CMU_15688_Team_Project (/github/spencial/CMU_15688_Team_Project/tree/master)
/
15688_final_project_review_rating_prediction.ipynb (/github/spencial/CMU_15688_Team_Project/tree/master/15688_final_project_review_rating_prediction.ipynb)

Review Rating Prediction

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- Install Packages
- Data Scraping
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- Model Training and Evaluation
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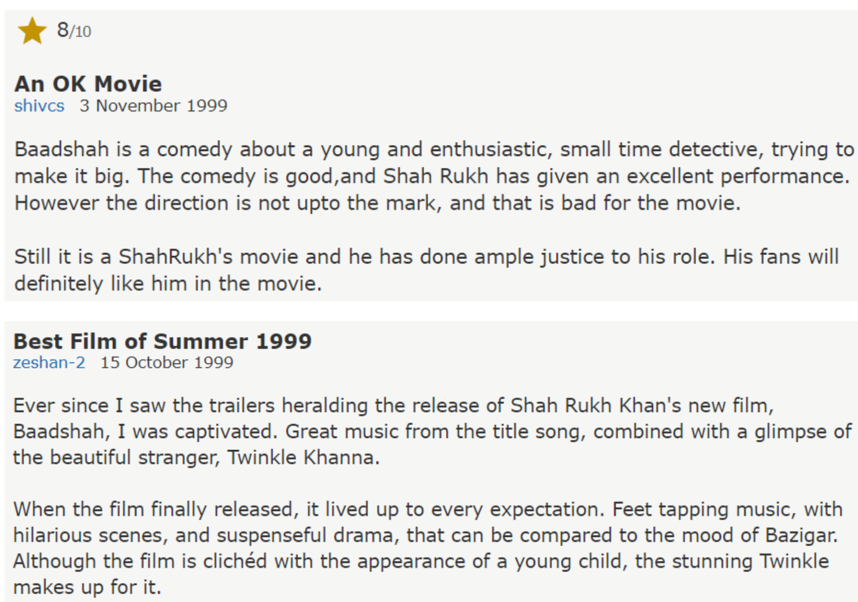
Introduction

Motivation

As the rising of E-commerce, the customer reviews become more and more important. When we want to watch a movie, buy a cloth or eat at somewhere, we always turn to the websites and look for other's reviews and ratings. So we need pay more attention to explore the information hidden in the reveiws and ratings.



However, while browsing the imdb website, we found that some people only wrote reviews but did not write ratings. When we look at these reviews, it's impossible to quickly tell what the reviewer's preference is for the movie. We also found that some reviews and ratings are not match, which means they may be fake reviews. So what we want to do with this project is through only analyzing the review text and then predict the rating. This allows us to quickly get a quantitative score when we encounter some raw review text. It also enables us to make a prediction of reviews which have rating to see whether they are reliable.

Problem

The problem we focus here is: while we are increasingly relying on reviews on websites, many of the reviews on websites have problems with missing ratings, fake ratings, etc., which makes it impossible for us to get real feedback from people about the products we care, thus misleading us.

To solve this problem, we build review rating prediction, which is aiming to predict the numeric rating from the text of the user’s review. It will enable us to produce a reliable rating by the review text quickly.

Besides the problem we found, it can be applied to many other tasks:

1. Determine the rating of reviews
2. Detect suspicious reviews where reviews and ratings do not match
3. Help better understand reviewers’ sentiment
4. Help website developers improve their review system

How to solve

To solve the review rating prediction problem, we followed these steps:

1. Scraping data: get review data from IMDb, Amazon and Yelp
2. Data preprocessing: normalize and handle punctuation
3. Data visualization: wordcloud and LDA
4. Modeling and Evaluation

Install Packages

Besides python packages, you need the following plugins/libraries for data scraping:

- PhantomJS: a headless browser for automation browsing.
  - In MacOS, you can run `brew cask install phantomjs` .
  - In Windows, you can download the phantomjs at `https://phantomjs.org/download.html` and put the `phantomjs.exe` into system path.

In [ ]:

```
!pip install selenium
!pip install wordcloud
!pip install gensim
!pip install beautifulsoup4
!pip install seaborn
!pip install lxml
!pip install nltk
!pip install pandas
!pip install numpy
!pip install scikit-learn==0.22
```

In [63]:
```
import os
import csv
import re
import nltk
import sklearn
import random
import pickle
import urllib3
import requests
import time
import json
import io
import collections
import string
import gensim
import seaborn
import pickle

import numpy as np
import pandas as pd

import sklearn.model_selection
import sklearn.naive_bayes
import sklearn.metrics
import urllib.request
import gensim.corpora as corpora
import matplotlib.pyplot as plt
import matplotlib.colors as mcolors

from lxml import html
from wordcloud import WordCloud, STOPWORDS
from pprint import pprint
from bs4 import BeautifulSoup
from selenium import webdriver
```

In [3]:
```
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/spencer/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /Users/spencer/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /Users/spencer/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[3]:
```
True
```

Data Scraping

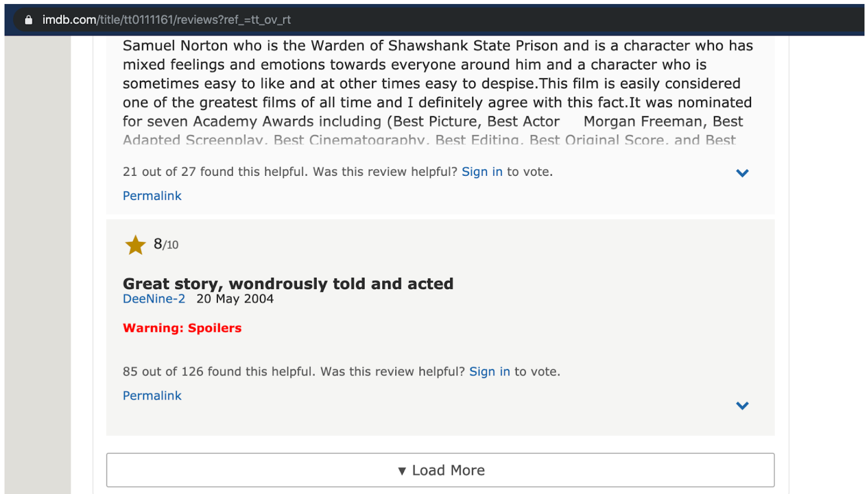
We scraped three websites: IMDB, Amazon and Yelp to build our datasets. All the raw dataset from data scraping and shuffled dataset are on github (https://github.com/spencial/CMU_15688_Team_Project). You can directly download the shuffled datasets from github, put them in the same directory of this notebook, skip this Data Scraping section and run the code after these section.

Attention: All the code cells in this section will take long time(over 10 hr) to run

Data Scraping on IMDB

Since websites like IMDB needs people to click the load more button to see more reviews, besides using beautifulsoup, we used the automated website framework (selenium) and headless browser (phantomjs) to simulate action of clicking button during scraping. We firstly got top 100 movies from `https://www.imdb.com/chart/moviemeter` and then gathered up to 500 reviews from every movie. We finally got 27534 reviews in total from IMDB website.

In the IMDB, the scale of rating of movie review is from 1 to 10. To make it consistent with the yelp and amazon dataset, we map the 1 to 10 star rating to 1 to 5 scale.



imdb.com/title/tt0111161/reviews?ref_=tt_ov_rt

Samuel Norton who is the Warden of Shawshank State Prison and is a character who has mixed feelings and emotions towards everyone around him and a character who is sometimes easy to like and at other times easy to despise.This film is easily considered one of the greatest films of all time and I definitely agree with this fact.It was nominated for seven Academy Awards including (Best Picture, Best Actor Morgan Freeman, Best Adapted Screenplay, Best Cinematography, Best Editing, Best Original Score, and Best

21 out of 27 found this helpful. Was this review helpful? Sign in to vote.

Permalink

8/10

Great story, wondrously told and acted
DeeNine-2 20 May 2004

Warning: Spoilers

85 out of 126 found this helpful. Was this review helpful? Sign in to vote.

Permalink

▾ Load More

In [ ]:

```
driver = webdriver.PhantomJS()

'''
To get the review for a particular movie, we firstly used code to simulate clicking the load more button for
up to 20 times and then we walk through the whole website for that movie and parsed the reviews.
To make sure that we will not be blocked by the website, we will pause the thread for 1 s
everytime we clicked the load more button.
'''
def get_reviewes(movie):
    url = f"https://www.imdb.com/title/{movie}/reviews"
    print(f"crawl {url}")
    driver.get(url)
    click_count = 1

#   Simulate clicking buttons
    while True:
        try:
            loadmore = driver.find_element_by_id("load-more-trigger")
            print("Click load more button...")
#             Click buttons for up to 20 times for each movie
            if click_count < 20 and loadmore:
                loadmore.click()
                click_count += 1
            else:
                break
            time.sleep(1)
        except Exception as e:
#             Exceptions are thrown when the webpage does not have click buttons (no more reviews to be displayed)
            print(e)
            break
# Parse page and find reviews
    soup = BeautifulSoup(driver.page_source)
    reviews = soup.find_all('div', class_=['imdb-user-review'])
    review_list = []
    for review in reviews:
        try:
            review_star = int(review.find('span', class_=['rating-other-user-rating']).find('span').getText())
            review_content = review.find('div', class_=["text", "show-more__control"]).getText()
            review_list.append([review_star, review_content])
        except Exception as e:
            print(e)
    return review_list

def write_to_csv(reviews, result_file):
    with open(result_file, mode='a') as review_file:
        writer = csv.writer(review_file, delimiter=',',
                            quotechar='"', quoting=csv.QUOTE_MINIMAL)
        for review in reviews:
            writer.writerow(review)


def get_movies(url):
    driver.get(url)
    soup = BeautifulSoup(driver.page_source,features="html.parser")
    titleCols = soup.find_all('td', class_=['titleColumn'])
    movies = []
    for titleCol in titleCols:
        link = titleCol.find('a', href=True)['href']
        movies.append(link.split('/')[2])

    return movies
```

In [ ]:

