PROJECT DOCUMENTATION

Reproduce A Paper: A cross-collection mixture model for comparative text mining

Overview

This code is used to discover latent themes across collections. We provide two models, the simple mixture model (simplemix.py) and the cross-collection mixture model (ccmix.py). The simple mixture model treats multiple collections as one single collection and discovers k latent common themes in it. The Cross-collection mixture model explicitly distinguishes themes from different collections. It not only captures k common themes that characterize common information across all collections but also k collection-specific themes for each collection. The value of k is set by users and each theme is characterized by a multinomial word distribution.

Implementation

Dataset

The paper uses 2 datasets: war news, and laptop reviews. We are not able to obtain exactly the same datasets as those are used in the paper.

For the war news, we manually searched and downloaded 30 news articles from BBC or CNN for each of the two wars, published in one-year span (May 2003 - April 2004 for Iraq war, Nov 2001 to Oct 2002 for Afghanistan war) to approximate the war news dataset that is used in the paper. (code/data/war_dataset.txt)

For the laptop reviews, we chose 3 laptops from the Amazon.com best sellers in laptop computers: Acer Aspire 5 Slim Laptop, Apple MacBook Air, HP Chromebook 14-inch HD Laptop, and manually downloaded the top 40 reviews from Amazon.com. (code/data/laptop_reviews.txt)

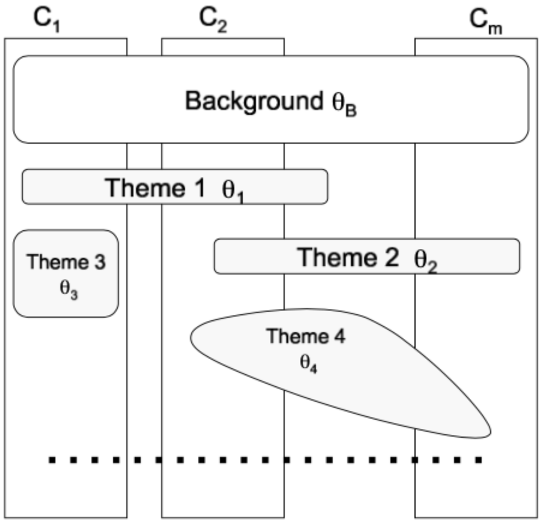
Each document occupies one line in the .txt file, prepended by an integer that indicates which collection the document is from.

Preprocessing

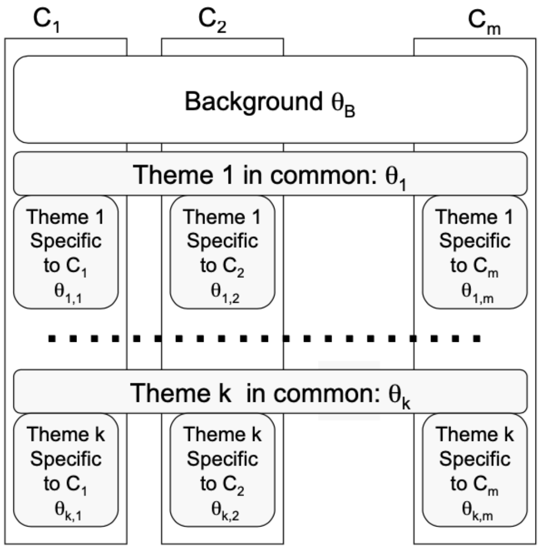
We preprocessed the data by removing stop words (including punctuation marks), words that contain less than 3 characters, and stemming the documents to map inflected words to their stems. Preprocessing is important to ensure that the resulting clusters after applying the mixture model would contain more meaningful words for evaluation.

Initialization

SimpMix Model (baseline)



CCMix Model



C_1
C_2
C_m
Background θ_B
Theme 1 in common: θ_1
Theme 1 Specific to C_1 $\theta_{1,1}$
Theme 1 Specific to C_2 $\theta_{1,2}$
Theme 1 Specific to C_m $\theta_{1,m}$
Theme k in common: θ_k
Theme k Specific to C_1 $\theta_{k,1}$
Theme k Specific to C_2 $\theta_{k,2}$
Theme k Specific to C_m $\theta_{k,m}$

In SimpMix model, there are two types of themes: the background theme, and the shared themes (between collections)

In the CCMix model, there are three types of themes: the background theme, the common themes throughout all collections, and themes specific to the collections.

