Capstone project task 1

Abstract

In order to finish this task, I used python and jupyter notebook to develop and run my code.
I used graphlab to run text alalytic algorithms and matplot to visualize.

Implementation

At first I imported all dataset. Because of the task requirement, I think that only the text reviews themselves are important, so I remove columns like: 'votes', 'data' and id columns.

```
reviews = gl.SFrame.read_json('yelp_dataset_challenge_academic_dataset/yelp_academic_dataset_
review.json',orient='lines')
reviews.remove_columns(['business_id','date','review_id','user_id','votes','type'])
```

After that, I created a dictionary map each word appeared in the review with its tf_idf score. I also removed stop words from the dictionary as they are mostly invaluable.

```
reviews['word_count'] = gl.text_analytics.count_words(reviews['text'],delimiters = delimiters)
dict_trim_by_keys(stopwords, exclude=True)
reviews['tf_idf'] = gl.text_analytics.tf_idf(reviews['word_count'])
```

Because the data is quite big, I only use 10% of all reviews (about 110,000 reviews) to analyse. The data after preprocessing look like this:

```
sample = reviews.sample(.1,seed = 317)
sample.head()
```

stars	text	word_count	tf_idf
5	Dr. Eric Goldberg is a fantastic doctor who has ...	{'accessible': 1L, 'fantastic': 1L, ...	{'accessible': 6.440940320962146, ...
3	Ate a Saturday morning breakfast at the Pine ...	{'saturday': 1L, 'madison': 1L, 'qualms': ...	{'saturday': 3.7162420980736974, ...
5	i rarely give five star reviews but for what ...	{'breakfasts': 1L, 'give': 1L, 'taste': 1L, ...	{'breakfasts': 6.55469249425622, 'gi ...
3	This is definitely not your usual truck stop. ...	{'good': 1L, 'rude': 1L, 'restaurant': 1L, ...	{'good': 0.9400482737462729, ...
4	Unlimited hot coffee. I don't have any ...	{'generous': 1L, 'good': 1L, 'restaurant': 1L, ...	{'generous': 4.523116918480465, ...
5	Californians are all about the In-N-Out, w ...	{'love': 1L, 'family': 1L, 'feel': 1L, 'almo ...	{'love': 1.8910237607652902, ...
4	My meaty goodness...why isn't Culvers a ...	{'cheese': 1L, 'picnic': 1L, 'chain': 1L, 'bac ...	{'cheese': 2.5850249953356883, ...
5	Love it!!!!! Love it!!!!!! love it!!!!!!! ...	{'love': 4L, "culver's": 1L} ...	{'love': 7.564095043061161, ...
3	If you live in Madison, you too probably have a ...	{'charter': 1L, 'love': 1L, 'inadequate': 1L, ...	{'charter': 9.46779250322994, 'lo ...
2	My arch-enemy.\n\nI've never encountered a ...	{'contacted': 1L, 'extra': 1L, 'lack': 1L, ...	{'contacted': 6.237942631329764, ...

[10 rows x 4 columns]

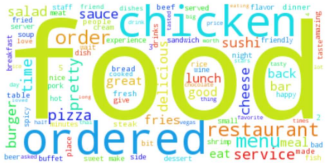
Task 1.1:

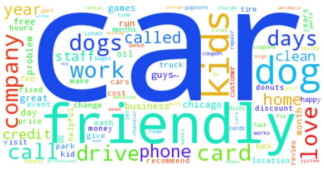
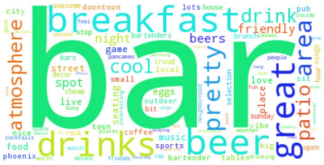
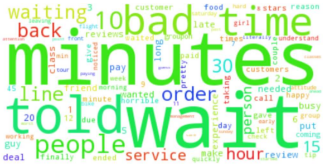
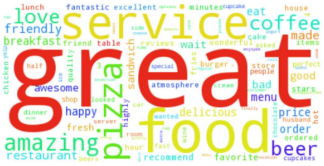
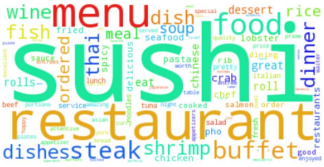
In this task, I will use 2 different methods of lda topic modeling named Collapsed Gibbs sampling (cgs) and AliasLDA method (alias) to create 10 topics each model. After that, I will creat visualization base on 2 model topics and compare them.

```
def model_cgs(data):
    return gl.topic_model.create(data,num_topics=topic_size, num_iterations=200,print_interval=50,method='cgs')
def model_alias(data):
    return gl.topic_model.create(data, num_topics=topic_size, num_iterations=50,print_interval=50,method='alias')

topic_model_cgs = model_cgs(sample['tf_idf'])

topic_model_alias = model_alias(sample['tf_idf'])
```

