

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

2. 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/>

3. 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。

4. 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

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

```
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 up
# 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 version.
# 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'
```

```
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 guarantee
    # 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

```

```

# 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

```

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

```

```

# The behaviors.tsv file contains the impression logs and users' news click histories.
# 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 this impression.
# - Impressions. List of news displayed in this impression and user's click behaviors on them (1 for click and 0 for non-click).
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

```

```

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

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

```

	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...
...

	impression_id	user_id	time	history	impressions
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

```
# The news.tsv file contains the detailed information of news articles involved in the behaviors.tsv file.
# 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
```

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

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

	id	category	subcategory	title	abstract	url	title_entities	abstract_en
0	N55528	lifestyle	lifestyleroys	The Brands Queen Elizabeth, Prince Charles, an...	Shop the notebooks, jackets, and more that the...	https://assets.msn.com/labs/mind/AAGH0ET.html	[{"Label": "Prince Philip, Duke of Edinburgh", ...	[]
1	N18955	health	medical	Dispose of unwanted prescription drugs during ...	NaN	https://assets.msn.com/labs/mind/AAISxPN.html	[{"Label": "Drug Enforcement Administration", ...	[]
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/mind/AAJgNsz.html	[]	[{"Label": "Ukraine", "G", "Wikida

	id	category	subcategory	title	abstract	url	title_entities	abstract_en
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/mind/AACk2N6.html	[]	[{"Label": "National Basketball Association"}]
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/mind/AAAEkt.html	[{"Label": "Skin tag", "Type": "C", "Wikidata..."}	[{"Label": "S tag", "Type": "Wikidata..."}
...
42411	N63550	lifestyle	lifestyleroys	Why Kate & Meghan Were on Different Balconies ...	There's no scandal here. It's all about the or...	https://assets.msn.com/labs/mind/BBWyynu.html	[{"Label": "Meghan, Duchess of Sussex", "Type": "..."}]	[]
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/mind/BBWyz7N.html	[]	[{"Label": "K Hudson", "Type": "P", "Wikida"}]
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/mind/BBWyzl8.html	[{"Label": "Tennessee", "Type": "G", "Wikidata..."}	[{"Label": "Tennesse of Appeals", "Type": "..."}]
42414	N44276	autos	autosports	Best Sports Car Deals for October	NaN	https://assets.msn.com/labs/mind/BBy5rVe.html	[{"Label": "Peugeot RCZ", "Type": "V", "Wikida..."}	[]
42415	N39563	sports	more_sports	Shall we dance: Sports stars shake their leg	NaN	https://assets.msn.com/labs/mind/BBzMpnG.html	[]	[]

42416 rows × 8 columns

```
# 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 vector values.
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
```

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

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

	entity	vector
0	Q34433	[0.017808, -0.073256, 0.102521, -0.059926, -0....

	entity	vector
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

```
# 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 vector values.
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
```

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

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

	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

```
behaviors_table = behaviors_table.dropna()
transaction = []
category = news_table['category'].unique().tolist()
print(category)
err_num = 0
for i in range(len(behaviors_table)):
    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_table.id == news_id].index.tolist()[0]]))
        transaction.append(tmp_list)
    except:
        err_num += 1
print('error count: ', err_num)
print(transaction[0:10])
```

```
['lifestyle', 'health', 'news', 'sports', 'weather', 'entertainment', 'foodanddrink', 'autos', 'travel', 'video', 'tv', 'finance', 'movies',
'music', 'kids', 'middleeast', 'games']
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, 11, 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, 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。

```
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。

```
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。

```

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。

```

measure = list(oaf.rules_stats(oaf.association_rules(dict(items), 0.5), dict(oaf.frequent_itemsets(transaction, 0.5)), len(behaviors_table)))
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

```

```

# 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] + rules[j][3])/2, 2))
    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，
 $\text{lift}(A,B) > 1$ 说明A与B正相关，
 $\text{lift}(A,B) = 1$ 说明A与B相互独立，
 $\text{lift}(A,B) < 1$ 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：

