

# 第五次作业

## 1 1. 推导概率潜在语义分析的共现模型的EM算法

潜在语义分析的共现模型定义如下：

因为共现模型假设在话题 $z$ 给定的情况下，单词 $w$ 与文本 $d$ 是条件独立的，所以每个单词-文本对 $(w, d)$ 的概率由以下公式决定：

$$P(w, d) = \sum_{z \in Z} P(z) P(w | z) P(d | z) \quad (7)$$

文本-单词共现数据  $T$  的生成概率为所有单词-文本对  $(w, d)$  的生成概率的乘积：

$$\begin{aligned} L = P(T) &= \prod_{(w, d)} P(w, d)^{n(w, d)} \\ &= \prod_{i=1}^M \prod_{j=1}^N P(w_i, d_j)^{n(w_i, d_j)} \end{aligned} \quad (8)$$

对似然函数取对数后得：

$$\begin{aligned} LL &= \sum_{i=1}^M \sum_{j=1}^N n(w_i, d_j) \log(P(w_i, d_j)) \\ &= \sum_{i=1}^M \sum_{j=1}^N n(w_i, d_j) \log \left( \sum_{k=1}^K P(z_k) \frac{P(w_i, d_j, z_k)}{P(z_k)} \right) \end{aligned} \quad (9)$$

其中 $n(w_i, d_j)$ 表示 $(w_i, d_j)$ 出现的次数。

根据Jensen不等式：

$$\begin{aligned} LL &= \sum_{i=1}^M \sum_{j=1}^N n(w_i, d_j) \log \left( \sum_{k=1}^K P(z_k) \frac{P(w_i, d_j, z_k)}{P(z_k)} \right) \\ &\geq \sum_{i=1}^M \sum_{j=1}^N n(w_i, d_j) \left( \sum_{k=1}^K P(z_k) \log \frac{P(w_i, d_j, z_k)}{P(z_k)} \right) \\ &= \sum_{i=1}^M \sum_{j=1}^N \sum_{k=1}^K n(w_i, d_j) (P(z_k) \log(P(w_i, d_j, z_k)) - P(z_k) \log(P(z_k))) \\ &\triangleq J(\theta, P(z)) \end{aligned} \quad (10)$$

**E (expectation) 步：**

$$\begin{aligned} P^{(t)}(z_k) &= \arg\max_{P(z_k)} J(w^{(t)}, d^{(t)}, P(z_k)) \\ &= P(z_k | w_i^{(t)}, d_j^{(t)}) \\ &= \frac{P(w_i^{(t)}, d_j^{(t)}, z_k)}{P(w_i^{(t)}, d_j^{(t)})} \\ &= \frac{P(z_k) P(w_i^{(t)} | z_k) P(d_j^{(t)} | z_k)}{\sum_{k=1}^K P(z_k) P(w_i^{(t)} | z_k) P(d_j^{(t)} | z_k)} \end{aligned} \quad (11)$$

**M (maximize) 步：**

$$\theta^{(t+1)} = \arg\max_{\theta} J(\theta, Q^{(t)}(z)) \quad (12)$$

又因为参数满足如下约束条件：

$$\begin{aligned} \sum_{k=1}^K P(z_k) &= 1 \\ \sum_{i=1}^M P(w_i|z_k) &= 1, k = 1, 2, \dots, K \\ \sum_{j=1}^N P(d_j|z_k) &= 1, k = 1, 2, \dots, K \end{aligned}$$

据此构建Lagrange函数，求解带有约束的优化问题，

$$\Lambda = J(\theta, P(z)) + \lambda \left( 1 - \sum_{k=1}^K P(z_k) \right) + \sum_{k=1}^K \tau_k \left( 1 - \sum_{i=1}^M P(w_i|z_k) \right) + \sum_{k=1}^K \rho_k \left( 1 - \sum_{j=1}^N P(d_j|z_k) \right)$$