Topic	Sample data using alias method	Sample data using cgs method
0		

Topic	Sample data using alias method	Sample data using cgs method
1		
2		
3		
4		
5		
6		
7		
8		
9		

It is clear that alias method did better job than cgs method.
Model using alias method can differentiate topics very good and topics look very distinct: restaurants, coffee shops, stores, movie theatres, ...
By contrast, cgs method did not do well its job because more than half the topics scored the word *'great'* as the most important words. Therefore, in task 1.2 I will only use alias method.

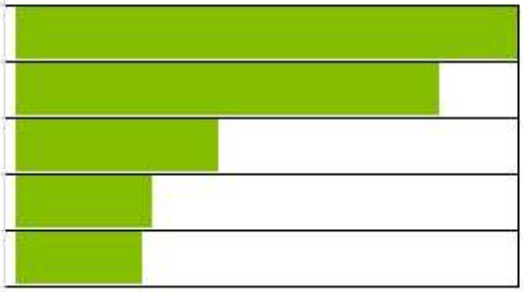
Task 1.2:

In this task, I will get about 100,000 positive reviews (5 stars) and about 100,000 negative reviews (1 or 2 stars) as sample and run topic models on them.

```
gl.canvas.set_target('ipynb')
reviews['stars'].show('Categorical')
```

Most frequent items from <*SArray*>

Value	Count	Percent
5	406,045	36.078%
4	342,143	30.4%
3	163,761	14.551%
1	110,772	9.842%
2	102,737	9.128%



It is clear that reviews with 4 or 5 stars account for 66% of original data and reviews with 3 or less stars share the remaining 33%. I will use 25% of positive reviews (5 stars) and 30% of negative reviews(less than 3 stars) as sample and run topic model on these samples.

```
positive_reviews = reviews[reviews['stars'] == 5]
sample_positive = positive_reviews.sample(.25 ,seed = 317)
sample_positive.shape
```

```
(101630, 4)
```

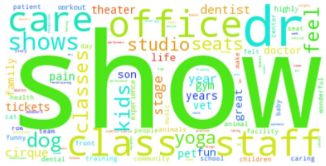
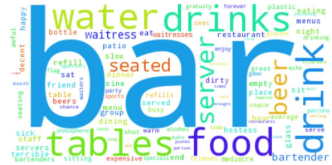
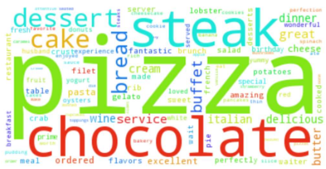
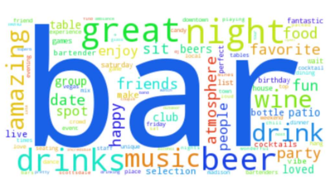
```
negative_reviews = reviews[reviews['stars'] < 3]
sample_negative = negative_reviews.sample(.5,seed = 317)
sample_negative.shape
```

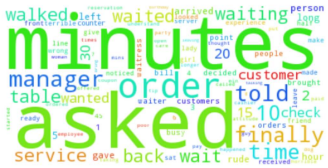
```
(106853, 4)
```

```
positive_model_alias = model_alias(sample_positive['tf_idf'])
```

```
negative_model_alias = model_alias(sample_negative['tf_idf'])
```

Topic	Positive	Negative

0	 show class staff office dr care shows	 bar water drinks drink tables food server
1	 lunch food fries chicken burger sandwich	 room hotel stay desk rooms bathroom front dirty
2	 pizza chocolate steak dessert cake	 sushi restaurant food ordered steak dish
3	 car work job customer company	 people kids line club girls group guys
4	 room vegas hotel pool strip stay	 rude waste reviews nails bad hair
5	 store coffee friendly find buy shop	 show vegas night music casino free strip
6	 cool awesome line time back	 store location items prices buy quality terrible
7	 sushi food beef menu dish rice	 car call called phone company told
8	 bar great night drinks music beer wine	 pizza ordered burger fries cheese

9		

Even though the most scored words in models are words that related to business categories of the places being reviewed. We can notice that there are words like *love*, *awsome* or *amazing* in positive feedbacks while in negative reviews there are many negative words like *rude*, *waste*, or *horrible*.