Goodreads

April 27, 2022

1 Step0: Importing libraries

```
[ ]: import pandas as pd
     import numpy as np
     import os
     import matplotlib.pyplot as plt
     import seaborn as sns
     import time
     from sklearn.feature_extraction.text import CountVectorizer

     %matplotlib inline

     import string
     import nltk
```

```
[ ]: # mount gdrive
     from google.colab import drive
     drive.mount('/gdrive')
```

```
Mounted at /gdrive
```

2 Step1: Loading Data

```
[ ]: # change root to the necessary path
     root = "/gdrive/MyDrive/ads_proj5/ads-spring-2022-prj5-group-4/"
     outputs_dir = root + "output/"
     lib_dir = root + "lib/"

     assert os.path.exists(root), 'Check the path to your root directory'
     assert os.path.exists(outputs_dir), 'Check the path to your outputs directory'
     assert os.path.exists(lib_dir), 'Check the path to your lib directory'
```

```
[ ]: data = pd.read_csv(outputs_dir+'goodreads_reviews_spoiler.csv')
```

```
[ ]: df = data.drop(["has_spoiler", 'Unnamed: 0'], axis=1)
     df = df.rename(columns={"class": "has_spoiler"}, errors="raise")
```

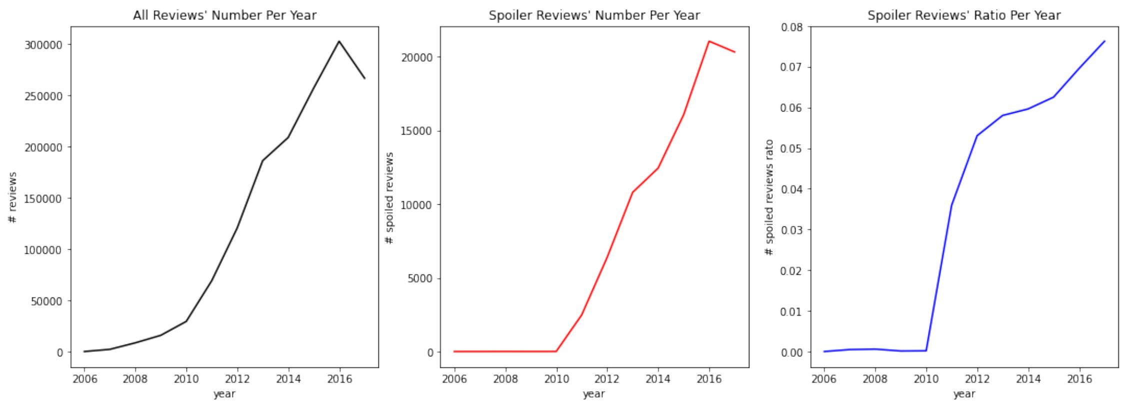
```
[ ]: print('There are {} rows and {} columns in subset data'.format(df.shape[0],df.
     ↪shape[1]))
```

```
There are 1466895 rows and 7 columns in subset data
```

3 Step2: Exploratory Data Analysis

3.1 Overview of original dataset

```
[ ]: df['year'] = pd.DatetimeIndex(df['timestamp']).year.values

     year_all = df.year.value_counts().reset_index().rename(columns={'index':'year',␣
     ↪'year':'count'})
     year_spoiler =  df[df.has_spoiler == 1].year.value_counts().reset_index().
     ↪rename(columns={'index':'year', 'year':'spoiler_count'})

     year_ratio = year_all.merge(year_spoiler, on='year', how='left').fillna(0)
     year_ratio['ratio'] = year_ratio['spoiler_count']/year_ratio['count']

     fig, ax = plt.subplots(1, 3, figsize=(18, 6))

     sns.lineplot(x='year', y='count', data=year_ratio, ax=ax[0], color='black')
     ax[0].set_ylabel('# reviews')
     ax[0].set_xlabel('year')
     ax[0].set_title("All Reviews' Number Per Year")

     sns.lineplot(x='year', y='spoiler_count', data=year_ratio, ax=ax[1],␣
     ↪color='red')
     ax[1].set_ylabel('# spoiled reviews')
     ax[1].set_xlabel('year')
     ax[1].set_title("Spoiler Reviews' Number Per Year")

     sns.lineplot(x='year', y='ratio', data=year_ratio, ax=ax[2], color='blue')
     ax[2].set_ylabel('# spoiled reviews rato')
     ax[2].set_xlabel('year')
     ax[2].set_title("Spoiler Reviews' Ratio Per Year")

     plt.show()
```