解得：

$$\begin{cases} P(z_k) = \frac{\sum_{i=1}^M \sum_{j=1}^N n(w_i, d_j) P(z_k|w_i, d_j)}{\sum_{i=1}^M \sum_{j=1}^N n(w_i, d_j)} \\ P(w_i|z_k) = \frac{\sum_{j=1}^N n(w_i, d_j) P(z_k|w_i, d_j)}{\sum_{i=1}^M \sum_{j=1}^N n(w_i, d_j) P(z_k|w_i, d_j)} \\ P(d_j|z_k) = \frac{\sum_{i=1}^M n(w_i, d_j) P(z_k|w_i, d_j)}{\sum_{i=1}^M \sum_{j=1}^N n(w_i, d_j) P(z_k|w_i, d_j)} \end{cases}$$

## 2.2. 新闻爬取

从[交大新闻网主页新闻栏目](#)爬取最新的100条新闻，编程实现概率潜在语义分析的生成模型或共现模型，并输出不同的话题数下各个话题的高频词

### 2.1 (1) 抓取新闻

```

1  from bs4 import BeautifulSoup
2  import requests
3  import pandas as pd
4  from urllib import parse
5
6
7  class XJTU_News():
8      def __init__(self, url):
9          self.current_url = url # 主url可以和path拼接
10         self.cookies = {"_ga": "GA1.3.1733503684.1647506450"}
11         self.news_urls = []
12         self.content = pd.DataFrame(
13             columns=["title", "date", "content", "source", "writer"])
14
15         def get_soup(self, url):
16             response = requests.get(url, cookies=self.cookies)

```

```

17     response.encoding = 'UTF-8-SIG'
18     soup = BeautifulSoup(response.text, "lxml")
19     return soup
20
21     def get_news_list(self, path):
22         self.current_url = parse.urljoin(self.current_url, path)
23         soup = self.get_soup(self.current_url)
24         self.news_urls.extend([parse.urljoin(self.current_url,
object["href"])
for object in soup.find_all("a",
class_="bt")])
25         next_page_path = soup.find(
26             "span", class_="p_next p_fun").next_element["href"]
27         return(next_page_path)
28
29     def get_news_lists(self, number):
30         next_page_path = ""
31         while(len(self.news_urls) < number):
32             next_page_path = self.get_news_list(next_page_path)
33
34     def get_content(self):
35         for url in self.news_urls:
36             soup = self.get_soup(url)
37             title = soup.title.string.split("-西安交通大学")[0]
38             try:
39                 content = soup.find("div", id="vsb_content_2").text.strip()
40             except:
41                 content = None # 有的新闻是视频，所以没有content正文
42                 print(url)
43             writer = soup.find("div", class_="zdf clearfix").text.strip()
44             source = None
45             date = None
46             for temp in soup.find("div", class_="shffffff").contents:
47                 if "来源" in temp.text:
48                     source = temp.text.split(": ")[-1].strip()
49                 elif "日期" in temp.text:
50                     date = temp.text.split(": ")[-1].strip()
51                 else:
52                     continue
53             self.content = self.content.append(
54                 {"title": title, "date": date, "content": content, "source":
55                 source, "writer": writer}, ignore_index=True)

```

```

1 main = XJTU_News(url="http://news.xjtu.edu.cn/zyxw.htm")
2 main.get_news_lists(110)
3 main.get_content()
4 main.content.to_csv("result.csv", index = None)

```

## 2.2 (2) 分词及数据预处理

```

1 import jieba
2 import pandas as pd
3 data = pd.read_csv("result.csv")
4 data["text"] = data["title"]+data["content"]

```

```

1 # 中文停用词表: https://github.com/goto456/stopwords
2 stopwords = []
3 f = open("cn_stopwords.txt", "r", encoding='utf-8')
4 line = f.readline() # 读取第一行
5 with open("cn_stopwords.txt", "r", encoding='utf-8') as f:
6     line = f.readline()
7     while line:
8         stopwords.append(line[:-1]) # 列表增加
9         line = f.readline()

```

```

1 data = data[data["content"].notna()][:100] # 删除正文为空的数据
2 words=[]
3 for i in range(data.shape[0]):
4     news = ' '.join(jieba.cut(data.iloc[i]["content"]))
5     words.append(news)

```

```

1 from sklearn.feature_extraction.text import CountVectorizer
2 # construct co-occurrence matrix
3 count_model =
4 CountVectorizer(max_features=2000, max_df=0.5, stop_words=stopwords)
5 word_vector = count_model.fit_transform(words).todense().T # co-
6 occurrence matrix
7 word_vector.shape

