Popular Topic Mining from Blog Text

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***Abstract*—Topic mining is an important way that provides insights of text data about opinions and preference of people. In this project, a complete topic mining solution is conducted, extracting two most popular topics among 19,320 blog posts grouped by the demographic of authors. Topics are generated from ranking objects that are mentioned in the dataset, and two ranking methods are used, one using word-count and the other based on TF-IDF. The result shows most topics are meaningful and coherent, but the topic from two methods are very different. The quality of mined topics are analysed and further discussions are presented. Meanwhile, some topics have relatively lower quality and the causes are analysed. In addition, with open issues and challenges pointed out, future works and possible improvements are provided.**

***Index Terms*—Topic mining, TF-IDF, Named entity recognition, Topic coherence**

I. Overview

People's concerns and opinions are important reference for innovations of new products or services. However, accomplishing such task by humans is expensive, time-consuming and difficult to scale. As a response, a number of individuals and organisations are leveraging text mining technologies to mining meaningful information from large volume of text such as news media [1]. Among a variety of studies and applications, topic modelling is an important method to extract hot topics which reflects public attention and opinion from massive texts [1]–[3]. However, effective method of extracting useful information from text on the Internet remains an open challenge [3].

Evaluation of topics mined from text is another challenge, mostly due to the lack of ground truth because topic modelling is an unsupervised learning task [4].

The goal of this project is to mine most popular topics that people were discussing from blog posts by utilising various text mining algorithms and tools. Specifically, we will find two most popular topics for each group in the following demographics:

- Males
- Females
- People 20 years old or younger
- People older than 20
- Everyone

The remainder of this article is organised as follows. In **??** related works on topic mining and evaluation will be reviewed. The methodology of topic mining are detailed in section III, while the results, analysis and evaluations are presented in section IV. The works of this article are summarised in section V and open issues and future works are discussed in section VI.

II. Literature Review

Jacobi, Atteveldt, and Welbers [1] conducted an in-depth study of how to apply topic modelling technologies on analysis of qualitative data in academic research. This work also included a case study of analysis on nuclear technology presented in New York Times from 1942. Waila, Singh, and Singh [2] conducted an analysis on blog text with combination of topic modelling, NER, and sentiment analysis. Key themes are extracted from the dataset, and topic perplexity is calculated for evaluation. In addition, important entities such as person, place, and organisation are also recognised and displayed by word cloud. Guo, Zhang, Tan, *et al.* [3] proposed a Frequent Pattern stream (FP-stream) mining algorithm for hot topic discovery on Twitter. The author argues that traditional clustering-based topic detection algorithms are not suitable for the short, sparse, and fast-spreading Twitter data. Experiments were carried out and the result showed the hot topics and the trend of change over time.

Boyd-Graber, Mimno, and Newman [4] provides a summary of topic evaluation methods, which are divided into three categories: human evaluation, diagnostic metrics, and coherent metrics. The first one needs human effort so it is expensive and time-consuming, while the other two can be calculated by computer without human interference.

Human Evaluation requires human involvement in the evaluation task. One method in this category is accomplished by word intrusion task. Specifically, a person will be presented by a list of words and is asked to find an intruder in the meaning of not belonging to others. The words list are constructed by first selecting highly possible words from a topic, and then randomly choose one word with low probability in the same topic but high probability in a different topic. If the intruders are easily to be identified, then the topic is more likely coherent [4].

Diagnostic Metrics only compute statistics of topics without requirements of external knowledge source. Some methods in this category are [4]:

- Topic Size: measured by the sum of numbers of tokens belonging to a certain topic. Generally speaking, small topic size means low quality.

- Word Length: average length of N most dominant words in a topic. The usefulness of this metric is corpus dependent.
- Corpus Distribution Distance: A probability distribution can be derived from a topic over the vocabulary, and further normalised by global word count in the whole dataset. The distance between different topics reflects how much these topics are separated.

Coherence Metrics is a type of methods which automatically compute score of topic coherence, and their accuracy is close to human performance. The basic idea is measuring how a pair of words from top N dominant words are associated [4]. It is formalised as

$$\text{TC-f}(\mathbf{w}) = \sum_{i<j} f(w_i, w_j), i, j \in \{1...N\}$$

where $\mathbf{w} = \{w_1, w_2, ..., w_N\}$ is the list of N most dominant words, and f is the scoring function of association between two words. A typical value of N is 10. There are a variety of ways to compute f, such as counting the co-occurrence of two words, or counting the number of documents containing both words. Two popular implementations of f are Pointwise Mutual Information (PMI) and Log Conditional Probability (LCP) [4].

$$\text{PMI}(w_i, w_j) = \log \frac{P(w_i, w_j)}{P(w_i)P(w_j)}$$

$$\text{LCP}(w_i, w_j) = \log \frac{P(w_i, w_j)}{P(w_j)}$$

Fang, Macdonald, Ounis, *et al.* [5] proposed a metric based on Word Embeddings (WE). Similar to Latent Semantic Analysis (LSA) which represents each word as a real number vector obtained by Singular Value Decomposition (SVD), the WE metric represents each word by a WE vector, and the association scoring function is defined by cosine similarity of two vectors:

$$f(w_i, w_j) = cosine(V(w_i), V(w_j))$$

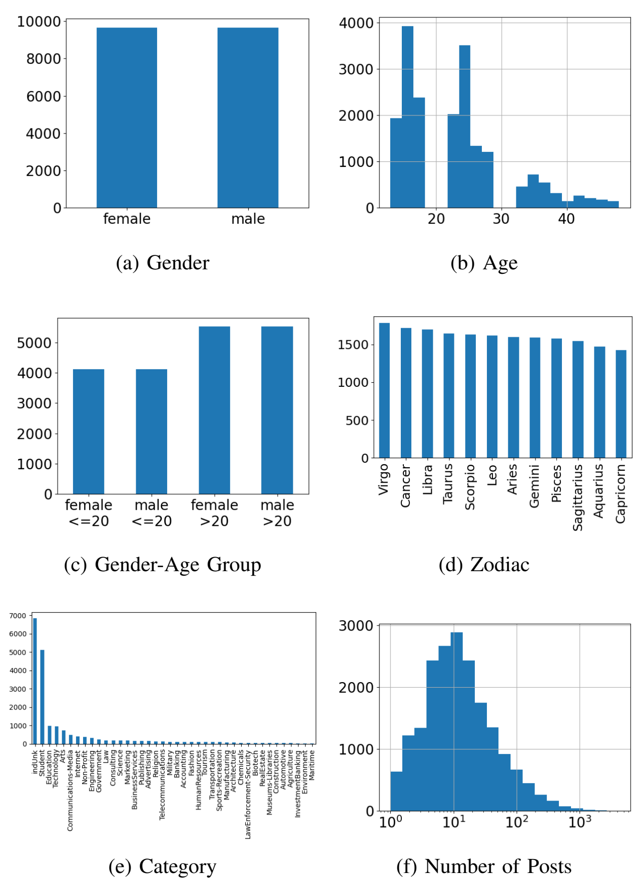
III. Research Design

In this section the solution will be described in detail. First an overview of the dataset is given, and then the algorithm of topic mining is detailed.