```
result_file = 'imdb_review.csv'
with open(result_file, mode='w') as review_file:
    writer = csv.writer(review_file, delimiter=',',
                        quotechar='"', quoting=csv.QUOTE_MINIMAL)
    writer.writerow(['review_rating', 'review_content'])

# popular movie chart
for movie in get_movies("https://www.imdb.com/chart/moviemeter"):
    reviews = get_reviewes(movie)
    write_to_csv(reviews, result_file)
```

```
crawl https://www.imdb.com/title/tt1302006/reviews
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
Click load more button...
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
'NoneType' object has no attribute 'find'
crawl https://www.imdb.com/title/tt8946378/reviews
Click load more button...
Click load more button...
Click load more button...
```

Data Scraping on Amazon

This script is used to gather reviews and ratings from Amazon website for specfic product.

In this section, we scraped over different department: Camera & Photo, Electronics, Clothing, Shoe & Jewelry, Grocery & Gourmet Food etc. It ensured that our reviews do not focus on narrow field, but get sampled under compound fields.

In [ ]:

```
# Clean the format of variable ;number_review'
def number_review_cleaner(str):
    cleaned = re.search('of (.*) reviews',str)
    cleaned = cleaned.group(1).replace(',','')
    return cleaned

# parse json info into csv file named '[ASIN].csv'
def json_parser(name,json,cutoff_number):
    with open('amazon_review.csv', mode='a+',newline='') as outfile:
        writer = csv.writer(outfile,delimiter=',')
        counter= 0
        for data in json['reviews']:
            writer.writerow(data.values())
            counter += 1
    print('FINISH WRITING DATA INTO CSV FILE')
    print('NAME OF THE PRODUCT:',json['product_name'])
    print('CUTOFF NUMBER OF COMMENTS:',cutoff_number)
    print('NUMBER OF REVIEWS:',counter)

'''
reference:

https://github.com/DavidRoldan523/amazon_reviews_allpages/blob/master/scraper_amazon_threading_version.py
'''

def user_agent_random():
    list_user_agent = ['Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/73
                       'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/72
                       'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/71
                       'Mozilla/5.0 (Windows NT 6.1; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/71.
                       'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/71
                       'Mozilla/5.0 (Windows NT 6.1; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/71.
                       'Mozilla/5.0 (Windows NT 6.1) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/71.0.3578.98 Sa
                       'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70
                       'Mozilla/5.0 (Windows NT 6.1; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.
                       'Mozilla/5.0 (Windows NT 6.1; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.
                       'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70
                       'Mozilla/5.0 (Windows NT 6.3; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.0.353
                       'Mozilla/5.0 (Windows NT 6.1; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.0.353
                       'Mozilla/5.0 (Windows NT 6.3; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.
                       'Mozilla/5.0 (Windows NT 6.3; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.
                       'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70
                       'Mozilla/5.0 (Windows NT 6.1) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.0.3538.67 Sa
    return random.choice(list_user_agent)
```

In [ ]:

```
'''
Amazon Standard Identification Numbers (ASINs) are unique blocks of 10 letters and/or numbers that identify items.
You can find the ASIN on the item's product information page on Amazon website.
In our project, a list of ASIN is selected manually among multiple popular product across different categories.
Cutoff number is used to filter comments out with few words.
Its value is picked manually as well, which is likely to influence the contribution of each comments.

Requests module was utilized to access the website and receive response.
Then lxml module was used to read response out with HTML format to extract specific information such as product na
The pattern of the review page was caught to form a list of urls for all pages of reviews. Reviews and ratings wer
'''

'''
Amazon scraper Ver 1.0

Use ASIN to download reviews and rating scores

reference:
1. https://github.com/DavidRoldan523/amazon_reviews_allpages/blob/master/scraper_amazon_threading_version.py
2. https://medium.com/@tusharseth93/scraping-the-web-a-fast-and-simple-way-to-scrape-amazon-b3d6d74d649f
'''

def get_reviews_ratings(asin,cutoff_number=0):
    # The final result including name and reviews text
    product_info = {}
    # List of reviews
    all_reviews = []
    try:
        # direct to the review page
        amazon_url = 'https://www.amazon.com/product-reviews/' \
                     + asin \
                     + '/ref=cm_cr_arp_d_paging_btm_next_1?pageNumber=1'
        # user agent
        # headers = {"User-Agent":"Mozilla/5.0 (Windows NT 10.0; Win64; x64; rv:66.0) Gecko/20100101 Firefox/66.0"
        headers = {"User-Agent": user_agent_random(),
                   "Accept-Encoding":"gzip, deflate",
                   "Accept":"text/html,application/xhtml+xml,application/xml;q=0.9,*/*;q=0.8",
                   "DNT":"1",
                   "Connection":"close",
                   "Upgrade-Insecure-Requests":"1"}
        urllib3.disable_warnings()
        response = requests.get(amazon_url,headers=headers,verify=False,timeout=30)
        time.sleep(1)
        cleaned_response = response.text.replace('\x00','')
        html_response = html.fromstring(cleaned_response)

        # name of the product
        product_name = ''.join(html_response.xpath('.//a[@data-hook="product-link"]//text()')).strip()
        product_info['product_name'] = product_name
        # get the total pages of reviews
        number_reviews = ''.join(html_response.xpath('.//span[@data-hook="cr-filter-info-review-count"]//text()'))
        pages_reviews = int(int(number_review_cleaner(number_reviews))/10)
        # promise the number of pages is correct
        if pages_reviews %2 == 0:
            pages_reviews += 1
        else:
            pages_reviews += 2

        # gather the urls to each page of reviews
        counter_5stars = 0
        for page in range(1, pages_reviews):
            print(f'Request the reviews in page {page}')
            url = 'https://www.amazon.com/product-reviews/' + \
                     asin + \
                     '/ref=cm_cr_arp_d_paging_btm_next_' + \
                     str(page) + \
                     '?pageNumber=' + \
                     str(page)

            page_response = requests.get(url,headers=headers,verify=False,timeout=20)
            time.sleep(1)
            cleaned_page_response = page_response.text.replace('\x00','')
            html_page_response = html.fromstring(cleaned_page_response)
            reviews = html_page_response.xpath('//div[contains(@id,"reviews-summary")]')

            if not reviews:
                reviews = html_page_response.xpath('//div[@data-hook="review"]')

            for review in reviews:
```

```
                # rating
                raw_review_rating = review.xpath('.//i[@data-hook="review-star-rating"]//text()')
                review_rating = ''.join(raw_review_rating).replace('out of 5 stars','')
                # skip condition
                if counter_5stars >= 5000 and int(float(review_rating))==5:
                    continue
                # comments
                raw_review_content1 = review.xpath('.//span[@data-hook="review-body"]//text()')
                raw_review_content2 = review.xpath('.//div//span[@data-action="columnbalancing-showfullreview"]/@d
                raw_review_content3 = review.xpath('.//div[contains(@id,"dpReviews")]/div/text()')

                # cleaning data
                review_content = ' '.join(' '.join(raw_review_content1).split())
                if not review_content:
                    continue

                # hidden reviews
                if raw_review_content2:
                    review_content_2 = json.loads(raw_review_text2[0])
                    review_content_2 = review_content_2['rest']
                    cleaned_review_content_2 = re.sub('<.*?>', '', review_content_2)
                    full_review_content = review_content + cleaned_review_content_2
                else:
                    full_review_content = review_content

                # if review 1 not exist
                if not raw_review_content1:
                    full_review_content = ' '.join(' '.join(raw_review_content3).split())


                if len(full_review_content.split()) < cutoff_number:
                    continue
                else:
                    review_dict = {
                        'review_rating':int(float(review_rating)),
                        'review_text':full_review_content
                    }
                    all_reviews.append(review_dict)

                    if int(float(review_rating)) == 5:
                        counter_5stars += 1
            product_info['reviews'] = all_reviews
        return product_info,cutoff_number
    except Exception as e:
        return None,None

# Given a list of ASIN number, generate csv file including reviews
def Amazon_scraper(asin_list,cutoff_number):
    for asin in asin_list:
        print('Downloading reviews and ratings for:', asin)
        reviews, cutoff_number = get_reviews_ratings(asin,cutoff_number=cutoff_number)
        json_parser(asin,reviews,cutoff_number)
```

In [ ]:

```
with open('amazon_review.csv', mode='a+',newline='') as outfile:
        writer = csv.writer(outfile,delimiter=',')
        writer.writerow(['rating', 'review_content'])

asin_list = ['B01L8JJ1GK', 'B075CYMYK6', 'B078HQBS21', 'B002NZJ4L6', 'B00KWR6G4A', 'B074CR89QG', 'B00VGR4YDU', 'B0
Amazon_scraper(asin_list,0)
```