Surprisingly the plots show that there are no spoiler reviews before 2011 and upon further research we found that GoodReads didn't support the spoiler tag until 2011. Therefore, when we subsetted the data we filtered out reviews before 2011

3.1.1 spoiler ratio

```
[ ]: def remove_punct(text):
         table=str.maketrans('','',string.punctuation)
         return text.translate(table)

     tokenizer = nltk.tokenize.WhitespaceTokenizer()

     sub_df['review'] = sub_df['review'].apply(lambda x: remove_punct(x))
     sub_df['token'] = sub_df['review'].apply(lambda x: tokenizer.tokenize(x))
```

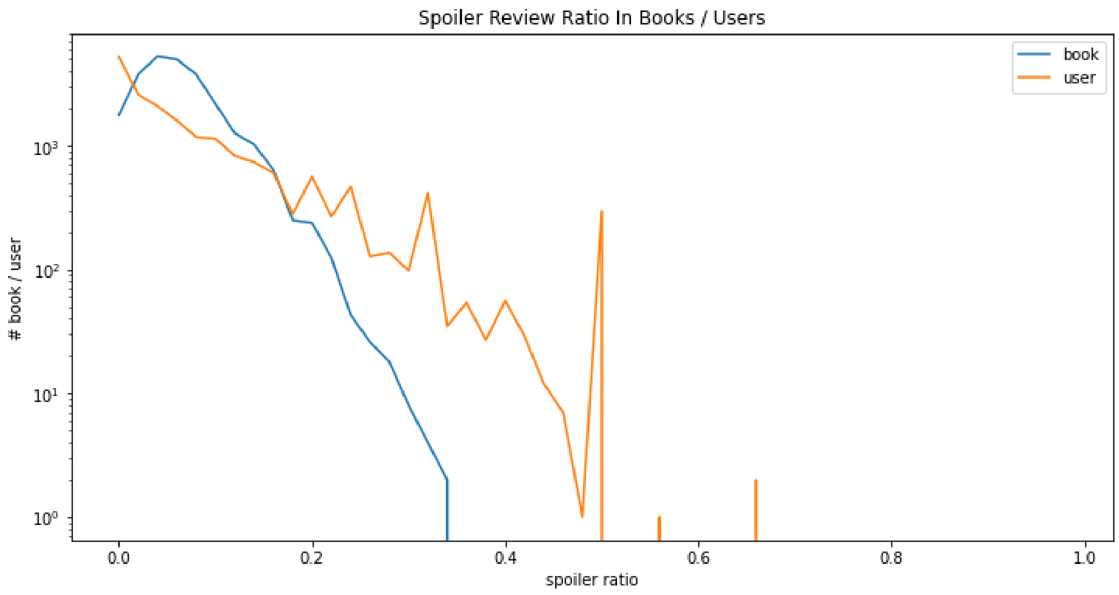
```
[ ]: df = df[df.year>=2011]

     spoiler_num_book = {}
     review_num_book = {}
     for index, line in df.iterrows():
         review_num_book[line['book_id']] = review_num_book.get(line['book_id'], 0)␣
      ↪+ 1
         if line['has_spoiler']:
             spoiler_num_book[line['book_id']] = spoiler_num_book.
      ↪get(line['book_id'], 0) + 1
     spoiler_ratio_book = {}
     for key in review_num_book:
         spoiler_ratio_book[key] = spoiler_num_book.get(key, 0) / ␣
      ↪review_num_book[key]
```

```
[ ]: spoiler_num_user = {}
     review_num_user = {}
     for index, line in df.iterrows():
```

```
    review_num_user[line['user_id']] = review_num_user.get(line['user_id'], 0)␣
 ↪+ 1
    if line['has_spoiler']:
        spoiler_num_user[line['user_id']] = spoiler_num_user.
 ↪get(line['user_id'], 0) + 1
spoiler_ratio_user = {}
for key in review_num_user:
    spoiler_ratio_user[key] = spoiler_num_user.get(key, 0) / ␣
 ↪review_num_user[key]
```