$\text{Kulc}([\text{'news'}][\text{'lifestyle'}]) = 0.83$

$\text{Kulc}([\text{'sports'}][\text{'news'}]) = 0.82$

$\text{Kulc}([\text{'tv'}][\text{'news'}]) = 0.81$

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：

$[\text{'lifestyle', 'tv'}] \rightarrow [\text{'news'}] \text{ 35192 0.95}$

$[\text{'finance'}] \rightarrow [\text{'news'}] \text{ 40412 0.95}$

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

```

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:

```

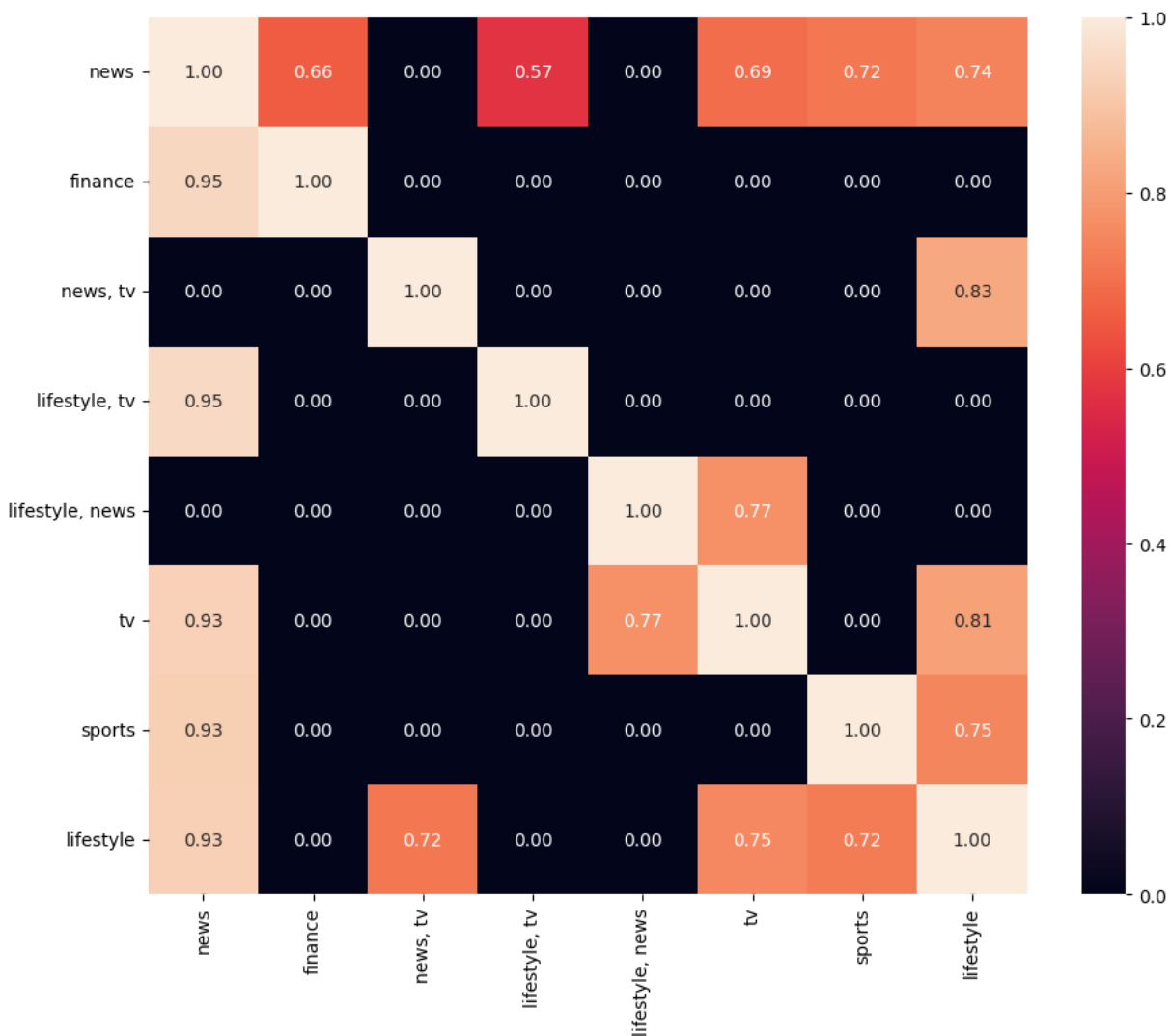


```

        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_column_list)
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = conf_pd, annot = True, fmt = ".2f")
plt.show()