```
DOWNLOADING REVIEWS AND RATINGS FOR: B01L8JJ1GK
Request the reviews in page 1
Request the reviews in page 2
Request the reviews in page 3
Request the reviews in page 4
Request the reviews in page 5
Request the reviews in page 6
Request the reviews in page 7
Request the reviews in page 8
Request the reviews in page 9
Request the reviews in page 10
Request the reviews in page 11
Request the reviews in page 12
Request the reviews in page 13
Request the reviews in page 14
Request the reviews in page 15
Request the reviews in page 16
Request the reviews in page 17
Request the reviews in page 18
Request the reviews in page 19
Request the reviews in page 20
Request the reviews in page 21
Request the reviews in page 22
Request the reviews in page 23
Request the reviews in page 24
Request the reviews in page 25
Request the reviews in page 26
Request the reviews in page 27
```

Data Scraping on Yelp

We scraped 20k+ review and rating data from Yelp. The data set contains a wide range of restaurants ranging from French, Italian, Japanese, and Chinese to restaurants with lower (1,2) overall rating and restaurants with higher (4,5) overall rating.

In random selection, we observed that Yelp has far more higher rating reviews than lower rating reviews. In order to ensure the balance and quality of the rating data, we extracted the first 400 reviews in desending order of rating per restaurant.

What's more, 5000+ reviews with lower ratings are particularly selected from 10 restaurants regarded as "The worst restaurants in the U.S." to better balance the data set. As more lower rating (1,2) data were added to review data, our dataset now contains balanced amount of stars, equally ranging from 1 to 5.

To run the following code, you should obtain the Yelp API by creating an app at https://www.yelp.com/developers/v3/manage_app (https://www.yelp.com/developers/v3/manage_app).

Reference: some of the code below are cited from our 15688 homework 1.

In [ ]:

```
#Extract low-rating restaurants from "The Worst Restaurants in the U.S."
open_url = urllib.request.urlopen("https://www.yelp.com/collection/1sSe82mEC_fHMXiDKzcCVQ")
time.sleep(0.5)
soup = BeautifulSoup(open_url, "html.parser")
low_rating_list = []
for url in soup.findAll('a',{'class':'biz-name js-analytics-click'},href=True):
    low_rating_list.append("https://www.yelp.com" + url['href'])
```

In [ ]:

```
'''
Extract restaurants from Pittsburgh sorting by rating
In the following code, we used Yelp API (Obtained by creating an app on
Yelp's Developers site) to extract review data from its website.
'''
def all_restaurants(api_key, query):
    limit = 20
    offset = 0
    urls = []
    while True :
        payload = {'location':query, 'limit': limit, 'offset': offset, 'categories': 'restaurants'}
        headers = {'Authorization':'Bearer '+api_key}
        r = requests.get('https://api.yelp.com/v3/businesses/search', headers = headers, params = payload)
        print(f'get requests with payload {payload}')
        data = json.loads(r.text)
        if 'total' not in data or data['total'] == 0:
            break
        for business in data['businesses']:
            urls.append(business['url'].split('?adjust_creative')[0])
        offset += limit
        time.sleep(1)
    return urls
```

In [ ]:

```
driver = webdriver.PhantomJS()

def extract_reviews(url):
    print(f"crawl {url}?{suffix_url}")
    driver.get(url+'?'+suffix_url)
    soup = BeautifulSoup(driver.page_source, "html.parser")
    divs = soup.find_all('div',itemprop = "review", itemtype="http://schema.org/Review")
    reviews = []
    for div in divs:
        try:
            rating=float(div.find('meta', itemprop="ratingValue")['content'])
            description=div.find('p', itemprop="description").get_text().strip()
            reviews.append([rating, description])
        except Exception as e:
            print(e)

    num_pages = min(int(soup.find('div', attrs={'aria-label':"Pagination navigation"}).div.get_text()[-2:]), 20)
    num_review_per_page = len(reviews)
    for num_page in range(1, num_pages):
        time.sleep(0.5)
        driver.get(url+f"?start={num_review_per_page*num_page}&{suffix_url}")
        print(f"crawl {url}?start={num_review_per_page*num_page}&{suffix_url}")
        soup = BeautifulSoup(driver.page_source, "html.parser")
        divs = soup.find_all('div',itemprop = "review", itemtype="http://schema.org/Review")
        for div in divs:
            try:
                rating = float(div.find('meta', itemprop="ratingValue")['content'])

                description = div.find('p', itemprop="description").get_text().strip()
                reviews.append([rating,  description])
            except Exception as e:
                print(e)
    return reviews
```

In [ ]:

```
def write_to_csv(reviews):
    with open('yelp_review.csv', mode='a') as review_file:
        writer = csv.writer(review_file, delimiter=',',
                                     quotechar='"', quoting=csv.QUOTE_MINIMAL)
        for review in reviews:
            writer.writerow(review)
```

In [ ]:

```
'''
Lower rating restaurants' URLs and Pittsburgh restaurants' URLs are extracted from Yelp's website.
Those URLs are used to scrap the review and rating data in the function extract_reviews.
Finally, reviews and rating data were written in CSV file with csv module.
'''
suffix_url = 'sort_by=rating_asc'
with open('yelp_review.csv', mode='w') as review_file:
    writer = csv.writer(review_file, delimiter=',',quotechar='"', quoting=csv.QUOTE_MINIMAL)
    writer.writerow(['rating', 'review_content'])

    yelp_rest_url = 'yelp_rest_urls.pkl'
    if os.path.exists(yelp_rest_url):
        with open(yelp_rest_url, 'rb') as f:
            urls = pickle.load(f)
    else:
        API_KEY = ""
        urls = all_restaurants(API_KEY, 'Pittsburgh')
        total_url = low_rating_list + urls
        with open(yelp_rest_url, 'wb') as f:
            pickle.dump(urls, f)

    for url in total_url[:400]:
        reviews = extract_reviews(url)
        write_to_csv(reviews)
```

```
crawl https://www.yelp.com/biz/colony-cafe-miami-beach?sort_by=rating_asc
crawl https://www.yelp.com/biz/colony-cafe-miami-beach?start=20&sort_by=rating_asc
crawl https://www.yelp.com/biz/colony-cafe-miami-beach?start=40&sort_by=rating_asc
crawl https://www.yelp.com/biz/colony-cafe-miami-beach?start=60&sort_by=rating_asc
crawl https://www.yelp.com/biz/the-copper-barrel-new-york?sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=20&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=40&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=60&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=80&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=100&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=120&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=140&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=160&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=180&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=200&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=220&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=240&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=260&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=280&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=300&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=320&sort_by=rating_asc
crawl https://www.yelp.com/biz/pepe-rosso-to-go-new-york?start=340&sort_by=rating_asc
crawl https://www.yelp.com/biz/worth-cafe-new-york?sort_by=rating_asc
crawl https://www.yelp.com/biz/worth-cafe-new-york?start=20&sort_by=rating_asc
crawl https://www.yelp.com/biz/steamers-landing-new-york?sort_by=rating_asc
crawl https://www.yelp.com/biz/mr-mikes-pizza-and-italian-restaurant-lake-placid-2?sort_by=rating_asc
```

Shuffle and Clean Scraper Data

Shuffled the dataset to reduce variance and make the model more general. We scraped the reviews for each product, so shuffling is applied to make the dataset random and ensure our training/validation/test sets are representative over the data's distribution.

In [ ]:

```python
def shuffle_csv(file_name, star_map = None):
    df = pd.read_csv(file_name)
    if star_map:
        df['rating'] = df.apply(lambda row: star_map[row['review_rating']], axis = 1)
    df.head()
    df[['review_content','rating']].to_csv(f'shuffle_{file_name}',sep=',', encoding='utf-8', index = False)
```

In the IMDB, the scale of rating of movie review is from 1 to 10. To make it consistent with the yelp and amazon dataset, we map the 1 to 10 star rating to 1 to 5 scale.

In [ ]:

```python
star_map = {1:1, 2:1, 3:2, 4:2, 5:3, 6:3, 7:4, 8:4, 9:5, 10:5}
shuffle_csv('imdb_review.csv', star_map)
shuffle_csv('amazon_review.csv')
shuffle_csv('yelp_review.csv')
```

Preprocess Data

In this section, we want to process and tokenize raw review contents. It contains following steps:

1. Lowercasing all review text data.
2. Not changing the order of each word in the sentence.
3. Lemmatizing the data into a common base form.
4. Only containing numbers and digits characters.
5. Removing stopwords and rare words.

Here, **stopwords** means the words appeared very commonly in a language, such as "and", "a", which are not useful for our problem. So we applied NLTK's list of English stopwords which was removed from our review text. **Rare words** are the words only appeared once in our dataset, which are also considered not helpful.

We also plot a histgram to show the distribution of the appearance number of words.

Reference: some of the code below are cited from our 15688 homework 3.

Text processing

Normalizes case and handles punctuation.

In [4]:
```
def read_data(file_name, columns =['review_content', 'rating'] ):
    df = pd.read_csv(file_name)
    data = df[columns].values.tolist()
    train_data, val_data = sklearn.model_selection.train_test_split(data, shuffle=False, train_size=0.9)
    return train_data, val_data
```

In [5]:
```
imdb_train_data, imdb_val_data = read_data('shuffle_imdb_review.csv')
```

Remove stopwords

1. Set and remove stopwords.
2. Map ten-stars rating standard into five-stars.

In [6]:
```
def preprocess(text, stopwords={}, lemmatizer=nltk.stem.wordnet.WordNetLemmatizer()):
    text = re.sub(r"\'s?", '', text.lower())
    text = re.sub(r'https?:\/\/t\.co\/[a-zA-Z0-9]{10}', ' ', text)
    text = re.sub(r'[^a-zA-Z0-9]',' ',text)