A. Data Description

The dataset contains 19,320 files in XML format, each containing articles of one person posted generally between 2001 and 2004. Metadata of the bloggers includes gender, age, category, and zodiac. In addition, the number of posts for each person are also counted. The result is summarised by Fig. 1, which is created by Python packages `pandas` and `matplotlib`. From this figure we can acquire some basic statistics of the dataset, including

1) Gender: data samples are quite evenly distributed over both genders.
2) Age: most bloggers are younger than 30, almost of them under 20. On the other hand, there are two gaps around 20 and 30 which may implies some missing data points in the dataset
3) Gender and age group: since we divide the dataset by the author's age, it is beneficial to inspect some data distribution over age groups. Therefor, we plot the histogram for gender distribution for each age group and the data amounts for both genders in either age group are shown to be evenly distributed.
4) Zodiac: The distribution over zodiac is reasonable even.
5) Category: the most frequent category is unknown, which is trivial, while the second frequent one is student, far more than other categories.
6) Number of posts: most bloggers published less than 100 posts, while the peak appears at 10, which implies people are most likely to write around 10 posts.



(a) Gender (b) Age

(c) Gender-Age Group (d) Zodiac

(e) Category (f) Number of Posts

Fig. 1. Data Overview. Histogram over (a) gender (b) age (c) gender and age group (d) zodiac (e) category (f) number of posts

B. Topic Mining Algorithm

The general idea for mining popular topics used in this project is to find the most significant "things" mentioned in the overall dataset, as well as the closely related information.

The overall architecture of the algorithm is shown as Fig. 2, and the details of each step are described in the following subsections.

1) Data Cleaning: Before applying any text mining techniques, it is important to do basic data cleaning to improve data quality. In this step, a few operations for preprocessing will be carried out based on the observations of the dataset, with details as follows.

- **Problem**: At some place there is no whitespace between a punctuation and the word following it, which causes wrong tokenisation. Specifically, the punctuation might be tokenised with the following word as one token.
  Solution: Add whitespace after a punctuation if a word immediately follows it.
  Example:
  - input: `I brought...stuff...like clothes`
  - output: `I brought... stuff... like clothes`
- **Problem**: Two or more consecutive quote symbols may cause wrong tokenisation.
  Solution: Replace two or more quotes as a double quote.
- **Problem**: The unicode quote may affect tokenisation and stopwords matching.
  Solution: Replace unicode quote by ASCII quote.
- **Problem**: The unicode quote may affect tokenisation and stopwords matching.
  Solution: Replace unicode quote by ASCII quote.
- **Problem**: Characters that are usually not part of normal English text may disturb tokenisation and POS tagging.
  Solution: Remove invalid characters such as "*", "#", and so on.
- **Problem**: Sometimes people repeat a certain letter in a word for emphasis, but it will result in wrong words and also increase the vocabulary size.
  Solution: No English word has more than two consecutive appearances of the same letter, so three or more repetition of a letter is squeezed into two.
  Example:
  - input: `going to be in deeeeep`
  - output: `going to be in deep`

These operations are implemented by regex matching and substitution, or simple text replacing. To use regex, the Python's `re` package are imported.

2) Tokenisation: Tokenisation is usually the first step of all text mining pipelines, which includes sentence and word tokenisation. Sentence tokenisation is to split the whole text into sentences, while word tokenisation splits a sentence into word or tokens. In this project we use `nltk` package to do such task. This package provides two functions `sent_tokenize()` and `word_tokenize()` for both tokenisation. A document is first tokenised into sentences, and then each sentence is tokenised into words. Finally, a document is represented as list of lists, as each sentence is a list of words.

3) POS Tagging: Part-Of-Speech (POS) tagging is the second step following tokenisation. In this step, each word is assigned by a POS tag. `nltk` provides a handy function `pos_tag()` to do this task. This function works on sentence level, and maps each word into a tuple which is the pair of word and POS tag.

4) Entity Extraction: In this project, a topic is defined as a "thing" or "object". Therefore, in order to find the topics, we need to find all "things" or "objects" first. There are a few options to do this task, among which two methods will be employed by this project: Named Entity Recognition (NER) and parsing.

a) NER: Named entities are ideal candidates of topics as they denote real-world objects. `nltk` provides a function `ne_chunk()` to extract entities from sentences. The input of the function should be a list of tokens with POS tags, which is another reason why POS tagging should be done in previous step. The return value of this function is a list of chunks, each of which is basically a list and may contain a `label` attribute if it is a recognised entity. The entity type can be acquired by `label()` and the entity itself should be acquired by joining all the elements of the chunk.

b) Parsing: Another way to extract objects is parsing by pre-defined patterns. For example, it is reasonable to treat definite nouns as objects according to the grammar, which can be extracted by matching of pattern "the + NOUN". However, due to limited time, this technique is not used in the experiment and might be considered in the future.

5) Stopwords Removal: Stopwords are most common words which carries no significant meanings. Removing stopwords can reduce the size of data to be proceeded as well as increase the result accuracy. `nltk` provides an out-of-the-box stopwords collection, but the experiment shows that some common words carrying no meaning are not included in the list. In order to expand the stopword list, more words are collected from website [1].

Stopwords removal is conducted after POS tagging and entity extraction because these two steps are sequence model, which means their performance rely on word order. If stopwords are removed before them, we will get sentences which do not comply with English grammar. In addition, stopwords removal are carried out on tagged documents as well as entities extracted. Theoretically, stopwords cannot be entity, but errors will happen in any POS tagging and NER model. Therefore, trying to remove stopwords can reduce the error introduced in previous steps.

6) Stemming and Lemmatisation: Stemming and lemmatisation are both techniques for text normalisation, that is, convert an inflected word into its root form. However, stemming and lemmatisation work in different way. Stemming removes suffix or prefix from a word, returning a word stem which is not necessarily a word. On the other hand, lemmatisation always looks for the lemma from word variations with morphological analysis [6]. For example, stemming against the third-person singular form "flies" returns "fli", while lemmatisation returns "fly". In this project, these two methods

[1] https://gist.github.com/sebleier/554280

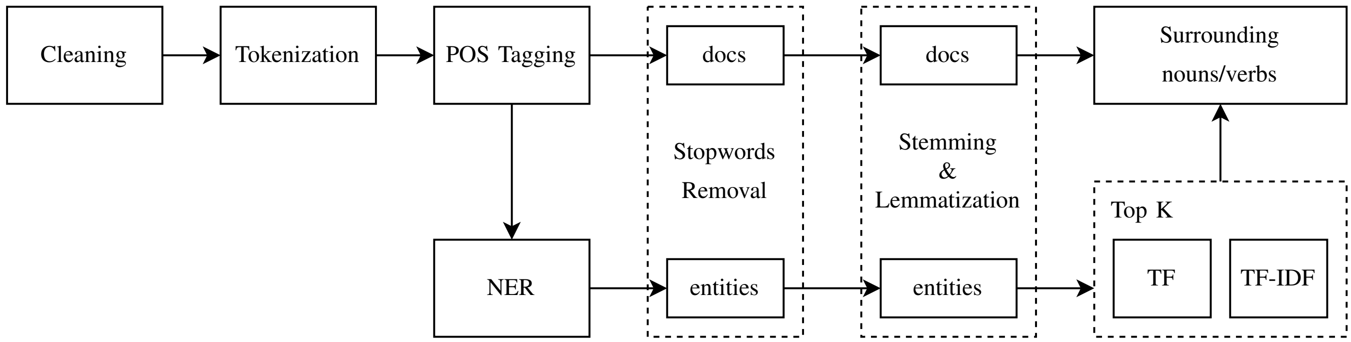


Fig. 2. Overall Architecture of Topic Mining Algorithm

are combined together to reach the maximum extent of word normalisation.

