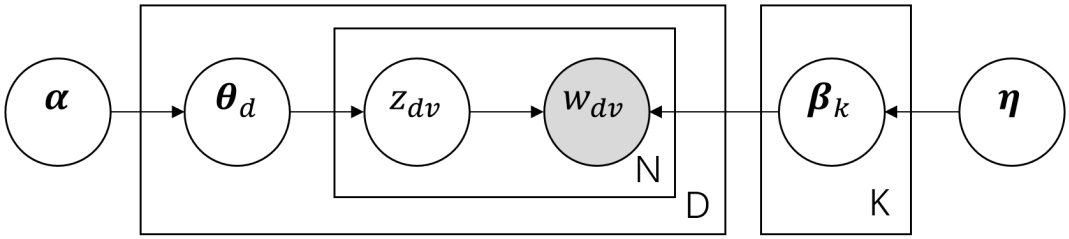
Topic model 实验

PB18071477 敖旭扬

原理

LDA的概率图模型如下：



假定数据集中共含 K 个话题和 D 篇文档，词来自含 V 个词的字典，观测数据为 D 篇文档

$$\mathcal{D}=\{\boldsymbol{d}_1,\boldsymbol{d}_2,\ldots,\boldsymbol{d}_D\}$$

其中每一篇文档

$$\boldsymbol{d}_m=(w_{m,1},w_{m,2},\ldots,w_{m,N_m})$$

是一个单词序列， $w_{m,n}$ 和 N_m是第 m 篇文档的第 n 个单词和长度（单词数）

单词集合为

$$\mathcal{W}=\{w_1,w_2,\ldots,w_V\}$$

话题数量是提前给定的，话题集合为

$$\mathcal{Z}=\{z_1,z_2,\ldots,z_K\}$$

LDA模型假设

$$p(z|\boldsymbol{d}_m)\sim Mult(\boldsymbol{\theta}_m) \tag{1}$$

$$p(w|z_j)\sim Mult(\boldsymbol{\varphi}_j) \tag{2}$$

其中 $\boldsymbol{\theta}_m$ 是所有 K 个主题在文档 $\boldsymbol{d}_m$ 中出现的概率， $\boldsymbol{\varphi}_j$ 是所有 V 个单词在主题 z_j 中出现的概率

同时假设

$$\boldsymbol{\theta}_m\sim Dir(\boldsymbol{\alpha}) \tag{3}$$

$$\boldsymbol{\varphi}_j\sim Dir(\boldsymbol{\beta}) \tag{4}$$

其中 $\boldsymbol{\alpha}\in[0,1]^K$ 和 $\boldsymbol{\beta}\in[0,1]^V$ 是超参数，提前给定

生成文档 $\boldsymbol{d}_m$ 的过程：

- 从以 $\boldsymbol{\alpha}$ 为参数的狄利克雷分布中随机采样一个话题分布 $\boldsymbol{\theta}_m$
- 根据 $\boldsymbol{\theta}_m$ 进行话题指派，得到文档 $\boldsymbol{d}_m$ 中第 n 词的话题 $z_{m,n}$
- 根据指派的话题 $z_{m,n}$ 所对应的的词分布随 $\boldsymbol{\varphi}_j$ 机采样生成词 $w_{m,n}$

求解模型时有

$$\sum_{k=1}^{K}\theta_{mk}=1,\quad \sum_{v=1}^{V}\varphi_{jv}=1$$

最后可得

$$\theta_{mk}=\frac{\sigma_{jk}+\alpha_k}{\sum_i^K \sigma_{ji}+\alpha_i} \tag{5}$$

$$\varphi_{kv}=\frac{\delta_{kv}+\beta_v}{\sum_r^V \delta_{kr}+\beta_r} \tag{6}$$

其中 σ_{jk} 是第 m 个文档第 k 个主题的单词个数， δ_{kv} 是第 k 个主题的第 v 个单词个数

训练过程：

- 选择 $\boldsymbol{\alpha}$ 和 $\boldsymbol{\beta}$ 为全 1 向量， z 随机初始化
- 对于每篇文档 d 的每个单词 w ，重复吉布斯采样更新主题编号 $z_{d,w}$