    words = nltk.word_tokenize(text)
    res = []
    for word in words:
        word = lemmatizer.lemmatize(word)
        if word in stopwords:
            continue
        res.append(word)

    return res


def preprocess_data(train_data, val_data, extra_stopwords=set()):
    stopwords = set(nltk.corpus.stopwords.words('english')) | set(["http", "co", "rt", "amp"]) | extra_stopwords
    train, val = [], []
    for i in range(len(train_data)):
        train.append([preprocess(train_data[i][0], stopwords), train_data[i][1]])

    for i in range(len(val_data)):
        val.append([preprocess(val_data[i][0], stopwords), val_data[i][1]])

    return train, val
```

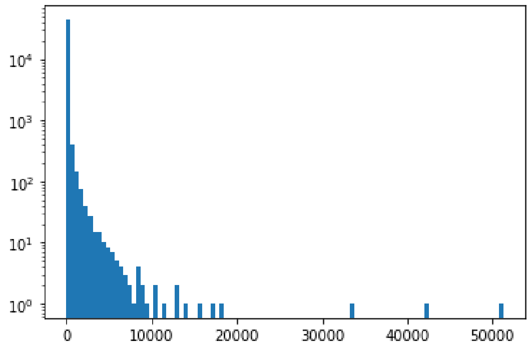
In [7]:
```
imdb_train_set, imdb_val_set = preprocess_data(imdb_train_data, imdb_val_data)
```

Plot histogram

Log-scaled histogram is plotted to show the distribution of the appearance frequency of words in dataset.

In [8]:
```
def get_distribution(data_train):
    counter = collections.defaultdict(lambda: 0)
    for data in data_train:
        for word in data[0]:
            counter[word] +=1
    return counter
```

In [9]:
```
imdb_dist = get_distribution(imdb_train_set)
plt.hist(imdb_dist.values(), bins=100)
plt.yscale('log')
```



Remove rare words

We selected the words which only appear once in the dataset as rare words and removed from our data. It enables to improve the efficiency and precision of our models.

In [10]:
```
def get_rare_words(dist):
    rare_words = set()
    dist = dict(dist)
    for word in dist.keys():
        if dist.get(word) == 1:
            rare_words.add(word)
    return rare_words
```

In [11]:
```
imdb_rare_words = get_rare_words(imdb_dist)
imdb_train_set, imdb_val_set = preprocess_data(imdb_train_data, imdb_val_data, imdb_rare_words)
```

Create features

We creates the feature and label for training and validation sets.

In [12]:
```
def do_nothing(x):
    return x

def create_features(train_data, val_data):
    tfidf = sklearn.feature_extraction.text.TfidfVectorizer(
        analyzer='word',
        tokenizer=do_nothing,
        preprocessor=do_nothing,
        token_pattern=None
    )
    train_words = [data[0] for data in train_data]
    train_labels = np.array([data[1] for data in train_data])
    val_words = [data[0] for data in val_data]
    val_labels = np.array([data[1] for data in val_data])
    tfidf.fit(train_words)
    train_features = tfidf.transform(train_words)
    val_features = tfidf.transform(val_words)

    return (train_features, train_labels, val_features, val_labels)
```

In [13]:
```
imdb_train_features, imdb_train_labels, imdb_val_features, imdb_val_labels = create_features(imdb_train_set, imdb_
```

In [14]:

```
amazon_train_data, amazon_val_data = read_data('shuffle_amazon_review.csv')
amazon_train_set, amazon_val_set = preprocess_data(amazon_train_data, amazon_val_data)
amazon_dist = get_distribution(amazon_train_set)
amazon_rare_words = get_rare_words(amazon_dist)
amazon_train_set, amazon_val_set = preprocess_data(amazon_train_data, amazon_val_data, amazon_rare_words)
amazon_train_features, amazon_train_labels, amazon_val_features, amazon_val_labels = create_features(amazon_train_
```

In [15]:

```
yelp_train_data, yelp_val_data = read_data('shuffle_yelp_review.csv')
yelp_train_set, yelp_val_set = preprocess_data(yelp_train_data, yelp_val_data)
yelp_dist = get_distribution(yelp_train_set)
yelp_rare_words = get_rare_words(yelp_dist)
yelp_train_set, yelp_val_set = preprocess_data(yelp_train_data, yelp_val_data, yelp_rare_words)
yelp_train_features, yelp_train_labels, yelp_val_features, yelp_val_labels = create_features(yelp_train_set, yelp_
```

Data Visualization

Through data visualization, we can represent some information in the data set in different forms. We can find the most frequent words through word cloud, and also find the words that have a greater impact on the model, so as to have a more intuitive understanding of the distribution of the data set.

WordCloud

“ Wordcloud is a data visualization tool which can represent text data in which the size of each word indicates its frequency or importance. ”（Cited from Generating Word Cloud in Python (https://www.geeksforgeeks.org/generating-word-cloud-python/))

In [16]:

```
def draw_cloud(text,max_words=20,width=1000,height=800):
    """Draw wordcloud plot
    args:
        text:str, preprocessed text
        max_words: int, maximum number of words in plot
        width, height: int, size of the plot
    """
    wordcloud = WordCloud(
        background_color="white",
        width=width,
        height=height,
        max_words=max_words
    ).generate(text)

    plt.imshow(wordcloud)
    plt.axis('off')
```

Wordcloud of top N words for movie ID

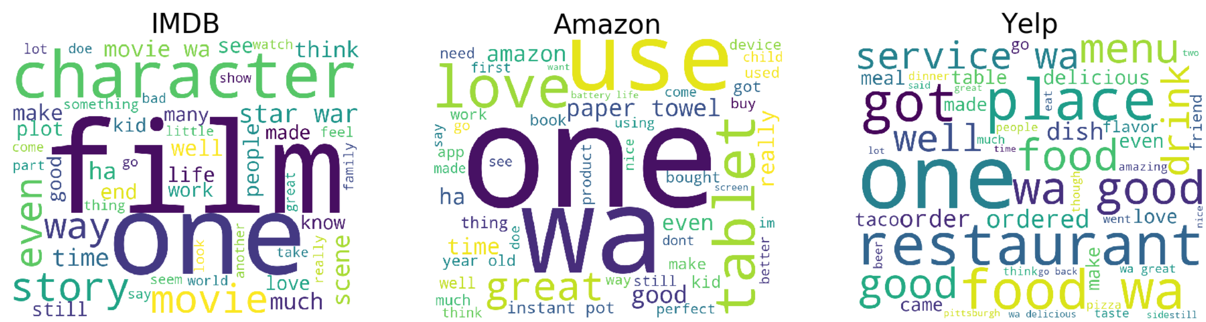
Generate the wordcloud plot for the top N words appearing in the reviews based on movie ID. Here, we selected the plot to show the top 50 words.

In [17]:

```
def draw_cloud_exe(train, val):
    allWords = []
    allRating = []

    for i in train:
        allWords += i[0]
        allRating.append(i[1])
    for i in val:
        allWords += i[0]
        allRating.append(i[1])

    allWordsString = ' '.join(allWords)
    draw_cloud(allWordsString,max_words=50)
```

In [18]:

```
fig = plt.figure(figsize=(32,8))

plt.subplot(1, 3, 1).set_title('IMDB', fontsize=40)
draw_cloud_exe(imdb_train_set, imdb_val_set)

plt.subplot(1, 3, 2).set_title('Amazon', fontsize=40)
draw_cloud_exe(amazon_train_set, amazon_val_set)

plt.subplot(1, 3, 3).set_title('Yelp', fontsize=40)
draw_cloud_exe(yelp_train_set, yelp_val_set)

plt.show()
```



Distribution of the length of reviews

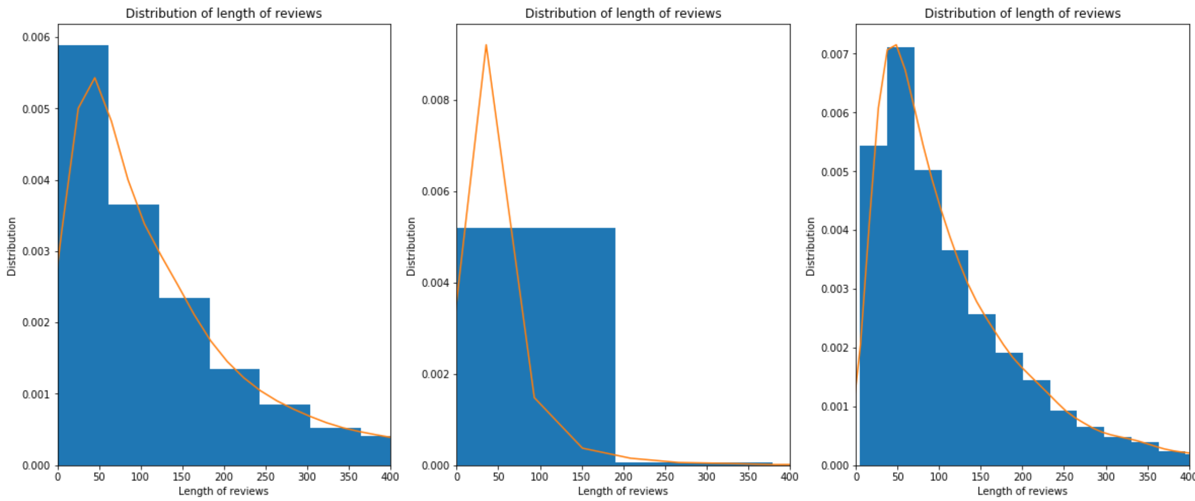
In [19]:

```
def review_length_distribution(filename):
    df = pd.read_csv(filename)
    lengthList = [i.count(" ") + 1 for i in df['review_content']]
    lengthList = pd.Series(lengthList)
    plt.hist(lengthList, bins=30, histtype='bar', normed=True)
    plt.xlim(0,400)
    plt.xlabel('Length of reviews')
    plt.ylabel('Distribution')
    plt.title('Distribution of length of reviews')

    seaborn.kdeplot(lengthList)
```

In [20]:

```
fig = plt.figure(figsize=(20,8))

plt.subplot(1, 3, 1).set_title('IMDB', fontsize=40)
review_length_distribution('shuffle_imdb_review.csv')

plt.subplot(1, 3, 2).set_title('Amazon', fontsize=40)
review_length_distribution('shuffle_amazon_review.csv')

plt.subplot(1, 3, 3).set_title('Yelp', fontsize=40)
review_length_distribution('shuffle_yelp_review.csv')

plt.show()
```

```
/Users/spencer/anaconda3/envs/project/lib/python3.7/site-packages/ipykernel_launcher.py:5: MatplotlibDeprecati
The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.
  """
```



Distribution of rating scores

We plotted a histogram of the rating scores. From the plot, we can see that

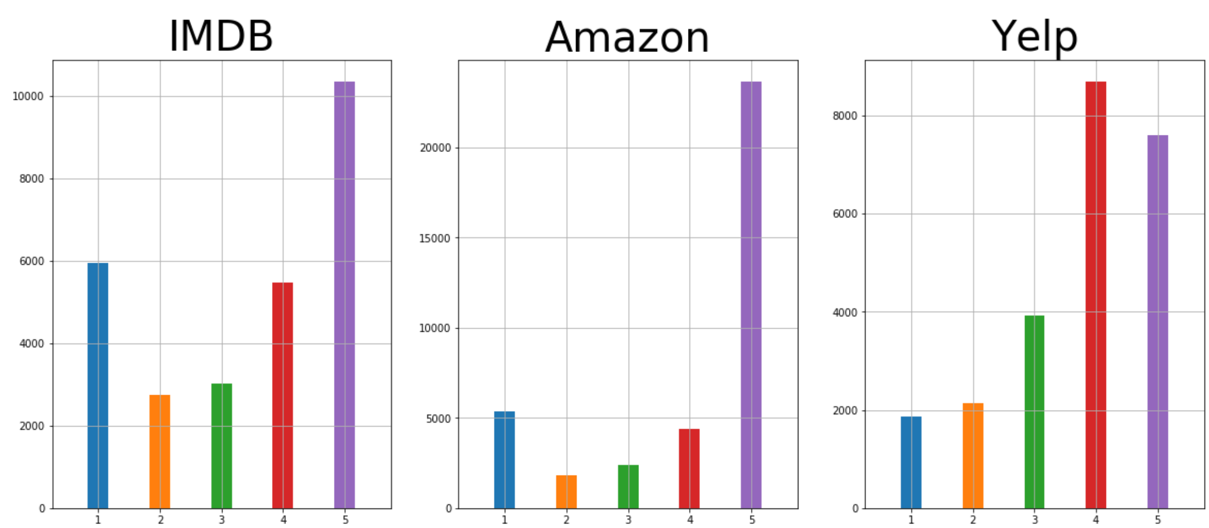
In [23]:

```
def show_class_distribution(filename):
    df = pd.read_csv(filename)
    rating_groups = df.groupby(df['rating'])['rating']
    rating_groups.hist(bins = 3)
    print(rating_groups.count())
    print(f"total: {rating_groups.count().values.sum()}")
```

In [24]:

```
fig = plt.figure(figsize=(20,8))

plt.subplot(1, 3, 1).set_title('IMDB', fontsize=40)
show_class_distribution('shuffle_imdb_review.csv')

plt.subplot(1, 3, 2).set_title('Amazon', fontsize=40)
show_class_distribution('shuffle_amazon_review.csv')

plt.subplot(1, 3, 3).set_title('Yelp', fontsize=40)
show_class_distribution('shuffle_yelp_review.csv')

plt.show()
```

```
rating
1     5935
2     2736
3     3029
4     5477
5    10357
Name: rating, dtype: int64
total: 27534
rating
1     5382
2     1810
3     2404
4     4375
5    23678
Name: rating, dtype: int64
total: 37649
rating
1    1870
2    2147
3    3933
4    8698
5    7601
Name: rating, dtype: int64
total: 24249
```



Word counts of keywords

LDA is an unsupervised bayesian model that can be used to identify underlying topic information in a document collection or corpus.

With the LDA model, we can find out some words appeared the most are not always meaningful, like **'one'**, which would not benefit our model. We can remove the words which appear in high frequency but with little weight to improve the quality of datasets.

Attention: All the code cells in this section will take long time(over 2 hr) to run

In [ ]:

```
'''
For each document in the corpus, LDA defines the following generation process:
1. For each document, extract a topic from the topic distribution;
2. Extract one word from the word distribution corresponding to the topic selected above;
3. Repeat the process until you iterate over each word in the document.
Each document in the corpus with four theme a multinomial distribution, corresponding to the multinomial distribut
Each topic in turn corresponds to a multinomial distribution of 10 words in the vocabulary, denoted as.
'''

def lda_modeling(train, val):
    data_ready = []
    for i in train:
        data_ready.append(i[0])
    for i in val:
        data_ready.append(i[0])