`nltk` provides various stemming algorithms such as `PorterStemmer` and `LancasterStemmer`, and one lemmatisation algorithm `WordNetLemmatizer`. In the code we use `WordNetLemmatizer` followed by `PorterStemmer`.

7) Word Count and TF-IDF: After all "objects" have been extracted and normalised, the next step is to find most popular ones as the most dominant topics. Popularity can be defined in various ways, and in this project two approaches are used: word count and Term Frequency-Inverse Document Frequency (TF-IDF). In the first method, we simply count the appearances of each entity and get the most two frequent ones. In the second method, we calculate the TF-IDF value of each entity word, following the equation [7]

$$\begin{aligned}\text{TF-IDF}(t_i, d_j) &= \text{TF}(t_i, d_j) \times \text{IDF}(t_i) \\ &= \text{TF}(t_i, d_j) \log \frac{N}{\text{DF}(t_i)}\end{aligned}$$

$\text{TF}(t_i, d_j)$ is the Term Frequency of term t_i in document d_j, which is computed by count of t_i in d_j divided by the total number of terms in d_j. $\text{DF}(t_i)$ is the Document Frequency, which is the number of documents that contains t_i. In order to avoid large IDF value for some terms only appearing in a few documents, penalty is given to small DF values by adding a smooth constant C_1 to DF

$$\overline{\text{TF-IDF}}(t_i, d_j) = \text{TF}(t_i, d_j) \log \frac{N}{\text{DF}(t_i) + C_1}$$

As we can see here, TF-IDF is a term-document-wise number so a term has different TF-IDF values in different documents. In order to rank all terms over the whole dataset, TF-IDF values of a term are averaged over all documents as the score of that term. Similarly, penalty is also given to terms having small DF values during the averaging process because terms appears in too few documents are hardly to be defined as popular. It is implemented by another smoothing constant C_2 which is not necessarily equal to C_1. The effect of the penalty will be further discussed in section IV-B2.

$$\text{score}(t_i) = \frac{1}{\text{DF}(t_i) + C_2} \sum_{d_j} \overline{\text{TF-IDF}}(t_i, d_j)$$

Two different methods might return different results, which will be compared and analysed in section IV.

C. Evaluation Method

Evaluation of topics is challenging due to its nature of unsupervised learning. There are several topic evaluation approaches, including human evaluation, diagnostic metrics, topic coherence, evaluation on classification corpus. Human evaluation requires manual works so it is costly and slow. Evaluation on classification corpus is a method using labelled text classification corpus and checking the consistency between topic words and class labels. Although we have categories in the metadata for each document, a large portion of categories are labelled as "unknown", so this approach is not suitable for this project. Therefore, diagnostic and coherence metrics are chosen to evaluate the result of the methodology. Details will be provided in section IV

IV. Result, Evaluation and Analysis

This section will show the results generated from the methodology described above, and provides evaluation and discussion of how good the topics are. Two hottest topics are extracted for each demographic, and each topic contains 10 words. In the TF-IDF-based method, penalty parameters are set to $C_1 = C_2 = 100$. Due to the large volume of the original dataset, the experiments were conducted with 5,000 and 10,000 documents randomly sampled out of the total 19,320 ones, and the results demonstrated consistency. Therefore, in the following part of this section, only results from 10,000 samples are presented. The complete implementation is listed in appendix A, including two files, one for topic mining algorithm and the other for result evaluation and visualisation.

A. Result and Evaluation

The results are displayed as word cloud generated by `wordcloud` and `matplotlib` package. Fig. 3 shows the topics mined by word count while Fig. 4 shows that by TF-IDF.

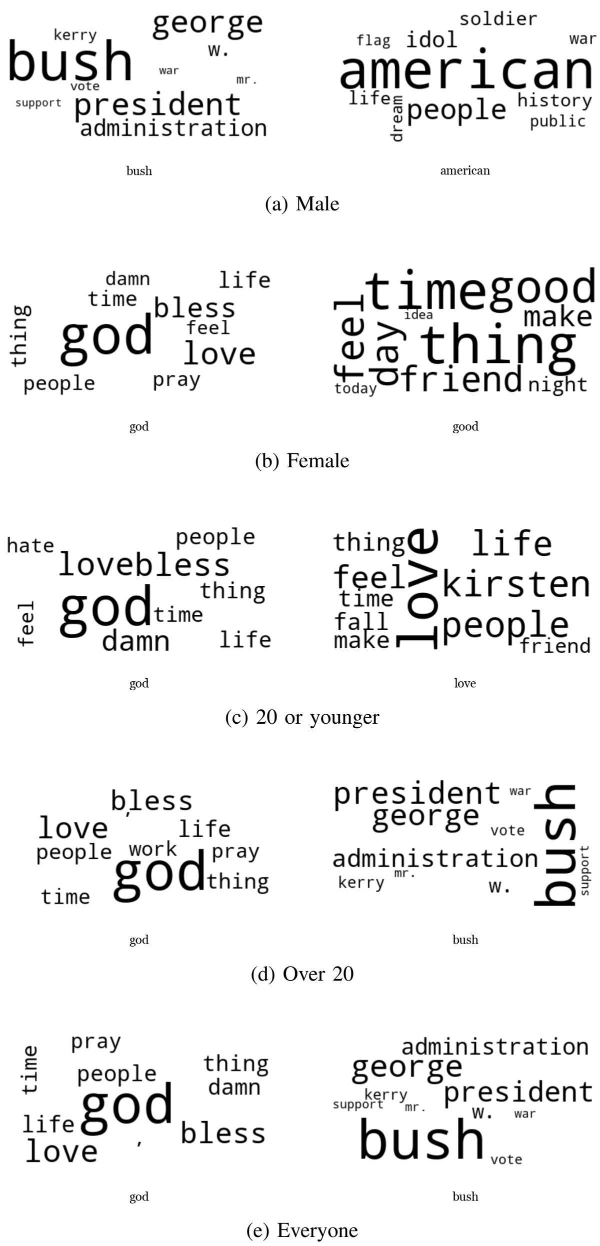


Fig. 3. Topics mined by word count. (a) male (b) female (c) 20 or younger (d) over 20 (e) everyone

Fig. 4. Topics mined by TF-IDF. (a) male (b) female (c) 20 or younger (d) over 20 (e) everyone

For evaluation of the quality of topics, we computed two diagnostic metrics, topic size and word length, and two coherence metrics, LSA and Word Embedding. The LSA vectors are provided by [8]. The pre-trained GloVe [9] word vectors with 100 dimension size are used as word embeddings. The metrics are summarised in table I and table II for two methods, respectively.

B. Analysis

In this section we will first conduct in-depth analysis on topics from both methods, and then compare these two results and discuss the pros and cons for each method.