Both SimpMix and CCMix models use the EM algorithm to find the clusters iteratively. The two models also share the same background theme (*topic_word_prob_background*, dimension: 1 * *vocabulary_size*) which is calculated by taking the maximal likelihood of each word in the whole corpus (includes all the collections) before the iterative EM steps.

$$\hat{p}(w|\theta_B) = \frac{\sum_{i=1}^{m} \sum_{d \in C_i} c(w,d)}{\sum_{i=1}^{m} \sum_{d \in C_i} \sum_{w' \in V} c(w',d)}$$

The other parameters λ_B(*lambda_B*) and λ_C(*lambda_C*) which are the probability of selecting the background theme and the common theme respectively. We used 0.95 for $\lambda_B$and 0.25 for $\lambda_C$as the paper suggested.

Expression	Name in code	Initialization function	Dimension
λ_B	lambda_B		Scalar, 0.95
λ_C	lambda_C		Scalar, 0.25
$c(w, d)$	term_doc_matrix	build_term_doc_matrix (self) This function counts the term frequency in each document, and computes the background distribution.	number_of_collections * number_of_documents * vocabulary_size
$p(w\|\theta_B)$	topic_word_prob_background		1 * vocabulary_size
$\pi_{d,j}$	document_topic_prob	initialize_randomly (self, number_of_topics) This function randomly initialize	number_of_collections * number_of_documents * number_of_topics
$p(w\|\theta_j)$	topic_word_prob		number_of_topics * vocabulary_size
$p(w\|\theta_{j,i})$	topic_word_prob_collection_specific		number_of_collections * number_of_topics * vocabulary_size
ε	epsilon		Scalar, 0.00001

The EM algorithm

The implementation of the baseline SimpMix model is very similar to MP3 except for introducing a background model. Therefore, in this section, we will focus on how to implement the EM algorithm for the CCMix model.

E step

E step is to estimate the hidden variables: probability of selecting a theme in a mixture model.

Expression	Name in code	Calculation function	Dimension
$p(z_{d,C_i,w} = j)$ Collection specific theme	topic_prob_j	expectation_step (self, number_of_topics, verbose) This function performs E step	number_of_collections * number_of_documents * vocabulary_size * number_of_topics

$p(z_{d,C_i,w} = B)$ Background theme	topic_prob_B		number_of_collections * number_of_documents * vocabulary_size * 1
$p(z_{d,C_i,w} = C)$ Common theme	topic_prob_C		number_of_collections * number_of_documents * vocabulary_size * number_of_topics

<u>M step</u>

M step is to use the hidden variables to re-estimate the distributions in each theme, maximizing the likelihood.

Expression	Name in code	Calculation function	Dimension
$\pi_{d,j}^{(n+1)}$	document_topic_prob	maximization_step(self, number_of_topics, verbose) This function performs M step	number_of_collections * number_of_documents * number_of_topics
$p^{(n+1)}(w\|\theta_j)$	topic_word_prob		number_of_topics * vocabulary_size
$p^{(n+1)}(w\|\theta_{j,i})$	topic_word_prob_collection_specific		number_of_collections * number_of_topics * vocabulary_size
$log\ p(C)$	likelihoods	calculate_likelihood(self) This function calculates likelihood	List of scalars

The iteration of E-M steps continues until the difference between likelihood in adjacent iterations is less than εor the maximum iteration number is reached.

Usage

Python version

Python 3.6

Download Repo

```
git clone https://github.com/luoxix/CourseProject.git
```

Install Dependencies

```
pip install metapy
pip install numpy
```

Run code

To run the simple mixture model:

```
python simplemix.py --input_path ./data/laptop_reviews.txt --
output_path ./result/result_simple_laptop.txt --lambda_b 0.95 --max_iterations 500 --
number_topics 5 --number_top_words 8 --verbose True
```

To run the cross-collection mixture model:

```
python ccmix.py --input_path ./data/laptop_reviews.txt --
output_common_path ./result/common_laptop.txt --
output_specific_path ./result/specific_laptop.txt --lambda_b 0.95 --lambda_c 0.25 --
max_iterations 1000 --number_topics 5 --number_top_words 8 --verbose True
```

```
python ccmix.py --input_path ./data/war_dataset.txt --
output_common_path ./result/common_war.txt --output_specific_path ./result/specific_war.txt --
lambda_b 0.95 --lambda_c 0.25 --max_iterations 1000 --number_topics 5 --number_top_words 8
--verbose True
```

Meaning of each argument

input_path: the path of the input file which contains all collections. Each line contains a document and the first number denotes which kind of collection it is from.
output_path: the path of the output file which contains k themes, for each theme, several top words with highest probability are shown.
output_common_path: the path of the output file which contains common themes

output_specific_path: the path of the output file which contains specific themes
lambda_b: the weight of the background model
lambda_c: the weight of common theme
max_iterations: the number of iterations for EM algorithm
number_topics: the number of latent themes
number_top_wods: the number of top words which are shown in the output file
verbose: whether to output the immediate information

Results and Evaluations

Run the code with instructions described above until the likelihood value converges.