```

```

1 (2000, 100)

```

## 2.3 (3) 潜在语义分析———共现模型

```

1 import numpy as np
2
3 class pLSA():
4     def __init__(self, step, topic_n, word_vector):
5         self.step = step # 最大步数
6         self.K = topic_n # 话题数量
7         self.words = word_vector # 词向量
8         self.M, self.N = word_vector.shape # M是词向量长度, N是文本数
9         self.p_w_z = np.random.rand(self.K, self.M) # p(w|z)
10        self.p_z_d = np.random.rand(self.N, self.K) # p(z|d)
11        self.p_z_wd = np.zeros((self.N, self.M, self.K)) # p(z|w,d)
12        ...
13        References
14        -----
15        [1] "Bayesian Reasoning and Machine Learning", David Barber
16        (Cambridge
17        Press, 2012).
18        [2] pLSA.PyPI https://github.com/yedivanseven/PLSA
19        ...
20    def E_step(self):
21        for j in range(self.N):
22            for i in range(self.M):

```

```

22         temp = np.zeros((self.K))
23         for k in range(self.K):
24             temp[k] = self.p_w_z[k, i] * self.p_z_d[j, k]
25             self.p_z_wd[j, i] = temp / np.sum(temp)
26     def M_step(self):
27         ## p(w|z)
28         for k in range(self.K):
29             temp = np.zeros((self.M))
30             for i in range(self.M):
31                 for j in range(self.N):
32                     temp[i] += word_vector[i, j] * self.p_z_wd[j, i, k]
33             self.p_w_z[k] = temp / np.sum(temp)
34
35         ## p(z|d)
36         for j in range(self.N):
37             for k in range(self.K):
38                 temp = 0
39                 for i in range(self.M):
40                     temp += word_vector[i, j] * self.p_z_wd[j, i, k]
41             self.p_z_d[j, k] = temp / np.sum(word_vector[:, j])
42
43     def fit(self):
44         for _ in range(self.step):
45             self.E_step()
46             self.M_step()
47         return self.p_w_z, self.p_z_d
48

```

```

1 topic_n = 3
2 model = pLSA(step = 10, topic_n = topic_n, word_vector = word_vector)
3 p_w_z, p_z_d = model.fit()

```

```

1 dict_ = count_model.get_feature_names()
2 topic_words = []
3 for k in range(topic_n):
4     topic_ = np.argsort(-p_w_z[k, :])[:10]
5     topic_composition = {dict_[i]: p_w_z[k, i] for i in topic_}
6     print("主题{k}: {topic_composition}\n".format(k = k+1, topic_composition =
7     topic_composition))
7     topic_words.append(topic_composition)

```

```
1 主题1: {'青年': 0.01862717415293134, '研究': 0.01543787285185595, '青春':  
0.009702259875018139, '时代': 0.009210889165625185, '交大':  
0.008298109863527114, '团队': 0.0065938244773482285, '科技':  
0.006312667471596037, '表示': 0.006157305897420258, '共青团':  
0.00607685885300087, '平台': 0.005269242534540203}  
2  
3 主题2: {'学生': 0.01779301337160576, '习近平': 0.0142531717358071, '总书记':  
0.014039085573739788, '西迁': 0.013307092219758378, '培养':  
0.013076798465364066, '教学': 0.010572538240392362, '课程':  
0.009712016007890774, '时代': 0.008596336032387243, '青年':  
0.0072026353658971995, '教育': 0.007145105821298227}  
4  
5 主题3: {'学生': 0.012331557568073697, '就业': 0.008983833242868363, '活动':  
0.008219019650107387, '服务': 0.007425761075039543, '教育':  
0.007236010927243649, '体育': 0.007005019234515966, '学科':  
0.006794192250061121, '开展': 0.0057322580687101474, '推进':  
0.005671051550816049, '加强': 0.005637810487683335}
```

```
1 C:\Users\zjchenb139\AppData\Local\Programs\Python\Python37\lib\site-  
packages\sklearn\utils\deprecation.py:87: FutureWarning: Function  
get_feature_names is deprecated; get_feature_names is deprecated in 1.0 and  
will be removed in 1.2. Please use get_feature_names_out instead.  
2 warnings.warn(msg, category=FutureWarning)
```