1) Method of Word Count: Most topics are meaningful and coherent. For instance, the topic "bush" is about U.S. president George W. Bush and relative concepts, such as his rival John Kerry in 2004 U.S. president election and the Iraq War began in 2003. The word length is relatively heigh and both LSA and GloVe coherences are also high. However, the topic size is low and the reason could be that it is specific on politics. Another example is "god" which appears in multiple demographics. Though the word length is low, the topic size and coherence are high. We can also see that the keywords in this topic are meaningful and relavent, such as "love", "life", "people", "bless", and so forth. On the other hand, the topics "love" and

TABLE I
METRICS FOR WORD COUNT

Demographic	Topic	Diagnostic		Coherence	
		Topic Size	Word Length	LSA	GloVe
male	bush	68k	5.7	0.189	0.541
	american	174k	5.4	0.154	0.424
female	god	792k	4.3	0.193	0.502
	good	1,223k	4.4	0.137	0.637
20 or younger	god	816k	4.3	0.199	0.508
	love	949k	4.8	0.177	0.485
over 20	god	897k	4.0	0.201	0.492
	bush	68k	5.7	0.189	0.541
everyone	god	792k	4.0	0.209	0.460
	bush	68k	5.7	0.189	0.541

TABLE II
METRICS FOR TF-IDF

Demographic	Topic	Diagnostic		Coherence	
		Topic Size	Word Length	LSA	GloVe
male	kerry	173k	5.5	0.214	0.473
	gmail	83k	5.5	0.087	0.346
female	josh	798k	4.6	0.119	0.294
	amanda	734k	4.3	0.151	0.435
20 or younger	singapore	391k	6.2	0.116	0.416
	sarah	633k	5.2	0.145	0.416
over 20	kerry	66k	6.0	0.203	0.523
	india	372k	5.5	0.156	0.379
everyone	singapore	587k	5.9	0.120	0.466
	kyle	771k	4.6	0.115	0.479

"good" are too generic, thus have lower coherence scores.

2) Method of TF-IDF: The topics ranked by TF-IDF are different from word count. A topic relavent to the result from word count is "kerry", which we can tell from the keywords respresents U.S. Senator John Kerry and also the Democratic nominee for presidency competing with George W. Bush. The coherence of this topic is also high. Several other topics are about artists, singers or movie stars, but the qualities vary. For example, the topic "sarah" contains Sarah McLachlan. By contrast, the topic "josh" actually contains two people, Josh Groban and Josh Hartnett, so it should be two topics. Accordingly, the coherence for topic "josh" is very low. However, some topics are hard to tell what they represent, such as "amanda" and "kyle", which are pobably just common names in English world.

Two other meaningful topics are "singapore" and "india", which are likely to be created by users from these two contries. An evidence of the significant number of Singaporean users is that the word "haiz" as a common saying of "sigh" in Singaporean English came out as a high ranked topic candidate before it was filtered out as a stopword. The "india" topic is more informative, which is telling us about the important job outsourcing in India which is consistent to our knowledge. However, the coherence metrics are not signifcantly high, which could be distracted by not-so-relavent words such as "today", "time", "day". The "india" topic has less distracting words and higher LSA coherence score, but the GloVe score is low, which is a possibile issue of WE coherence metrics.

The topic "gmail" is a different case. From human's point of view, it is a meaningful topic representing the launch of beta release of Google's mail service at 1 April, 2004. However, both coherence scores are quite low, which may implies some drawbacks in the metrics definition.

3) Comparison: As can be seen from above results and analysis, the topics mined by two methods are highly different and share little in common. The difference comes from difference natures of these two methods.

The word-count-based method takes the "thing" mentioned the most times as the most popular one. This approach is simple and straightforward, and consistent to humans' concept of popularity. The more widely spreaded across the dataset an object is, the more likely it is selected as the hottest topic. That is why we got very general topics such as "god", "good", "love", as well as "bush" during the period of U.S. president election.

On the other hand, the TF-IDF-based method gives larger score on less frequent terms. However, if some term is mentioned too few times, it cannot be a hot topic. Therefore, penalty is given to such terms to make them lower ranked, leading to a trade-off between specialty and frequency and the choice of parameter representing the penalty is more a trick. Experimental shows that if the penalty is too high, the result from TF-IDF is quite similar to that from word count; but if it is too small, result is more likely to be some concept only mentioned in a few document. Generally speaking, this approach prefers topics that are frequently mentioned in a certain subgroup of people, for example, pop and movie stars, and people from a specific country such as Singapore and India.

Each method has its own advantages and disadvantages, but some topics from word-count- based method may be less valuable because they are too general. For instance, the topic "good" or "love" hardly provides any value to marketing or product decision-making because it is somthing that people are always talking about. By contrast, though the result from TF-IDF-based method may be only popular in a small group of people, it does provide insights into the opinion of that group. However, some topic from the first method is also valuable, such as the topic "bush" capturing people and events related to then U.S. president George W. Bush.

V. CONCLUSION

This project has designed and implemented a complete solution to mine most popular topics from blogs. A variety of text mining technologies are employed and combined together to reach the goal. In order to rank topics from a candidate list formed by objects, two methods are used: word-count-based and TF-IDF-based. The results are displayed by word cloud and metrics are computed and summarised. The results are also discussed, compared and evaluated in detail, and the retionale is given. Further and in-depth analysis is also provided.

VI. Open Issues and Future Works

There are still a few open issues remaining in the solution which can be improved by future work or changed if re-do this project.

An important concern is the quality of NER which has big influence on the final results. The NER result is used for topic candidate generating and wrong entities will cause wrong topics. The experiment showed that the quality of NER is moderate and needs improvement. To do that we can use other NER tools such as `spaCy` and combine the results for better performance.

Data cleaning is also an important stage in the whole algorithm. The data from internet is quite noisy. Though we employed several pre-processing to clean it, there are still many noises. For example, the advertisment in blog posts is a great inteferential factor because the same advertisment appears in the text very frequently thus looks like a popular topic.

Spell checking is another means that can be used as an improvement because blog text as a kind of informal text often has many spelling errors which makes it more difficulty to do POS tagging and NER correctly. There a few spell checking packages in Python, but they requires very long time to finish large dataset, so they are not included in the current methodology. Therefore, faster and more scalable spell checking algorithms is another direction of future work.