    id2word = corpora.Dictionary(data_ready)
    # create Corpus: Term Document Frequency
    corpus = [id2word.doc2bow(text) for text in data_ready]
    # build LDA model
    lda_model = gensim.models.ldamodel.LdaModel(corpus=corpus,
                                               id2word=id2word,
                                               num_topics=4,
                                               random_state=100,
                                               update_every=1,
                                               chunksize=10,
                                               passes=100,
                                               alpha='symmetric',
                                               iterations=100,
                                               per_word_topics=True)
    return lda_model
```

In [ ]:

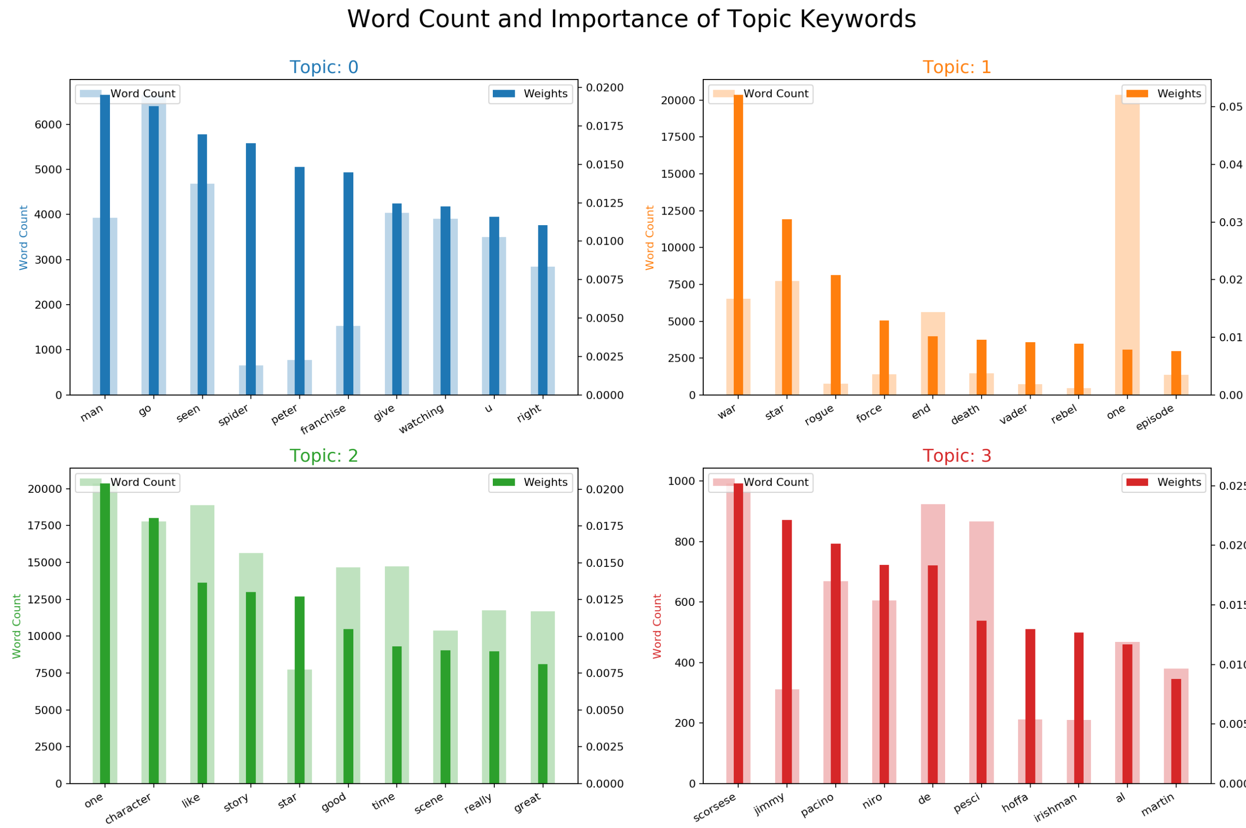
```
lda_model = lda_modeling(imdb_train_set, imdb_val_set)
```

Chose 4 topics as the number of classes for LDA model and top 10 words for each topic.

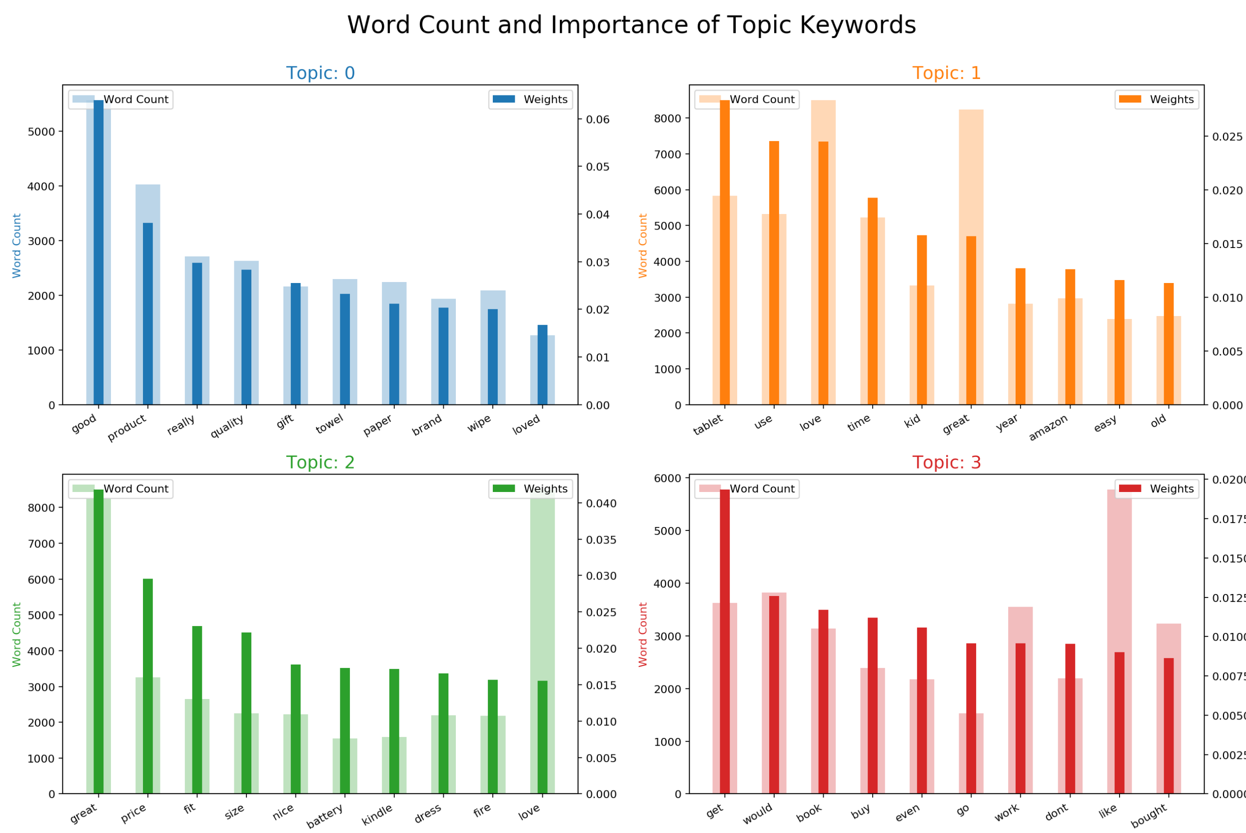
In [ ]:

```
topics = lda_model.show_topics(formatted=False)
data_flat = [w for w_list in data_ready for w in w_list]
counter = Counter(data_flat)

out = []
for i, topic in topics:
    for word, weight in topic:
        out.append([word,i,weight,counter[word]])

df = pd.DataFrame(out, columns=['word', 'topic_id', 'importance', 'word_count'])

# Plot Word Count and Weights of Topic Keywords
fig, axes = plt.subplots(2, 2, figsize=(16,10), dpi=160)
cols = [color for name, color in mcolors.TABLEAU_COLORS.items()]
for i,ax in enumerate(axes.flatten()):
    ax.bar(x='word', height="word_count", data=df.loc[df.topic_id==i, :], color=cols[i], width=0.5, alpha=0.3, lab
    ax_twin = ax.twinx()
    ax_twin.bar(x='word', height="importance", data=df.loc[df.topic_id==i, :], color=cols[i], width=0.2, label='We
    ax.set_ylabel('Word Count', color=cols[i])
    ax.set_title('Topic: ' + str(i), color=cols[i], fontsize=16)
    ax.set_xticklabels(df.loc[df.topic_id==i, 'word'], rotation=30, horizontalalignment= 'right')
    ax.legend(loc='upper left'); ax_twin.legend(loc='upper right')