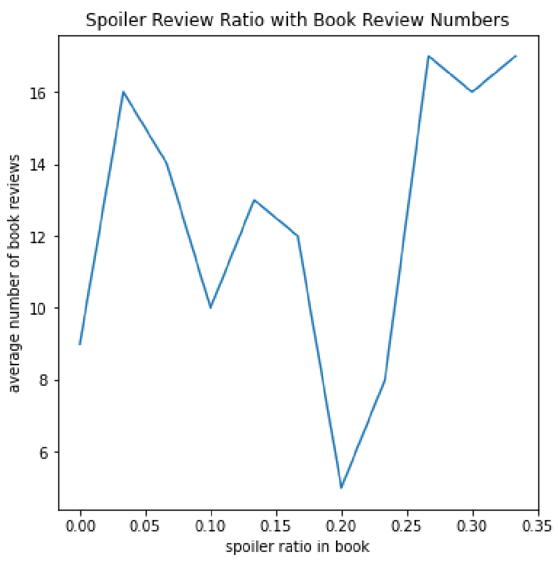
[ ]:
```
def plot(lists, bin_= 50):
    result = {}
    for element in lists:
        result[int(element*bin_)] = result.get(int(element*bin_), 0) + 1
    return result
```

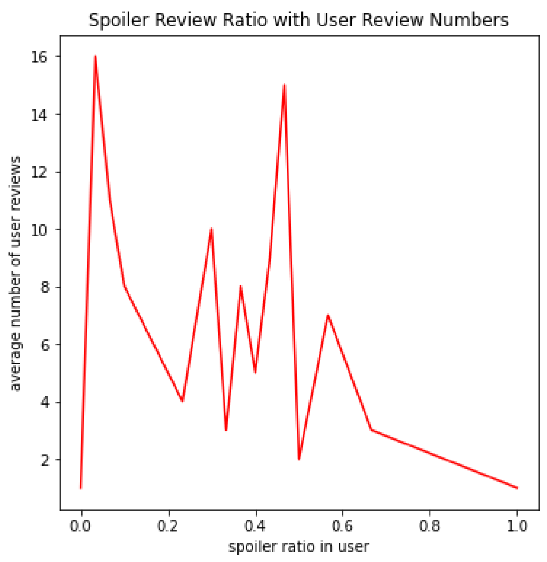
[ ]:
```
fig = plt.figure(figsize=(12, 6))
result = plot(list(spoiler_ratio_book.values()))
y = []
X = []
for key in range(50):
    y.append(key/50)
    X.append(result.get(key, 0))
plt.plot(y, X, label='book')
result = plot(list(spoiler_ratio_user.values()))
y = []
X = []
for key in range(50):
    y.append(key/50)
    X.append(result.get(key, 0))
plt.plot(y, X, label='user')
plt.ylabel('# book / user')
plt.xlabel('spoiler ratio')
plt.yscale('log', nonposy='clip')
plt.title("Spoiler Review Ratio In Books / Users")
plt.legend()
plt.show()
```