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APPENDIX
SOURCE CODE IN PYTHON

A. Code for topic mining

```
#!/usr/bin/env python
# -*- coding: utf-8 -*-

import sys
import os.path
from glob import glob
from tqdm import tqdm
import pickle
import json
from datetime import date
import pprint
pp = pprint.PrettyPrinter(indent=2)

import random
import itertools
from collections import namedtuple, Counter, OrderedDict, defaultdict
import heapq
from operator import itemgetter
import re
from bs4 import BeautifulSoup
import numpy as np

import nltk
from nltk.corpus import stopwords
from nltk.corpus import wordnet
from nltk.stem import PorterStemmer, LancasterStemmer, WordNetLemmatizer

# 10000 documents are sampled from the whole dataset due to limited computing capacity.
_DEBUG = False
NUM_SAMPLES = 10000


STOPWORDS = set(stopwords.words("english"))
# Add more stopwords manually
with open('stopwords1.txt') as f:
    STOPWORDS.update(w.strip().lower() for w in f)
STOPWORDS.update(['i\'m', 'dont', '\'t', '\'m', '\'s', '\'re', '\'ve',
    'haha', 'hah', 'wow', 'hehe', 'heh',
    'ah', 'ahh', 'hm', 'hmm', 'urllink', 'ok', 'hey', 'yay', 'yeah'])

################################################################################
#                         Utility functions                                    #
################################################################################

def len2d(iter2d):
    return sum(len(d) for d in iter2d)

def list2d(iter2d):
    return [[x for x in inner] for inner in iter2d]

def flatten2d(list2d):
    return itertools.chain.from_iterable(list2d)

def flatten3d(list3d):
    return itertools.chain.from_iterable(flatten2d(list3d))

def mapbar(f, seq, desc):
    for e in tqdm(seq, desc):
        yield f(e)

def map2d(f, docs):
    '''Map a list of lists to a new list of lists by applying f to the elements
    of the inner lists. Usually works on the sentence-level
    '''

    with tqdm(total=len2d(docs)) as pbar:
        def _helper(sent):
            pbar.update(1)
            return f(sent)
```

```python
        return [list(map(_helper, doc)) for doc in docs]

def map3d(f, docs):
    '''Map a list of lists of lists to a new list of lists of lists
    by applying f to the elements of the inner lists.
    Usually works on the token-level.
    '''

    with tqdm(total=len2d(docs)) as pbar:
        def _helper(sent):
            pbar.update(1)
            return [f(word) for word in sent]

        return [list(map(_helper, doc)) for doc in docs]

def foreach3d(f, docs):
    with tqdm(total=len2d(docs)) as pbar:
        for doc in docs:
            for sent in doc:
                for word in sent:
                    f(word)
                pbar.update(1)

def foreach2d(f, docs):
    with tqdm(total=len2d(docs)) as pbar:
        for doc in docs:
            for sent in doc:
                f(sent)
                pbar.update(1)

def filter3d(f, docs):
    ret = []
    with tqdm(total=len2d(docs)) as pbar:
        def _helper_doc(doc):
            for sent in doc:
                pbar.update(1)
                out = [word for word in sent if f(word)]
                if len(out) > 0:
                    yield out

        for doc in docs:
            out = list(_helper_doc(doc))
            ret.append(out)
    return ret

def load_pkl(fpath):
    print('load dataset from cached pickle file ' + fpath)
    with open(fpath, 'rb') as f:
        dataset = pickle.load(f)
    return dataset

def save_pkl(obj, fpath):
    if _DEBUG:
        fpath = fpath.replace('.pkl', '-debug.pkl')
    with open(fpath, 'wb') as f:
        print('save dataset to pickle file ' + fpath)
        pickle.dump(obj, f)

def save_json(obj, fpath, indent=2):
    with open(fpath, 'w', encoding="utf8") as f:
        print('save dataset to json file ' + fpath)
        json.dump(obj, f, indent=indent)

###############################################################################
#               Codes for data reading & transformation                       #
###############################################################################

Record = namedtuple('Record', ['meta', 'posts'])
Post = namedtuple('Post', ['date', 'text'])
MetaData = namedtuple('MetaData', ['id', 'gender', 'age', 'category', 'zodiac'])

def parse_meta_data(meta_data_str):
    arr = meta_data_str.lower().strip().split('.')
```

```python
    return MetaData(arr[0], arr[1], int(arr[2]), arr[3], arr[4])

def read_blog_file(fpath):
    '''Read one XML file and extract texts
    '''

    try:
        with open(fpath, encoding='utf-8', errors='ignore') as f:
            soup = BeautifulSoup(f.read(), "xml")
        blog = soup.Blog
    except:
        print('Error: invalid xml file {}'.format(fpath))
        return []

    posts = []
    state = 'date'
    for c in blog.find_all(recursive=False):
        if c.name != state:
            # The <date> and <text> tags should appear alternatively
            print('Warning: inconsistent format in file {}'.format(fpath))
        if state == 'date':
            try:
                date_str = c.text.strip()
                date = date_str
            except ValueError:
                print('Warning: invalid date {} in file {}' \
                        .format(c.text, fpath))
            state = 'post'
        else:
            text = c.text.strip()
            state = 'date'
            posts.append(Post(date, text))
    posts.sort(key=lambda p: p.date)
    return posts

def read_blogs(path, force=False, cache_file='blogs.pkl'):

    dataset = read_blogs_xml(path)

    # save to pickle file for fast loading next time
    if cache_file is not None:
        save_pkl(dataset, cache_file)

    return dataset

def read_blogs_xml(path):
    '''Read all blog files from the data directory
    '''

    print('reading all data files from directory {} ...'.format(path))
    dataset = []

    if _DEBUG:  # use small files for fast debugging
        files = [os.path.join(path, fname) for fname in ['3998465.male.17.indUnk.Gemini.xml',
            '3949642.male.25.indUnk.Leo.xml', '3924311.male.27.HumanResources.Gemini.xml']]
    elif NUM_SAMPLES is None:
        files = glob(os.path.join(path, '*'))
    else:
        files = random.sample(list(glob(os.path.join(path, '*'))), NUM_SAMPLES)

    for fpath in  tqdm(files):
        fname = os.path.basename(fpath)
        meta_data = parse_meta_data(fname)
        posts = read_blog_file(fpath)
        rec = Record(meta_data, posts)
        dataset.append(rec)
    return dataset

###############################################################################
#               Codes for topic mining                           #
###############################################################################

punct_re = re.compile(r'([\.!?,:;])(?=[a-zA-Z])')  # add space between a punctuation and a word
# replace two or more consecutive single quotes to a double quote
```

```
#   e.g. '' -> "       ''' -> "
quotes_re = re.compile(r"[\']{2,}")
def preprocess(text):
    '''Text pre-processing, removing invalid characters by regex substitution
    '''

    out = punct_re.sub(r'\1 ', text)
    out = quotes_re.sub(r'"', out)
    out = remove_invalid(out)
    return out

leading_quote_re = re.compile(r'[\'\.~=*&^%#!|\-]+([a-zA-Z].*)')
def clean_word(word):
    if word in ("'ve", "'re", "'s", "'t", "'ll", "'m", "'d", "'", "''"):
        return word
    word = leading_quote_re.sub(r'\1', word)
    return word.strip()

def tokenise(dataset):
    '''
    consider all the blogs from one person as a document

    Returns
    ---------
    docs: list of list of list
        a list of documents, each of which is a list of sentences,
        each of which is a list of words.
    '''

    print('tokenising the text dataset...')
    docs = []
    with tqdm(total=sum(len(rec.posts) for rec in dataset)) as pbar:
        for rec in dataset:
            doc = []
            for post in rec.posts:
                for sent_str in nltk.sent_tokenize(post.text):
                    sent_str = preprocess(sent_str)
                    sent = [clean_word(w) for w in nltk.word_tokenize(sent_str)]
                    sent = [w for w in sent if w != '']
                    doc.append(sent)
                pbar.update(1)
            docs.append(doc)

    return docs

def calc_vocab(docs):
    '''Calculate the vocabulary (set of distinct words) from a collection
      of documents.
    '''

    print('calculating the vocabulary...')
    vocab = set()

    def _helper(sent):
        vocab.update(sent)

    foreach2d(_helper, docs)
    return sorted(vocab)

def calc_pos_tags(docs):
    print('POS tagging...')
    def _f(sent):
        try:
            return nltk.pos_tag(sent)
        except IndexError:
            print('error sentence: {}'.format(sent))
            raise
    tagged_docs = map2d(_f, docs)
