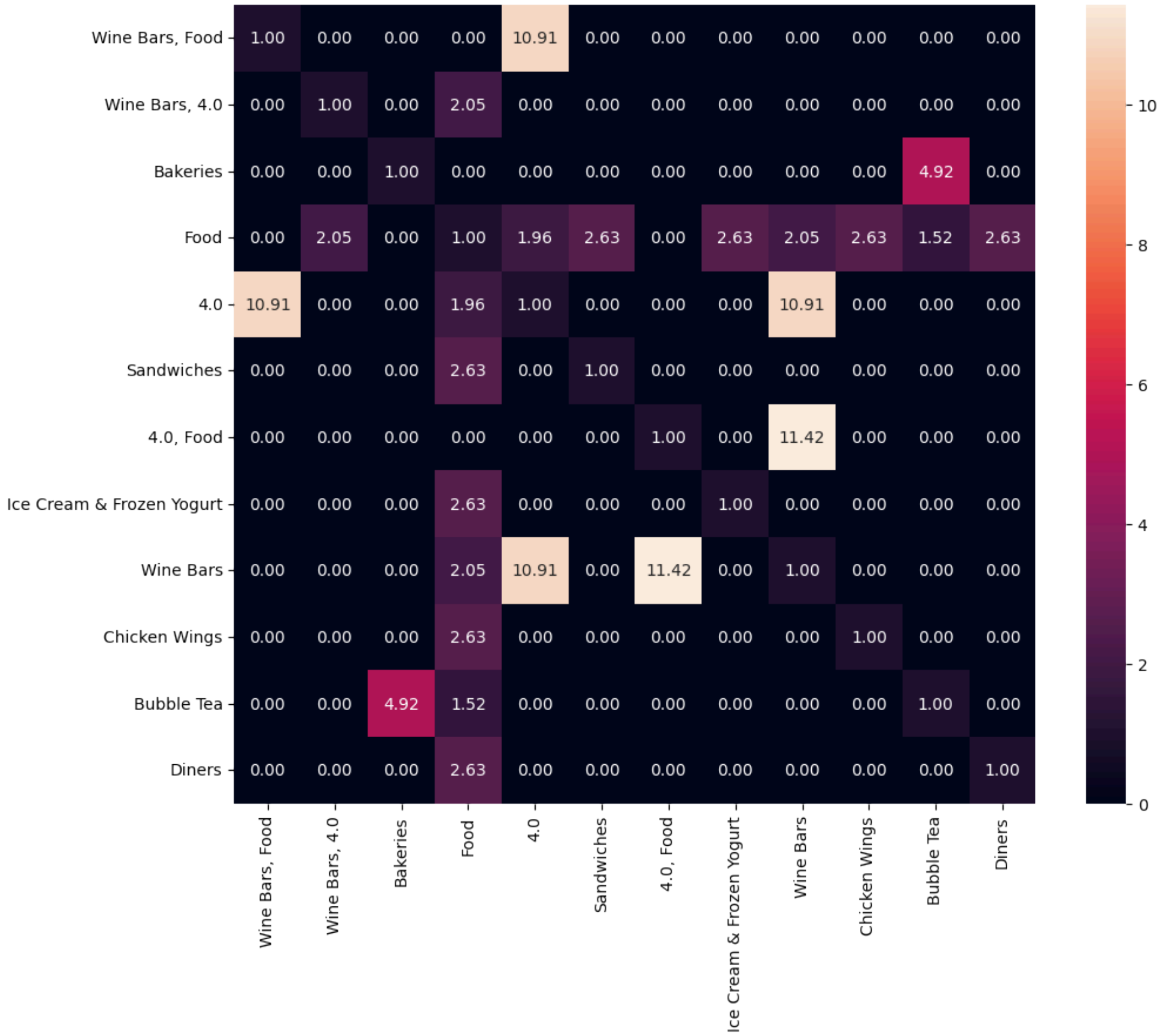
conf_pd = pd.DataFrame(conf_matrix, columns = rules_column_list, index = rules_colum
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = conf_pd, annot = True, fmt = ".2f")
plt.show()
```



In [33]:

```
# 使用Lift值绘制热图
# 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:
                    one.append(measure[k][6])
                    flag = True
            if flag == False:
                one.append(0)
    lift_matrix.append(one)