[ ]:
```
fig, ax = plt.subplots(1, 2, figsize=(13,6))

review_num_to_ratio = {}
for book in review_num_book:
    review_num_to_ratio[int(spoiler_ratio_book.get(book,0)*30)] =␣
 ↪review_num_book.get(book,0)
keys = list(review_num_to_ratio.keys())
for num in keys:
    review_num_to_ratio[num] = np.mean(review_num_to_ratio[num])
X = sorted(list(review_num_to_ratio.keys()))
y = []
for x in X:
    y.append(review_num_to_ratio[x])
ax[0].plot(np.array(X)/30, y)
ax[0].set_xlabel('spoiler ratio in book')
ax[0].set_ylabel('average number of book reviews')
ax[0].set_title("Spoiler Review Ratio with Book Review Numbers")


review_num_to_ratio_user = {}
for book in review_num_user:
    review_num_to_ratio_user[int(spoiler_ratio_user.get(book,0)*30)] =␣
 ↪review_num_user.get(book,0)
keys = list(review_num_to_ratio_user.keys())
for num in keys:
    review_num_to_ratio_user[num] = np.mean(review_num_to_ratio_user[num])
X = sorted(list(review_num_to_ratio_user.keys()))
```

```
y = []
for x in X:
    y.append(review_num_to_ratio_user[x])
ax[1].plot(np.array(X)/30, y, color='red')
ax[1].set_xlabel('spoiler ratio in user')
ax[1].set_ylabel('average number of user reviews')
ax[1].set_title("Spoiler Review Ratio with User Review Numbers")
plt.show()
```





There appears to be a negative correlation between the number of book revies and the spoiler ratio of book reviews. This suggests that when there are more reviews then readers tend to not write spoiler reviews. Another possible explanation may be that when the number of reviews for a particular book grows, the spoiler ratio decreases to match

3.2 EDA on subset data

```
[ ]: sub_df = df[df.year>=2011].sample(20000,random_state=21)
```

Example of a review that did not contain a spoiler tag

```
[41]: from tabulate import tabulate
part = pd.DataFrame(sub_df[sub_df.has_spoiler == 0].review[-3:])

print(part.values)
```