编程实现

矩阵运算使用`python`的`numpy`库实现，部分文本预处理使用了`nltk`库的功能。

训练主要算法如下：

```python
class LDA:
    def gibbs_sampling(self, epoch=100):
        print("吉布斯采样......")
        for _ in tqdm.tqdm(range(epoch)):
            for m in range(self.D):
                for v in range(len(self.Dset[m])):
                    self.z[m][v] = self.topic_updated(m, v)

    def topic_updated(self, m, v):
        topic_old = int(self.z[m][v])
        self.delta[topic_old][self.Vset_to_index[self.Dset[m][v]]] -= 1
        self.n_k[topic_old] -= 1
        self.sigma[m][topic_old] -= 1
        self.n_m[m] -= 1
        p = np.zeros(self.K)
        for k in range(self.K):
            p[k] = (self.sigma[m][k] + self.alpha[k]) / \
                (self.n_m[m] + np.sum(self.alpha)) * \
                (self.delta[k][self.Vset_to_index[self.Dset[m][v]]] +
                 self.beta[self.Vset_to_index[self.Dset[m][v]]]) / \
                (self.n_k[k] + np.sum(self.beta))
        p = p / np.sum(p)
        topic_new = np.argmax(np.random.multinomial(1, p))
        self.delta[topic_new][self.Vset_to_index[self.Dset[m][v]]] += 1
        self.n_k[topic_new] += 1
        self.sigma[m][topic_new] += 1
        self.n_m[m] += 1
        return topic_new

    def cal_theta_varphi(self):
        for j in range(self.D):
            for k in range(self.K):
                self.theta[j][k] = (
                    self.sigma[j][k] + self.alpha[k]) / \
```

```
                    (self.n_m[j] + np.sum(self.alpha))
        for k in range(self.K):
            for v in range(self.V):
                self.varphi[k][v] = (
                    self.delta[k][v] + self.beta[v]) / \
                    (self.n_k[k] + np.sum(self.beta))

    def train(self, epoch):
        for m in range(self.D):
            self.n_m[m] = len(self.Dset[m])
            for v in range(len(self.Dset[m])):
                topic = int(np.random.randint(0, self.K))
                self.z[m][v] = topic
                self.delta[topic][self.Vset_to_index[self.Dset[m][v]]] += 1
                self.n_k[topic] += 1
                self.sigma[m][topic] += 1
        self.gibbs_sampling(epoch)
        self.cal_theta_varphi()
```

完整实验源码见压缩包中的LDA.py。

运算结果

实例

在主函数中调用下面的实例，其中 α 和 β 为全 1 向量

```
texts = np.load("./data/text.npy")
lda = LDA(texts, K=20, cold_count=8)

# 训练模型
lda.train(60)

# 输出20个主题的top10的词
top10words = lda.top_words(10)
for i in range(lda.K):
    print(top10words[i])
    np.savetxt("top10words.txt", top10words, '%s', delimiter=',')
```

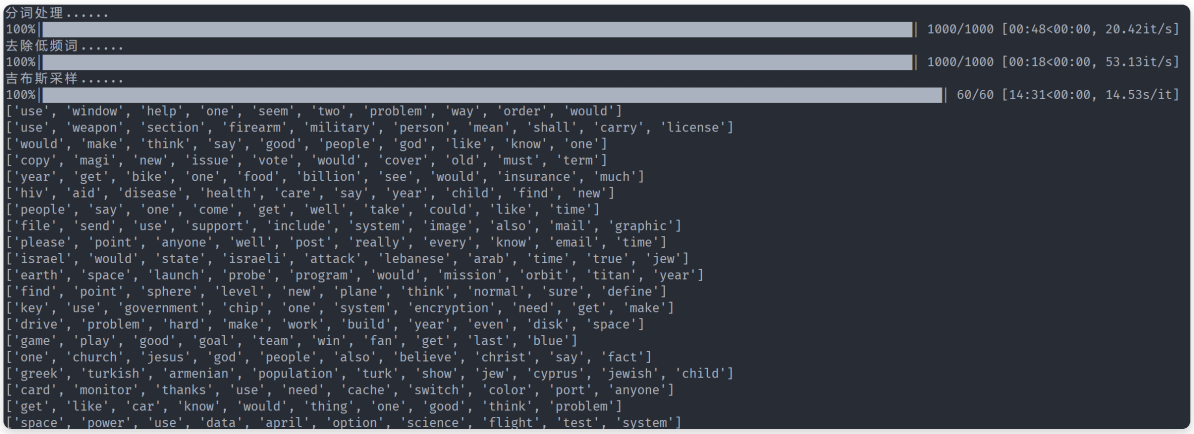
某一次运行后文件`top10words.txt`中为

```
use,window,help,one,seem,two,problem,way,order,would
use,weapon,section,firearm,military,person,mean,shall,carry,license
would,make,think,say,good,people,god,like,know,one
copy,magi,new,issue,vote,would,cover,old,must,term
year,get,bike,one,food,billion,see,would,insurance,much
hiv,aid,disease,health,care,say,year,child,find,new
people,say,one,come,get,well,take,could,like,time
file,send,use,support,include,system,image,also,mail,graphic
please,point,anyone,well,post,really,every,know,email,time
israel,would,state,israeli,attack,lebanese,arab,time,true,jew
earth,space,launch,probe,program,would,mission,orbit,titan,year
find,point,sphere,level,new,plane,think,normal,sure,define
key,use,government,chip,one,system,encryption,need,get,make
drive,problem,hard,make,work,build,year,even,disk,space
game,play,good,goal,team,win,fan,get,last,blue
```

```
one,church,jesus,god,people,also,believe,christ,say,fact
greek,turkish,armenian,population,turk,show,jew,cyprus,jewish,child
card,monitor,thanks,use,need,cache,switch,color,port,anyone
get,like,car,know,would,thing,one,good,think,problem
space,power,use,data,april,option,science,flight,test,system

```

训练结果



主题top10关键词