    return tagged_docs

pattern = re.compile(r'([^\.])\1{2,}')
pattern_ellipse = re.compile(r'\.{4,}')
invalid_chars = re.compile(r'[*\^#]')
def remove_invalid(text):
```

```
    '''Basic cleaning of words, including:

      1. rip off characters repeated more than twice as English words have a max
         of two repeated characters.
      2. remove characters which are not part of English words
    '''

    text = invalid_chars.sub(' ', text)
    text = pattern.sub(r'\1\1', text)
    text = pattern_ellipse.sub('...', text)
    return text.strip()

def remove_invalid_all(docs):
    print('reduce lengthily repreated characters...')
    return filter3d(lambda w: len(w) > 0, map3d(remove_invalid, docs))


def correct_spelling(word):
    spell = SpellChecker()
    if not wordnet.synsets(word) and not word in STOPWORDS:
        return spell.correction(word)
    else:
        return word

def correct_spelling_all(docs):
    print('running spelling correction...')
    return map3d(correct_spelling, docs)

def remove_stopwords(docs):
    print('removing stopwords...')
    return filter3d(lambda wp: wp[0].lower() not in STOPWORDS, docs)

lemmatizer = WordNetLemmatizer()
porter = PorterStemmer()
lancaster = LancasterStemmer()
def stem_word(word):
    '''Do stemming followed by lemmatisation for maximum normalisation
    '''

    return porter.stem(lemmatizer.lemmatize(word))

def do_stemming(docs):
    print('stemming or lemmatising words...')
    return map3d(lambda wp: (stem_word(wp[0]), wp[1]), docs)

def calc_ne_all(docs):
    print('extracting named entities...')
    def _calc_ne(sent):
        ne = []
        for chunk in nltk.ne_chunk(sent):
            if hasattr(chunk, 'label'):
                ne.append((' '.join(c[0] for c in chunk), chunk.label()))
        return ne
    return map2d(_calc_ne, docs)


def calc_df(docs):
    '''Calculate the Document Frequency (DF) for each token
    '''

    df = defaultdict(lambda: 0)
    for doc in docs:
        for w in set(doc):
            df[w] += 1
    return df

def calc_tfidf(docs):
    '''The original TF-IDF is a document-wise score. This function will
    calculate the average TF-IDF on whole dataset as an overall scoring.
    '''

    tf_idf = defaultdict(lambda: 0)
    df = calc_df(docs)
    num_docs = len(docs)
```

```
    total_doc_len = sum(len(doc) for doc in docs)
    total_df = sum(i for t, i in df.items())
    num_words = len(set(flatten2d(docs)))
    avg_doc_len = total_doc_len / num_docs
    avg_count = total_doc_len / num_words
    avg_df = total_df / num_words
    print('num docs', num_docs, 'num words', num_words, len(df), 'avg_len', avg_doc_len, \
            'avg word count:', avg_count, 'avg DF', avg_df)
    min_df = 100
    print('give penalty for DF less than the minimum of', min_df)
    for doc in docs:
        counter = Counter(doc)
        num_words = len(doc)
        for token in set(doc):
            tf = (counter[token] + avg_count) / (num_words + avg_doc_len)
            df_i = df[token]
            idf = np.log(num_docs / (df_i + 100))
            tf_idf[token] += tf * idf

    for token in tf_idf:
        # Smooth the average to avoid tokens with large TF-IDF value but
        #   only appeared in a few documents
        tf_idf[token] /= (df[token] + min_df)

    return tf_idf

def get_top_topics(named_entities, n=5, method='tf'):
    '''Get most dominant objects as popular topics by either word count or TF-IDF
    '''

    print('calculating most popular topics by ' + method + '...')
    if method == 'tf':
        ranks = nltk.FreqDist(w for w, t in flatten3d(named_entities))
        print(ranks.most_common(50))
        ranks = dict(ranks)
    elif method == 'tfidf':
        ranks = calc_tfidf([[w for w, t in flatten2d(doc)] for doc in named_entities])
    ranks = [(k, v) for k, v in ranks.items()]
    topics = heapq.nlargest(n, ranks, key=itemgetter(1))
    return topics

def get_surroundings(words, docs, n=4):
    '''expand the topic to be 2 verb/noun before and 2 verb/noun after the topic
    '''

    print('get surrounding 2 nouns/verbs for words {}'.format(words))

    sur = {}
    for w, c in words:
        sur[w] = Counter()

    # POS tags list for searching verbs/nouns

    def _helper(sent):
        sent_w = [w for w, p in sent]
        for w, c in words:
            try:
                idx = sent_w.index(w)
            except ValueError:
                continue

            after = 0
            vicinity = [sent[i] for i in [idx-2, idx-1, idx+1, idx+2]
                    if i >= 0 and i < len(sent)]
            for (wi, pi) in vicinity:
                if wi != w and (pi.startswith('N') or pi.startswith('V')):
                    sur[w][wi] += 1

    foreach2d(_helper, docs)
    ret = []
    for w, c in words:
        ret.append({'topic': w, 'score': c, 'keywords': sur[w].most_common(n)})
    return ret
```

```
def calc_intermediate_data(dataset):
    docs = tokenise(dataset)
    save_pkl(docs, 'tokenised_docs.pkl')
    vocab = calc_vocab(docs)
    print('Size of vocabulary: {}'.format(len(vocab)))



    tagged_docs = calc_pos_tags(docs)
    docs = vocab = None

    named_entities = calc_ne_all(tagged_docs)

    # Remove stopwords after POS tagging and NER finished
    tagged_docs = remove_stopwords(tagged_docs)
    named_entities = remove_stopwords(named_entities)

    tagged_docs = do_stemming(tagged_docs)
    named_entities = do_stemming(named_entities)
    return tagged_docs, named_entities

def mine_topics(dataset, intermediate_data, group='all'):
    print('-' * 80)
    print('mining most popular topics for group ' + group)
    print('-' * 80)
    tagged_docs, named_entities = intermediate_data

    if group != 'all':
        if group == 'male' or group == 'female':
            idx = [i for i, rec in enumerate(dataset) if rec.meta.gender == group]
        elif group == '<=20':
            idx = [i for i, rec in enumerate(dataset) if rec.meta.age <= 20]
        elif group == '>20':
            idx = [i for i, rec in enumerate(dataset) if rec.meta.age > 20]
        else:
            raise NotImplementedError()
        tagged_docs = [tagged_docs[i] for i in idx]
        named_entities = [named_entities[i] for i in idx]

    entity_set = set(w for w, t in flatten3d(named_entities))
    print('selected docs: {}, {}'.format(len(tagged_docs), len(named_entities)))

    entity_words = named_entities

    ret = {}
    num_keywords = 200
    print('-------------- result from TFIDF ------------------')
    topics = get_top_topics(entity_words, n=50, method='tfidf')
    keywords = get_surroundings(topics, tagged_docs, n=num_keywords)
    ret['tfidf'] = keywords

    print('-------------- result from TF ------------------')
    topics = get_top_topics(entity_words, n=50, method='tf')
    keywords = get_surroundings(topics, tagged_docs, n=num_keywords)
    ret['tf'] = keywords
    return ret

def main_intermediate():
    if not _DEBUG:
        dataset = read_blogs('blogs')
    else:
        dataset = read_blogs('blogs', cache_file=None)

    intermediate_data = calc_intermediate_data(dataset)
    save_pkl(intermediate_data, 'intermediate_data.pkl')
    return dataset, intermediate_data

def main_mine_topics(dataset=None, intermediate_data=None):
    if dataset is None:
        dataset = load_pkl('blogs.pkl')
    if intermediate_data is None:
        intermediate_data = load_pkl('intermediate_data.pkl')

    def _post_filter(word):
```

```
        return len(word[0]) > 0 and word[0] not in ('lol', 'fuck', 'Im',
            'urllink quizilla', 'urllink hello', 'haiz',
            ',', '`', '\'', '@', ';', '.', '\\', '/', '!', '?')

    docs, entities = intermediate_data
    docs = filter3d(_post_filter, docs)
    entities = filter3d(_post_filter, entities)
    intermediate_data = docs, entities

    topics = {}
    topics['male'] = mine_topics(dataset, intermediate_data, group='male')
    topics['female'] = mine_topics(dataset, intermediate_data, group='female')
    topics['less_or_20'] = mine_topics(dataset, intermediate_data, group='<=20')
    topics['over_20'] = mine_topics(dataset, intermediate_data, group='>20')
    topics['all'] = mine_topics(dataset, intermediate_data, group='all')
    if _DEBUG:
        suffix = 'debug'
    else:
        suffix = date.today().strftime('%Y%m%d')
        if NUM_SAMPLES > 0:
            suffix += '-' + str(NUM_SAMPLES)

    save_json(topics, 'topics-{}.json'.format(suffix))

def main():
    if len(sys.argv) <= 1:
        phases = [1, 2]
    else:
        phases = [int(i) for i in sys.argv[1].split(',')]

    dataset = intermediate_data = None
    for ph in phases:
        if ph == 1:
            dataset, intermediate_data = main_intermediate()
        elif ph == 2:
            main_mine_topics(dataset, intermediate_data)

if __name__ == '__main__':
    main()
```