fig.tight_layout(w_pad=2)
fig.suptitle('Word Count and Importance of Topic Keywords', fontsize=22, y=1.05)
plt.show()
```

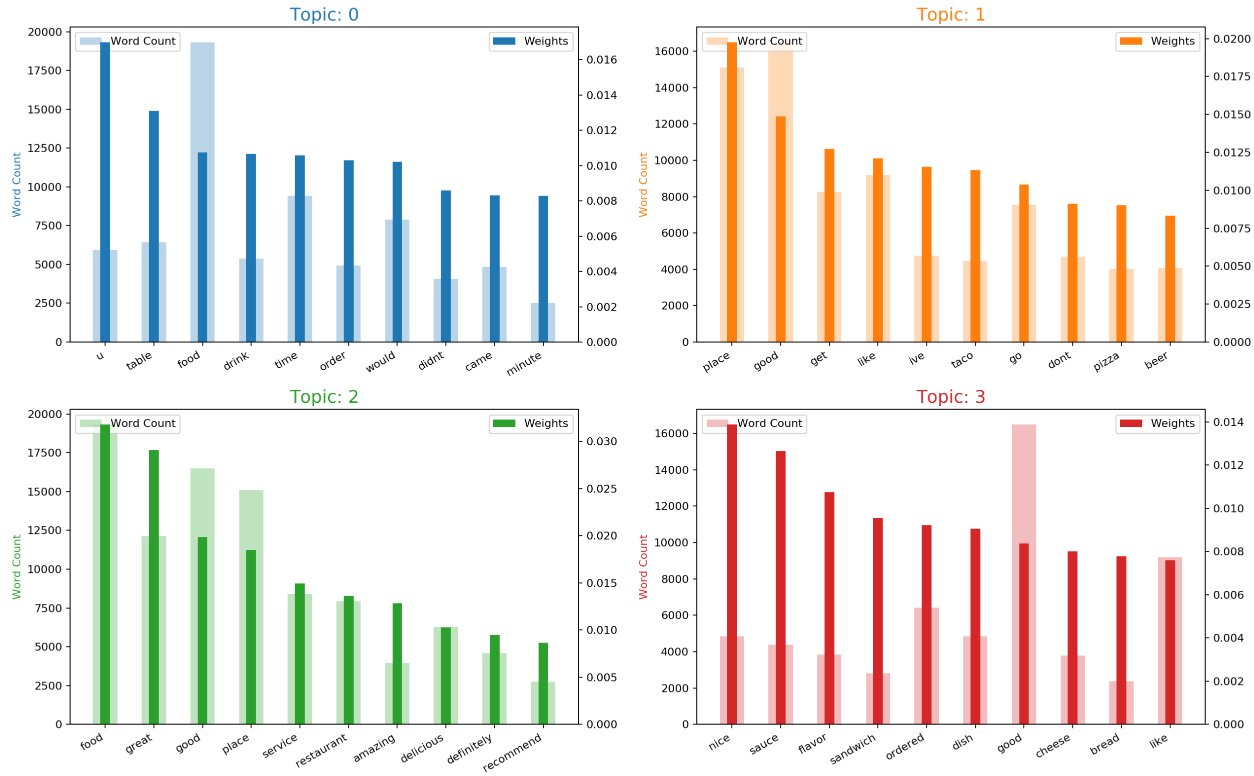
IMDB


Word Count and Importance of Topic Keywords
Topic: 0
Word Count
Weights
man go seen spider peter franchise give watching u right
Topic: 1
war star rogue force end death vader rebel one episode
Topic: 2
one character like story star good time scene really great
Topic: 3
scorsese jimmy pacino niro de pesci hoffa irishman al martin

Amazon


Word Count and Importance of Topic Keywords
Topic: 0
Word Count
Weights
good product really quality gift towel paper brand wipe loved
Topic: 1
tablet use love time kid great year amazon easy old
Topic: 2
great price fit size nice battery kindle dress fire love
Topic: 3
get would book buy even go work dont like bought

Yelp



In [25]:
```
extra_stopwords = set(['one'])
```

In [26]:
```
imdb_train_set, imdb_val_set = preprocess_data(imdb_train_data, imdb_val_data, imdb_rare_words|extra_stopwords)
imdb_train_features, imdb_train_labels, imdb_val_features, imdb_val_labels = create_features(imdb_train_set, imdb_
```

In [27]:
```
amazon_train_set, amazon_val_set = preprocess_data(amazon_train_data, amazon_val_data, amazon_rare_words|extra_stc
amazon_train_features, amazon_train_labels, amazon_val_features, amazon_val_labels = create_features(amazon_train_
```

In [28]:
```
yelp_train_set, yelp_val_set = preprocess_data(yelp_train_data, yelp_val_data, yelp_rare_words|extra_stopwords)
yelp_train_features, yelp_train_labels, yelp_val_features, yelp_val_labels = create_features(yelp_train_set, yelp_
```

Model Training and Evaluation

SVM

"Support Vector Machine (SVM) is a supervised machine learning algorithm which can be used for both classification and regression problems."(Cited from Understanding Support Vector Machine algorithm from examples (https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example-code/)) Since our project deals with a multiclass classification problem, it's reasonable to apply SVM to classify the multi-classes review and rating data.

Reasons for using SVM (linear Kernel):

1. Since our text data set is linearly separatable, it is a good choice to use SVM, especially linear Kernel.
2. Linear kernel works well with linearly separatable data and has better performance on our dataset compared with RBF Kernel.

In [29]:
```
def train_svm(train_features, train_labels):
    svc = sklearn.svm.SVC(kernel = 'linear')
    svc.fit(train_features, train_labels)
    return svc
```

Naive Bayes

Naive Bayes classifier is a classification algorithm based on Bayes' theorem. The classification principle of bayes classifier is to calculate the posterior probability through prior probability and use bayes formula to select the classification result corresponding to the maximum posterior probability.

Reasons for using Naive Bayes:

1. Naive bayesian model originates from classical mathematical theory and has stable classification efficiency.
2. Good at small-scale data, able to handle multiple classification tasks, suitable for incremental training.
3. It is not sensitive to missing data, and the algorithm is relatively simple, which is often used for text classification.

In [30]:
```
def train_nb(train_features, train_labels):
    nb = sklearn.naive_bayes.MultinomialNB(alpha=1.0, fit_prior=False, class_prior=None)
    nb.fit(train_features, train_labels)
    return nb
```

Logistic Regression

"Logistic egression (LR) is named for its underlying function ---- the logistic function." (Cited from Logistic Regression for Machine Learning (https://machinelearningmastery.com/logistic-regression-for-machine-learning/)). Despite the name logistic regression, it is commonly used in classification, which is suitable for our case.

In multi-class logistic regression, we use the multi-class parameter to determine the choice of our classification method: ovr or multinomial. (The default parameter is OvR) During parameter tuning, we found that multinomial has the same performance with OvR, but OvR performs quicker than multinomial. Therefore, we decided to use OvR to train our data, which is efficient.

Reasons for using LR:

1. No need for tuning.
2. Implementing LR algorithm is easy and of high efficiency.

In [31]:
```
def train_lr(train_features, train_labels):
    lr = sklearn.linear_model.LogisticRegression(max_iter=1000)
    lr.fit(train_features, train_labels)
    return lr
```

In [32]:
```
def evaluate(model, val_features, val_labels):
    pred = model.predict(val_features)
    print(f'accuracy: {sklearn.metrics.accuracy_score(val_labels, pred)}')
    disp = sklearn.metrics.plot_confusion_matrix(model, val_features, val_labels,
                                     cmap=plt.cm.Blues,
                                     normalize='true')
    return pred
```

In [33]:
```
imdb_svm = train_svm(imdb_train_features, imdb_train_labels)
imdb_nb = train_nb(imdb_train_features, imdb_train_labels)
imdb_lr = train_lr(imdb_train_features, imdb_train_labels)
```

In [34]:
```
amazon_svm = train_svm(amazon_train_features, amazon_train_labels)
amazon_nb = train_nb(amazon_train_features, amazon_train_labels)
amazon_lr = train_lr(amazon_train_features, amazon_train_labels)
```

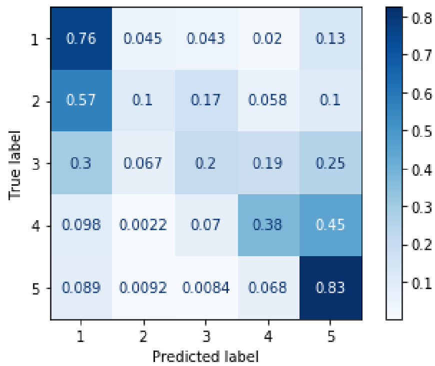
In [35]:
```
yelp_svm = train_svm(yelp_train_features, yelp_train_labels)
yelp_nb = train_nb(yelp_train_features, yelp_train_labels)
yelp_lr = train_lr(yelp_train_features, yelp_train_labels)
```

IMDB Results

In [36]:
```
evaluate(imdb_svm, imdb_val_features, imdb_val_labels)
```

```
accuracy: 0.6089324618736384
```

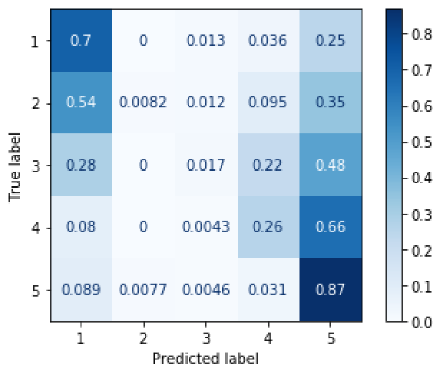
Out[36]:
```
array([5, 5, 5, ..., 1, 1, 1])
```



In [37]:
```
evaluate(imdb_nb, imdb_val_features, imdb_val_labels)
```

```
accuracy: 0.5708061002178649
```

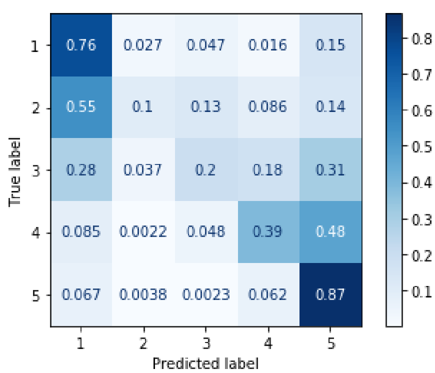
Out[37]:
```
array([5, 5, 5, ..., 1, 1, 1])
```



In [38]:
```
evaluate(imdb_lr, imdb_val_features, imdb_val_labels)
```

```
accuracy: 0.6292665214233841
```

Out[38]:
```
array([5, 5, 5, ..., 1, 1, 1])
```

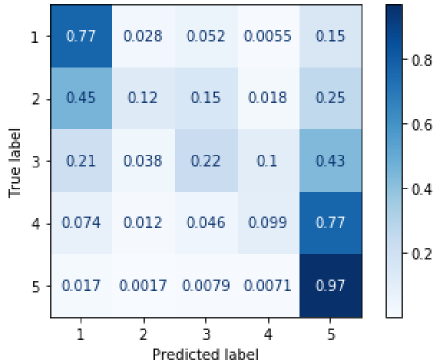


Amazon Results

In [39]:
```
evaluate(amazon_svm, amazon_val_features, amazon_val_labels)
```

```
accuracy: 0.7543160690571049
```

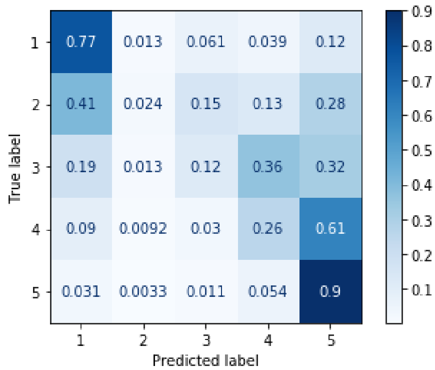
Out[39]:
```
array([5, 5, 5, ..., 1, 1, 5])
```



In [40]:
```
evaluate(amazon_nb, amazon_val_features, amazon_val_labels)
```

```
accuracy: 0.7205843293492696
```

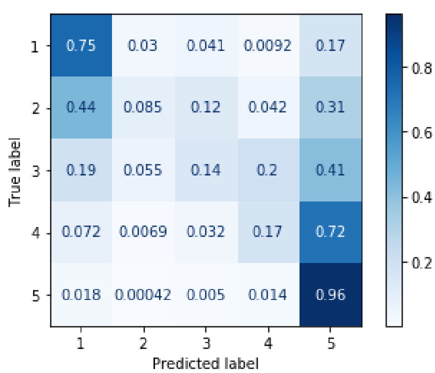
Out[40]:
```
array([5, 5, 5, ..., 1, 1, 5])
```



In [41]:
```
evaluate(amazon_lr, amazon_val_features, amazon_val_labels)
```

```
accuracy: 0.751660026560425
```

Out[41]:
```
array([5, 5, 5, ..., 1, 4, 5])
```

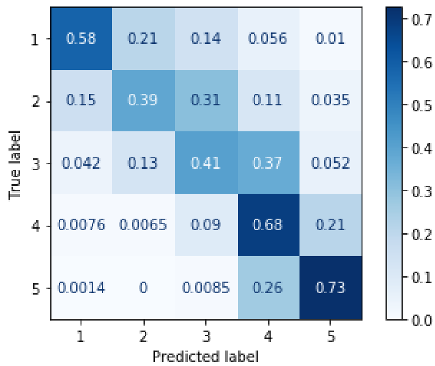


Yelp Results

In [42]:
```
evaluate(yelp_svm, yelp_val_features, yelp_val_labels)
```