```

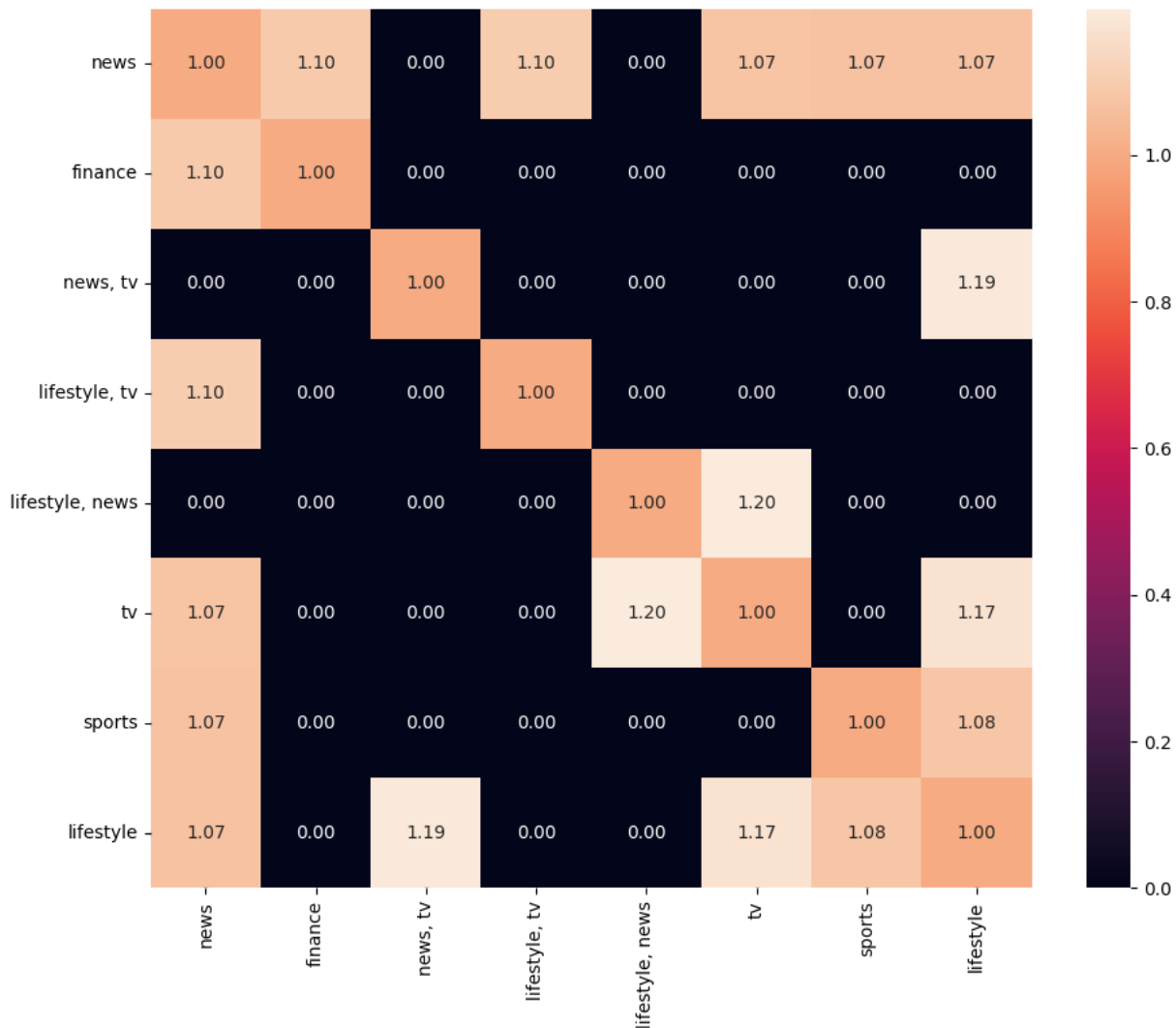


```

# 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_column_list)
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = lift_pd, annot = True, fmt = ".2f")
plt.show()

```



```

# 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_column_list)
plt.figure(figsize=(11, 9),dpi=100)
sns.heatmap(data = kulc_pd, annot = True, fmt = ".2f")
plt.show()

```