B. Code for analysis, evaluation and visualisation

```
#!/usr/bin/env python
# -*- coding: utf-8 -*-

import sys
import json
from glob import glob
from tqdm import tqdm
from collections import Counter, defaultdict
import numpy as np
from numpy.linalg import norm
import pandas as pd
from as2 import load_pkl, save_pkl, Record, MetaData, Post, \
    stem_word, flatten3d, foreach3d, lemmatizer
import matplotlib.pyplot as plt
from wordcloud import WordCloud

MAX_FONT_SIZE = 80

def show_summary(dataset):
    '''This function describes the summary of dataset or human inspection.
    It's not necessary for the mining process.

    Parameters
    --------------
    dataset : list of Record
        The blog dataset
    '''

    df = pd.DataFrame([d.meta for d in dataset])
    df['blog_count'] = [len(d.posts) for d in dataset]
    df['char_count'] = [sum(len(p.text) for p in d.posts) for d in dataset]

```

```python
    print(df.describe(include='all'))
    print('{} possible values for "gender": {}'.format(
            len(df.gender.unique()), ', '.join(sorted(df.gender.unique()))))
    print('{} possible values for category: {}'.format(
            len(df.category.unique()), ', '.join(sorted(df.category.unique()))))
    print('{} possible values for zodiac: {}'.format(
            len(df.zodiac.unique()), ', '.join(sorted(df.zodiac.unique()))))

    plt.rcParams.update({'font.size': 20})
    df['gender'].value_counts().plot(kind='bar')
    plt.xticks(rotation=0)
    plt.gcf().tight_layout()
    plt.savefig('img/show-gender.png')

    plt.rcParams.update({'font.size': 10})
    plt.clf()
    df['category'].value_counts().plot(kind='bar')
    plt.gcf().tight_layout()
    plt.savefig('img/show-category.png')

    plt.rcParams.update({'font.size': 18})
    plt.clf()
    df['zodiac'].value_counts().plot(kind='bar')
    plt.xticks(rotation=90)
    plt.gcf().tight_layout()
    plt.savefig('img/show-zodiac.png')

    plt.rcParams.update({'font.size': 20})
    plt.clf()
    age = df['age']
    df['age'].hist(bins=20)
    plt.gcf().tight_layout()
    plt.savefig('img/show-age.png')

    plt.clf()
    cnt = df['blog_count']
    logbins = np.logspace(np.log10(cnt.min()),np.log10(cnt.max()), 20)
    cnt.hist(bins=logbins)
    plt.xscale('log')
    plt.gcf().tight_layout()
    plt.savefig('img/show-blog-count.png')

    plt.clf()
    cnt = df['char_count']
    logbins = np.logspace(np.log10(cnt.min()),np.log10(cnt.max()), 20)
    cnt.hist(bins=logbins)
    plt.xscale('log')
    plt.gcf().tight_layout()
    plt.savefig('img/show-char-count.png')

    plt.clf()
    df['gender_age'] = [g + '\n' + ('<=20' if a <= 20 else '>20') \
            for (g, a) in zip(df['gender'], df['age'])]
    df['gender_age'].value_counts()[[2, 3, 1, 0]].plot(kind='bar')
    plt.xticks(rotation=0)
    plt.gcf().tight_layout()
    plt.savefig('img/show-gender-age.png')

def calc_stem_map():
    '''Map word stem back to the most representative word so we can display valid
    English words in the word cloud, and also for calculating the coherence score
    '''

    print('building map from stem to words ...')
    docs = load_pkl('tokenised_docs.pkl')

    stem2word = defaultdict(lambda *_, **__: Counter())
    def _helper(w):
        s = stem_word(w)
        stem2word[s][lemmatizer.lemmatize(w.lower())] += 1

    print('calculating map...')
    foreach3d(_helper, docs)