```
accuracy: 0.6177319587628866
```

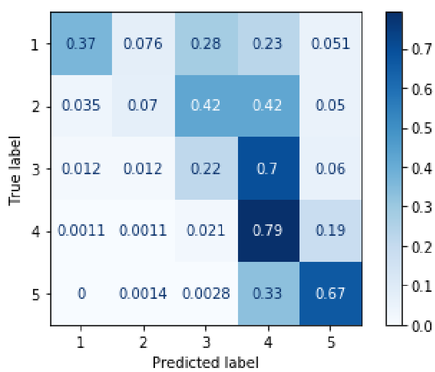
Out[42]:
```
array([5, 4, 5, ..., 4, 5, 5])
```



In [43]:
```
evaluate(yelp_nb, yelp_val_features, yelp_val_labels)
```

```
accuracy: 0.5657731958762887
```

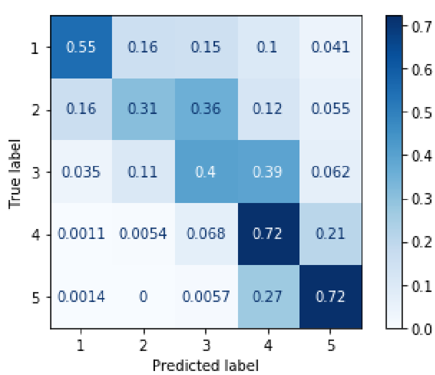
Out[43]:
```
array([4, 3, 4, ..., 4, 5, 5])
```



In [44]:
```
evaluate(yelp_lr, yelp_val_features, yelp_val_labels)
```

```
accuracy: 0.6202061855670103
```

Out[44]:
```
array([4, 3, 5, ..., 4, 5, 5])
```



Result Summary

Model	IMDB	Amazon	Yelp
SVM	60.89%	75.43%	61.77%
Naive Bayes	57.08%	72.06%	56.58%
Logistic Regression	62.92%	75.16%	62.02%

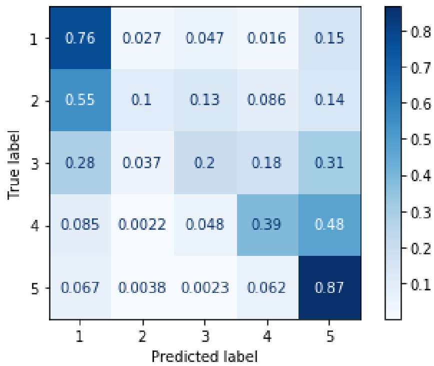
We can find that among the three models, the Logistic Regression model and Support Vector Machine model perform better than Naive Bayes model. Among three datasets, Amazon dataset performs better than IMDB dataset and Yelp dataset.

Result Analysis

We choose the best model and IMDB dataset to analyse the prediction.

In [45]:
```
imdb_pred_labels = evaluate(imdb_lr, imdb_val_features, imdb_val_labels)
```

```
accuracy: 0.6292665214233841
```



The result showed that 86% 1-star reviews and 86% 5-star reviews are predicted correctly. There are also some 2-star reviews being predicted as 1-star and some 3-star, 4-star reviews being predicted as 5-star. As when people give a rating in middle range, their wording might seems 'good' or 'bad', so these mispredictions are reasonable. However, there are 12% 2-star reviews which are predicted as 5-star. They deviate heavily from the true rating. So we tried to find these instances to figure out where the problem lies.

In [46]:
```
def get_t1p5(val_labels, pred_labels, val_data):
    true_label = set(np.where(val_labels == 1)[0])
    pred_label = set(np.where(pred_labels == 5)[0])
    index_list = true_label & pred_label
    T1P5 = list(index_list)
    t1p5_list = []
    for i in T1P5:
        t1p5_list.append(val_data[i])

    return t1p5_list
```

In [53]:
```
bad_predictions = get_t1p5(imdb_val_labels, imdb_pred_labels, imdb_val_data)
```

We picked several reviews which should be 1 score but get 5 in prediction to analyse why the prediction is wrong, which will help us improve the model and feature extraction process in the future:

```
1. 'Just came back from movie. Wow was it great. Best Star Wars movie ever. The new Solo is unlike any character in any
movie. Old grumpy Harrison can't compete with this new actor.'
2. 'The back story of such a comp!ex and likable character as Hans Solo should be exciting, interesting and worth
watching.\nPity the film managed to make me not care anymore.'
3. 'The best part of this film is when the end credits come on!'
```

We can see that the wrongly predicted reviews all have some positive words like 'great', 'best' and some reviews even use irony, which is really hard for our model to detect the true underlying sentiment. We should consider more complex model such as bi-direction LSTM.

And we even find the review with replicated phrases in the dataset:

```
'This is basically FSOG but for kiddies. Insert text, insert text, insert text, insert text, insert text, inser
t text, insert text, insert text, insert text, insert text, insert text, insert text, insert text, insert text,
insert text, insert text, insert text, insert text, insert text, insert text, insert text, insert text, insert
text, insert text, insert text, insert text, insert text, insert text, insert text, insert text, insert text, i
nsert text, insert text, insert text, insert text, insert text, insert text, insert text, insert text, insert t
ext, insert text, insert text, insert text, insert text, insert text, insert text, insert text, insert text, in
sert text, insert text, insert text, insert text.'
```

We should further clean the dataset more carefully to get rid of the above reviews.

Apply IMDB model on Amazon and Yelp

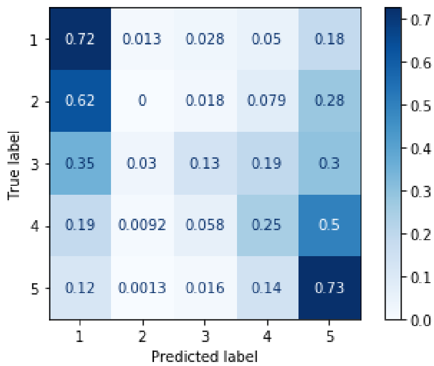
We further use the IMDB model to predict rating scores on Amazon and Yelp dataset to see whether the IMDB model is general and can be expaned furth.

In [48]:
```
cross_amazon_train_features, cross_amazon_train_labels, cross_amazon_val_features, cross_amazon_val_labels = creat
```

In [49]:
```
cross_yelp_train_features, cross_yelp_train_labels, cross_yelp_val_features, cross_yelp_val_labels = create_featur
```

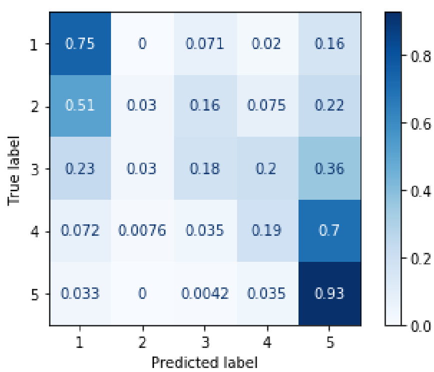
In [50]:
```
imdb_amazon = evaluate(imdb_lr, cross_amazon_val_features, cross_amazon_val_labels)
```

```
accuracy: 0.601593625498008
```



In [51]:
```
imdb_yelp = evaluate(imdb_lr, cross_yelp_val_features, cross_yelp_val_labels)
```

```
accuracy: 0.4329896907216495
```



Conclusion

1. By constructing and comparing different machine learning models, we found that the logistic regression model could get the accuracy of 62.92% on the IMDB dataset, 75.16% on the Amazon dataset, and 62.02% on the Yelp dataset. This shows that the trained logistic regression model can be applied to different websites to predict the score by analyzing the review text, so as to solve the problems raised by us.
2. Based on the results, we can extend our model trained on movie reviews to shopping reviews. However, the model may not be applied to restaurant reviews because of the distance between language models of movie and restaurant are larger than the distance between language models of movie and shopping.
3. In addition, the data mining tools and data visualization tools we provide can be applied to most websites to obtain the information people need and carry out some analysis.

Future Works

1. Data Collection: get more data from IMDB, Amazon and Yelp website to make the model more general. More carefully clean the dataset to get rid of review with simple replicated words.
2. Feature Extraction: Use GPU to train deep learning models like bi-directional LSTM to extract the features or make prediction on the reviews.
3. Model: Hyperprameter tuning for the three models. And can try to train a general model on the combined three dataset.
4. Analysis: Pick more wrongly predicted data to review.

Reference and Further Readings

- Code from Homework 1 and Homework 3
- DavidRoldan523/amazon_reviews_allpages (https://github.com/DavidRoldan523/amazon_reviews_allpages/blob/master/scraper_amazon_threading_version.py)
- Scraping the Web: A fast and simple way to scrape Amazon (https://medium.com/@tusharseth93/scraping-the-web-a-fast-and-simple-way-to-scrape-amazon-b3d6d74d649f)
- Understanding Support Vector Machine algorithm from examples (https://www.analyticsvidhya.com/blog/2017/09/understaing-support-vector-machine-example-code/)
- Logistic Regression for Machine Learning (https://machinelearningmastery.com/logistic-regression-for-machine-learning/)
- The Logistic Regression Algorithm (https://machinelearning-blog.com/2018/04/23/logistic-regression-101/)
- Generating Word Cloud in Python (https://www.geeksforgeeks.org/generating-word-cloud-python/)