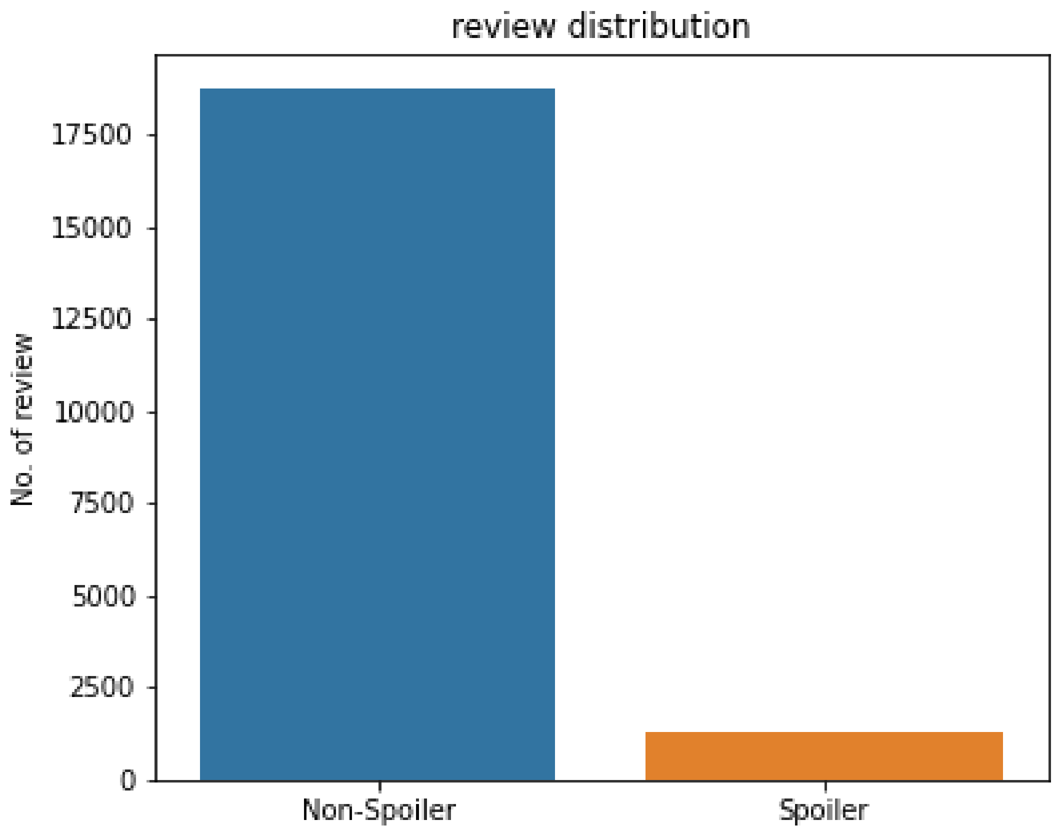
```
[["meh… just not feeling it, but I think it's my mood. I may try again in the
future, for now it's dnf"]
 ["** spoiler alert ** The later books in this series are something of a blur in
my memory, but this felt a bit more readable. A less fae-centric plot helped.
The cast of supporting characters, however, is beginning to feel so large that
the book sometimes seems like a long series of cameo. Oh, there's Bill! And
here's Amelia and Bob! And so on. In a spoilery note, Harris has clearly written
herself out the corner she wrote herself into with the whole Eric-Sookie thing,
and the love triangle is definitely going to be back on in the next book.
Probably a series that has gone on a few too many books to far at this point,
but who am I kidding? I'll keep picking them up as I go on. We all need fluff
reading."]
 ["ANDREW PARRISH you gorgeous motherf*** (pardon my French) you almost gave me
a heart attack!!! I freakin' love that guy. Camryn is a 20 year old girl who
just had about enough of all the shit in her life: Her parents got divorced, her
brother is in jail cause he killed a man while driving drunk, the love of her
life (or so she thinks), Ian, died in a car accident and her next boyfriend
Christian, cheated on her. But when Natalie, her best friend decides to trust
Damon - her boyfriend, more than Camryn, she gets up an leaves. Where? No where.
Anywhere. What she didn't count on was meeting Andrew Parrish on a bus to Idaho.
Every conversation with him brings her closer to everything she swore she would
never do but how can she help it? Andrew, trying to hide all the pain he's going
through for his father, who is in his death bed and who Andrew is going to
visit, has another secret. But he can't resist Camryn, and no matter how much he
wants to break things up before they get in too deep, he cant. So they get into
Andrew's dad car and they are headed for nowhere. And, as if a hot, delicious
body with a six pack and all, gorgeous green eyes and dimples weren't enough,
the guy can sing and play the guitar. Some serious hotness right there. By the
end, i literally couldn't stop crying and my whole body was shaking, and that
letter… Ooh, my GOD that letter! Even the Notebook wasn't that good! I LOVE
YOU, ANDREW PARRISH!!"]]
```