```

```python
    out = {}
    for k, cnt in stem2word.items():
        out[k] = cnt.most_common(10)
    save_pkl(out, 'stem2word.pkl')
    return out

# Colour functions for word cloud
def color_black(word, *args, **kwargs):
    return '#000000'

def grey_color_func(word, font_size, position, orientation, random_state=None, **kwargs):
    return 'hsl(0, 0%, {:d}%)'.format((MAX_FONT_SIZE - font_size) // (MAX_FONT_SIZE * 1))

STEM2WORD = None
def eval_topics(fpath, method='tf', top_k=2, num_words_in_topic=10):
    '''Evaluate topics by:
      1. plotting the word cloud
      2. calculating the diagnostic and coherence metrics
    '''

    with open(fpath, encoding='utf8') as f:
        result = json.load(f)

    global STEM2WORD
    if STEM2WORD is None:
        STEM2WORD = load_pkl('stem2word.pkl')

    def _2w(w):
        if w in STEM2WORD:
            return STEM2WORD[w][0][0]
        else:
            return w

    topics_formatted = {}
    for group, topics2 in result.items():
        topics = topics2[method]
        topics_formatted[group] = []
        for i, topic in enumerate(topics[:top_k]):
            topic_name = _2w(topic['topic'])
            words = {}
            words.update((_2w(kw[0]), kw[1]) for kw in topic['keywords'][:(num_words_in_topic-1)])
            if method == 'tf':
                words[topic_name] = topic['score']
            else:
                try:
                    words[topic_name] = topic['keywords'][0][1] * 2  # fake frequency for display
                except IndexError:
                    words[topic_name] = 1
            topics_formatted[group].append((topic_name, words))

    print(topics_formatted)
    plot_topics(topics_formatted, method=method)
    return calc_coherence_all(topics_formatted, method=method)

LSA = None
def load_lsa():
    global LSA
    if LSA is None:
        print('loading LSA model...')
        try:
            LSA = load_pkl('lsa.pkl')
        except:
            print('failed')
            print('loading LSA model...')
            with open('semilar/LSA-MODELS/LSA-MODEL-TASA-LEMMATIZED-DIM300/voc.txt') as f:
                vocab = [x.strip() for x in f]
            print('vocab size:', len(vocab))

            with open('semilar/LSA-MODELS/LSA-MODEL-TASA-LEMMATIZED-DIM300/lsaModel.txt') as f:
                vec = [np.array([float(x) for x in line.split()]) for line in f]
            print('vector size:', len(vec), len(vec[0]))
            LSA = {w: v for w, v in zip(vocab, vec)}
            save_pkl(LSA, 'lsa.pkl')
    return LSA
```

```
WIKI_PMI = None
def load_wiki_pmi():
    global WIKI_PMI
    if WIKI_PMI is None:
        print('loading wiki PMI model...')
        try:
            WIKI_PMI = load_pkl('wiki-pmi.pkl')
        except:
            print('load from original files...')
            WIKI_PMI = {}
            for fname in tqdm(glob('semilar/wiki-pmi/*')):
                with open(fname) as f:
                    next(f)
                    next(f)
                    next(f)
                    next(f)
                    for line in f:
                        a, b, s = line.strip().split()
                        s = float(s)
                        WIKI_PMI[(a, b)] = s

            save_pkl(WIKI_PMI, 'wiki-pmi.pkl')

    return WIKI_PMI

GLOVE = None
def load_glove(ndim=100):
    global GLOVE
    if GLOVE is None:
        print('loading glove embeddings...')
        try:
            GLOVE = load_pkl('glove{}.pkl'.format(ndim))
        except:
            print('failed')
            GLOVE = {}
            fname = 'embeddings/glove.6B.{}d.txt'.format(ndim)
            print('load from file', fname)
            with open(fname) as f:
                for line in f:
                    arr = line.strip().split()
                    GLOVE[arr[0].strip()] = np.array([float(f) for f in arr[1:]])

            save_pkl(GLOVE, 'glove{}.pkl'.format(ndim))

    return GLOVE

def cosine_similarity(a, b):
    return np.dot(a, b)/(norm(a)*norm(b))

def lsa_score(wi, wj):
    lsa = load_lsa()
    vi = lsa[wi]
    vj = lsa[wj]
    return cosine_similarity(vi, vj)

def pmi_score(wi, wj):
    pmi = load_wiki_pmi()
    p = (wi, wj)
    if p in pmi:
        return pmi[p]
    else:
        return pmi[wj, wi]

def glove_score(wi, wj):
    lsa = load_glove()
    vi = lsa[wi]
    vj = lsa[wj]
    return cosine_similarity(vi, vj)

def calc_coherence(words, f):
    n = 0
    score = 0.0
    for i in range(len(words)):
```

```
        for j in range(i+1, len(words)):
            try:
                score += f(words[i], words[j])
            except KeyError:
                print('warning: cannot find pairwise association: {} {}' \
                        .format(words[i], words[j]))
                continue
            n += 1
    return score / n

def calc_word_length(words):
    return sum(len(w) for w in words) / len(words)

WORD_COUNT = None
def calc_topic_size(words):
    global WORD_COUNT
    if WORD_COUNT is None:
        docs, _ = load_pkl('intermediate_data.pkl')
        WORD_COUNT = Counter(w for w, t in flatten3d(docs))
    return sum(WORD_COUNT[w] for w in words)

def calc_coherence_all(topics_all, method):
    metrics = []
    for group, topics in topics_all.items():
        for i, (topic_name, words_freq) in enumerate(topics):
            if len(words_freq) <= 1:
                continue
            words = sorted(words_freq.keys())
            print('topic:', topic_name, words)
            lsa = calc_coherence(words, lsa_score)
            print('lsa score', lsa)
            we_glove = calc_coherence(words, glove_score)
            print('we glove score', we_glove)
            wl = calc_word_length(words)
            print('avg word length', wl)
            ts = calc_topic_size(words)
            print('avg topic size', ts)
            metrics.append((group, i, topic_name, words, lsa, we_glove, wl, ts))
    return metrics

def print_metrics_as_table(metrics, fpath):
    '''Plot metrics as \LaTeX table
    '''

    with open(fpath, 'w') as f:
        for group, i, topic, keywords, lsa, we_glove, wl, ts in metrics:
            if i > 0:
                group = ' '
            elif group == 'less_or_20':
                group = '20 or younger'
            elif group == 'over_20':
                group = 'over 20'
            elif group == 'all':
                group = 'everyone'
            f.write(f'{group} & {topic} & {ts//1000:,}k & {wl:.1f} & {lsa:.3f} & {we_glove:.3f} \\\\\n')
            if i == 1:  # two topics for each group
                f.write('\\hline\n')
            else:
                f.write('\\cline{2-6}\n')

def plot_topics(topics_json, method):
    '''Plot word cloud for the keywords in each topic
    '''

    for group, topics in topics_json.items():
        for i, (topic_name, words) in enumerate(topics):
            print('topic: ', topic_name, 'number of keywords:', len(words))
            wc = WordCloud(background_color="white",
                    max_font_size=80,
                    max_words=len(words)+1,
                    color_func=grey_color_func)
            wc.generate_from_frequencies(words)

            plt.clf()
```

```
            plt.imshow(wc, interpolation="bilinear")
            plt.axis("off")
            plt.title(topic_name, y=-0.25, fontsize=20, fontname='Georgia')
            plt.gcf().tight_layout()
            fig_path = 'img/{}-{}-{}.png'.format(group, method, i+1, topic_name)
            print('drawing ' + fig_path)
            plt.savefig(fig_path)

def main():
    cmd = sys.argv[1]
    if cmd == 'show':
        show_summary(load_pkl('blogs.pkl'))
    elif cmd == 'eval':
        fpath = sys.argv[2]
        metrics_tf = eval_topics(fpath, top_k=2, method='tf')
        metrics_tfidf = eval_topics(fpath, top_k=2, method='tfidf')
        print('tf metrics', metrics_tf)
        print_metrics_as_table(metrics_tf, 'metrics-tf.tex')
        print('tfidf metrics', metrics_tfidf)
        print_metrics_as_table(metrics_tfidf, 'metrics-tfidf.tex')
    elif cmd == 'stem2word':
        calc_stem_map()

if __name__ == '__main__':
    main()
```