Laptop Reviews

	Cluster 1	Cluster 2	Cluster 3
Common theme words	catalina0.0198	samsung 0.0169	fan 0.0311
	remov 0.0148	2400 0.0169	2020 0.0311
	harddriv 0.0148	numer 0.0169	temperatur 0.0271
	ad 0.0148	tech 0.0169	thermal 0.0271
	new 0.0102	top 0.0169	cpu 0.0216
	second 0.0102	edg 0.0169	zoom 0.0203
	internet 0.0099	left 0.0169	extern 0.0203
	found 0.0099	hour 0.0148	bar 0.0203

	Cluster 1	Cluster 2	Cluster 3
Common	air 0.0252	mode 0.0247	call 0.0304
	connect 0.024	app 0.0179	cpu 0.0162
	2020 0.022	differ 0.0172	amazon 0.0156
	thermal 0.0165	side 0.0169	charg 0.0155
	pictur 0.0137	2400 0.0162	thermal 0.0153
	poor 0.0125	samsung 0.0162	brand 0.015
	bar 0.0124	support 0.014	noth 0.012
	new 0.0124	download 0.013	bar 0.0115
Acer	drive 0.0274	remov 0.0204	call 0.0354
	ad 0.0201	mode 0.0163	amazon 0.0191
	harddriv 0.0197	harddriv 0.0146	did 0.0166
	remov 0.0194	ad 0.0146	tech 0.0157
	click 0.0178	wouldn't 0.0129	bla 0.0155
	pictur 0.0175	veri 0.0121	brand 0.015
	new 0.0165	second 0.0121	wait 0.0139
	second 0.0142	case 0.0114	minut 0.0135

HP	connect 0.0347 amaz 0.0221 pictur 0.0206 love 0.017 unit 0.016 chrome 0.0158 drive 0.0151 nice 0.0151	cuz 0.0413 love 0.028 i'm 0.0207 didn't 0.0207 daughter 0.0207 polici 0.0207 glad 0.0207 aren't 0.0207	call 0.0306 charg 0.0204 brand 0.0197 amazon 0.0163 noth 0.0157 minut 0.0145 did 0.0139 differ 0.0136
Macbook Air	upgrad 0.1062 hard 0.0704 16gb 0.0551 drive 0.0522 probabl 0.0475 beauti 0.0475 instal 0.0452 suppos 0.0448	receiv 0.0258 lock 0.0234 dissapoint 0.0162 possibl 0.0162 owner 0.0162 anazon 0.0162 recoveri 0.0162 immedi 0.0162	call 0.0304 cpu 0.0162 amazon 0.0156 charg 0.0155 thermal 0.0153 brand 0.015 noth 0.012 poor 0.0115

From the result, we can see that SimpMix model is only able to find the themes in the whole corpus. The themes are shared among collections. It tells about what topics the overall corpus covers, but it is not able to identify topic differences between different collection. On the other hand, the CCMix model is able to find the common themes throughout the collections, and is also able to identify the different specific themes in each collection. For example, in Cluster 2, all three collections share the same common theme. However, there is a high frequency of "love" in HP collection, whereas there is a high frequency of "disappoint" in the Macbook Air collection. We may infer these two opposite attitudes maybe towards the same topic in the common theme. Probably this HP laptop provides app or support that buyers love, whereas Macbook Air disappointed buyers in these two aspects. Therefore, we can conclude that, in reviews evaluation, the CCMix model is able to identify different performance of similar products on the same aspects.

Another observation is that not all specific themes are well distinguished from the common theme / other specific themes within the same cluster (e.g., Cluster 3). This is probably because we use a uniform λ_C for all clusters. However, for some clusters, there are more overlaps in topics among collections and less differences, and λ_C should be larger to account for the common topics.

The data we use are from Amazon, and many of them are expression of feelings, and purchase experience with Amazon, instead of technical reviews. Therefore, the results are more on customer satisfaction. On the other hand, performing CCMix model on technical reviews will find more about the performance of each laptop.