Example of a review that contained spoiler tag

[40]:
```python
from tabulate import tabulate
part = pd.DataFrame(sub_df[sub_df.has_spoiler == 1].review[:3])

print(part.values)
```

```
[["The parts of the story about Rill's family and childhood were interesting,
albeit devastating; the plotline of the Staffords not wanting a family secret
revealed as if anyone would care that a senator's mother was adopted as a child
! Your heart breaks for Rill and her siblings particularly Camellia , but you
have a hard time caring about Avery's situation."]
 ["It seemed they were growing apart with all the drama and secrets, so Jacob's
new found psychic talents   have given them common ground again."]
 ['"Miaka shook her head. "I\'ll write it down, but it\'s unlikely. If it were
that simple, Elizabeth would have killed dozens of men by now." "Not dozens!"
she protested. "But, yes, I\'ve shared plenty of…fluids with human men. And
other have done that before us. Nothing like this has come of it." "Anyone who
could make Akinli smile like that…and he shaved today. He asked me about
cutting his hair" -Julie (AKINLI YOU LIL BBY I LOVE YOU.) that moment when the
TV was talking about a sinking and Kahlen couldn\'t deal with it so Akinli,
being the massive sweetheart he is, held her until she was ok: "I grabbed the
remote out of Akinli\'s grasp, smashing buttons, trying to cut it off. \'Hey,
hey, hey,\' he said, taking hold of my hands. "But, you know what, that didn\'t
even happen today. It happened yesterday. And today is going to be the best day,
remeber?" that moment when Akinli actually researched why people don\'t talk
(whatta cutie) and found out that it\'s usually a physical thing or an emotional
thing and when Kahlen signed it was an emotional thing he said: "Okay. Well,
then I\'ll cross my finger that one day it\'ll be possible for you again. I have
this feeling you have enough thoughts to fill books. And I\'d love to hear
them." AND THEN IT HAPPENED AT THE END OF THE BOOK WHOOP. "His eyes were soft,
and that safe feeling that surrounded him enveloped me." that moment when Akinli
came into Kahlens room when he thought she was asleep and said: "Where in the
world did you come from, you beautiful, silent girl?" that moment when Akinli
found Kahlen on the beach washed up and this lil cutie "poked his fingers into
the grass, fidgeting, deciding" and then finally said "okay then, come with me"
"I didn\'t know how to tell Her that simply being alive was not enough to be
called living." damn. "you look like you\'ve made and broken a lot of things and
then made them all over again" …"I liked the idea that maybe, somewhere deep
inside me, I was also capable of fixing things" that moment when they were
baking and Akinli was worried he was talking too much "Am I talking too much?"
He paused, staring into my eyes, genuine worry colouring his face." can we
please talk about the ending - holy moly. For some reason I was actually really
emotional when the girls left a bottle of the Ocean for her. That\'s just so
cute. When people\'s minds are wiped it is absoluty devastating. But I hope
that, in whatever world they are living in, Kahlen and Akinli are happily
married and Elizabeth, Mikala and Padma are happy in their lives, watching their
sister flourish.']]
```

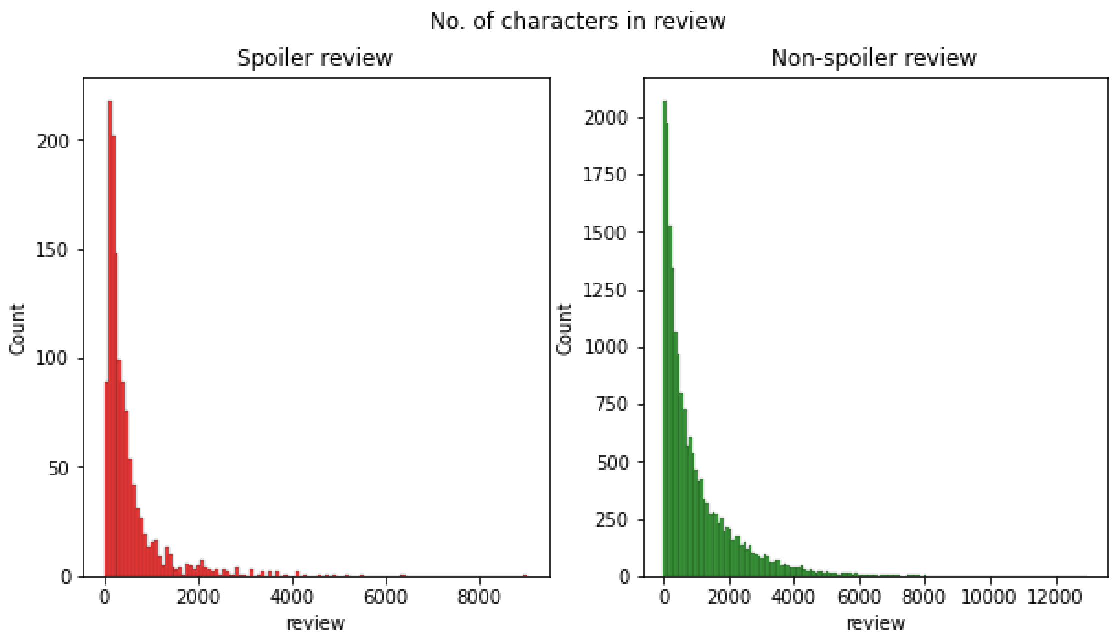
[ ]:
```python
count_sen = sub_df.has_spoiler.value_counts().reset_index()
count_sen['index'] = ['Non-Spoiler', 'Spoiler']

fig, ax = plt.subplots(1, 1, figsize=(6,5))
sns.barplot(x='index', y='has_spoiler', data=count_sen, ax=ax)
ax.set(xlabel=None, ylabel='No. of review', title='review distribution');
```