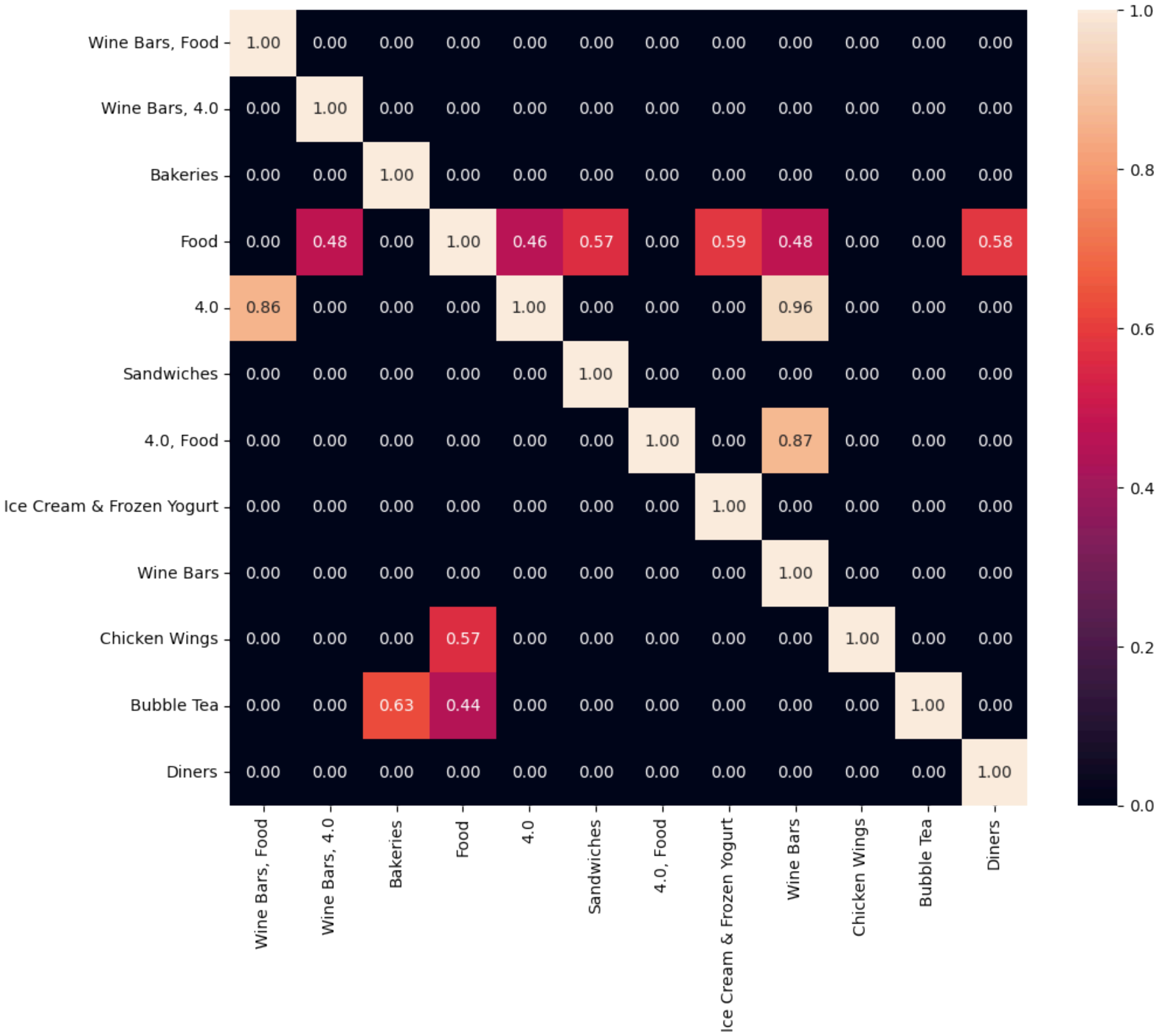
lift_pd = pd.DataFrame(lift_matrix, columns = rules_column_list, index = rules_colum
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = lift_pd, annot = True, fmt = ".2f")
plt.show()
```



In [34]:

```
# 使用Kulc值绘制热图
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_colum
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = kulc_pd, annot = True, fmt = ".2f")
plt.show()
```


Wine Bars, Food
Wine Bars, 4.0
Bakeries
Food
4.0
Sandwiches
4.0, Food
Ice Cream & Frozen Yogurt
Wine Bars
Chicken Wings
Bubble Tea
Diners
1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
0.00 0.48 0.00 1.00 0.46 0.57 0.00 0.59 0.48 0.00 0.00 0.58
0.86 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.96 0.00 0.00 0.00
0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.87 0.00 0.00 0.00
0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00
0.00 0.00 0.00 0.57 0.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00
0.00 0.00 0.63 0.44 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00
0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00
1.0
0.8
0.6
0.4
0.2
0.0