War Dataset

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Common theme words	khalifa 0.0307	mirror 0.0161	flag 0.0475	woodward0.0247	draft 0.0237
	o'neil 0.0199	threat 0.0139	gun 0.0158	powel 0.0220	opium 0.0211
	newsweek0.0174	palac 0.0134	design 0.0091	kerri 0.0210	hamdi 0.0202
	quran 0.0154	wmd 0.0122	nasratullah0.0088	marin 0.0201	rape 0.0169
	hous 0.0141	religi 0.0113	kit 0.0088	matti 0.0174	wolfowitz0.0149
	dyke 0.0113	morgan 0.0092	equip 0.0087	gen 0.0125	farmer 0.0149
	cbs 0.0102	nuclear 0.0087	zardad 0.0083	clinton 0.0114	poppi 0.0132
	kennedi 0.0092	pictur 0.0076	leak 0.0072	bandar 0.0110	erad 0.0114

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Common theme words	Flag 0.0450	gun 0.0332	Wolfowitz 0.0403	mirror 0.0277	marin 0.0178
	chang 0.0158	draft 0.0296	soro 0.0370	religion 0.0218	woodward 0.0165
	design 0.0131	leak 0.0173	group 0.0304	god 0.0207	powel 0.0147
	women0.0096	kennedi 0.0158	rumsfeld 0.0277	zardad 0.0195	coalit 0.0145
	repres 0.0095	katharin 0.0154	independ 0.0230	koran 0.0164	matti 0.0123
	new 0.0086	o'neil 0.0143	money 0.0220	morgan 0.0164	gen 0.0122
	threat 0.0085	prosecut 0.0130	rais 0.0185	dearing 0.0158	opium 0.0101
	equip 0.0084	secret 0.0128	moveon.org 0.0168	cramer 0.0135	sunday 0.0095
Iraq theme words	flag 0.0450	gun 0.0338	wolfowitz 0.0403	mirror 0.0277	zapatero 0.0295
	chang 0.0158	draft 0.0295	soro 0.0370	religion 0.0218	spain 0.0269
	design 0.0133	leak 0.0172	group 0.0304	god 0.0207	spanish 0.0167
	women 0.0096	kennedi 0.0158	rumsfeld 0.0277	zardad 0.0195	coalit 0.0134
	repres 0.0095	katharin 0.0153	independ 0.0230	koran 0.0164	sunday 0.0132
	new 0.0088	o'neil 0.0142	money 0.0220	morgan 0.0164	marin 0.0124
	threat 0.0085	prosecut 0.0129	rais 0.0185	dearing 0.0158	woodward 0.0115
	equip 0.0084	secret 0.0128	moveon.org 0.0168	cramer 0.0135	powel 0.0102
Afghan theme words	women 0.0326	kerri 0.0389	money 0.1082	mirror 0.0654	newsweek 0.0554
	rape 0.0119	hamdi 0.0382	group 0.1033	zardad 0.0472	quran 0.0489
	elect 0.0118	hous 0.0315	rumsfeld 0.0746	morgan 0.0396	magazin 0.0274

	soviet 0.0117 khalifa 0.0112 live 0.0099 nasratullah 0.0092 villag 0.0091	clinton 0.0217 cohen 0.0186 wednesday 0.0154 foam 0.0152 polystyren 0.0133	million 0.0695 rais 0.0515 candid 0.0456 link 0.0384 campaign 0.0375	daili 0.0285 tortur 0.0244 qlr 0.0216 pictur 0.0212 goldsmith 0.0202	toilet 0.0228 desecr 0.0228 isikoff 0.0196 dirita 0.0196 investig 0.0151

Similarly, the result for the war dataset also demonstrates the ability of CCMix in differentiating the specific themes between collections. For example, in Cluster 1, we can see that in Iraq war news, people are more interested in reporting flag and mental changes, whereas in Afghanistan war news, women raped were reported in the highest frequency. In Cluster 2, Iraq war news reported more on gun and draft, while Afghanistan war news reported more on the two persons: Kerry and Hamdi.

Another observation with the war dataset is that in Cluster 1 to 4, the common theme has high similarity with the Iraq theme, and has much smaller overlap with the Afghan theme. This is probably because the Iraq specific theme is a very tight cluster where the top words have very high frequencies, such that the common theme is only able to account for partial frequencies of the top words. Only in Cluster 5, both themes are very different from the common theme.

Conclusion

In conclusion, we can see that CCMix model is able to address the task of comparative text mining by its capability to discover the latent common themes across all collections, and to summarize the similarity and differences of the collections along each common theme. However, the performance of CCMix varies on the choice of λ_C and the characteristics of the dataset that it is applied on.

Contribution

Xi Luo (xiluo4)	Yuheng Zhang (yuhengz2)
Algorithm implementation: CCMix Documentation: - Implementation - Results and Evaluations	Algorithm implementation: SimpMix Documentation: - Overview - Usage Tutorial presentation