There are totally 18736 (93.68%) non-spoiler reviews and 1264 (6.32%) spoiler reviews in subset data. This histogram shows that our data is quite imbalanced

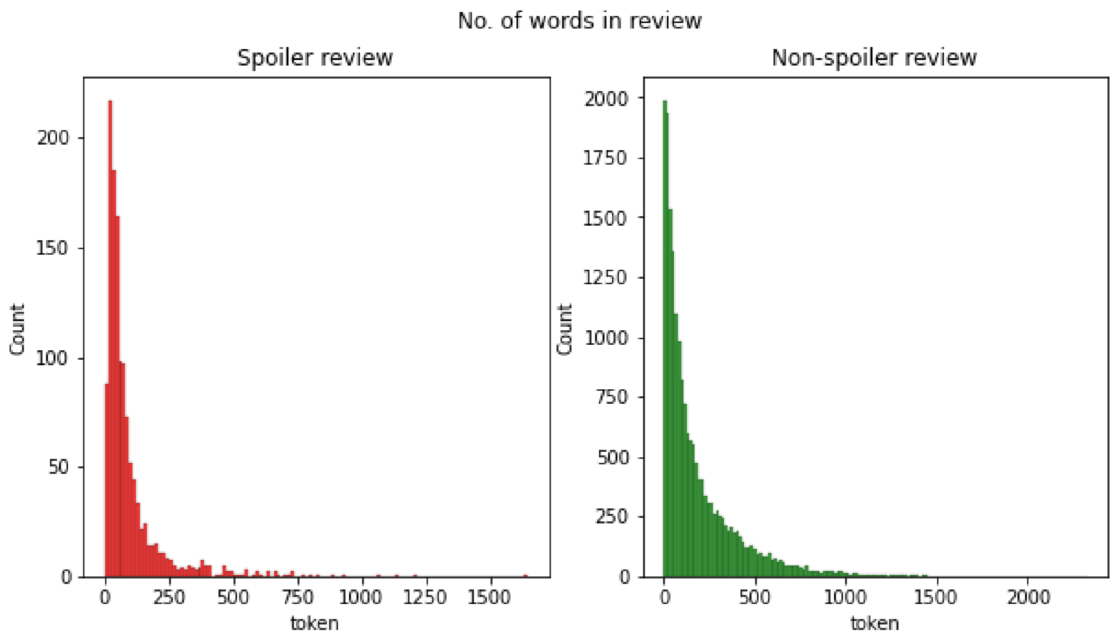
3.2.1 Exploring Review Length

[ ]:
```
fig, ax = plt.subplots(1,2,figsize=(10,5))
cha_len=sub_df[sub_df['has_spoiler']==1]['review'].str.len()
sns.histplot(cha_len, color='red', ax=ax[0])
ax[0].set_title('Spoiler review')
cha_len=sub_df[sub_df['has_spoiler']==0]['review'].str.len()
sns.histplot(cha_len,color='green', ax=ax[1])
ax[1].set_title('Non-spoiler review')
fig.suptitle('No. of characters in review')
plt.show()
```



The two distributions are similar, indicating that the number of characters per review has little correlation with whether or not a spoiler appears in a review

```
[ ]: sub_df['token'].map(lambda x: len(x))

fig, ax = plt.subplots(1,2,figsize=(10,5))
word_len=sub_df[sub_df['has_spoiler']==1]['token'].map(lambda x: len(x))
sns.histplot(word_len,color='red', ax=ax[0])
ax[0].set_title('Spoiler review')
word_len=sub_df[sub_df['has_spoiler']==0]['token'].map(lambda x: len(x))
sns.histplot(word_len,color='green', ax=ax[1])
ax[1].set_title('Non-spoiler review')
fig.suptitle('No. of words in review')
plt.show()
```

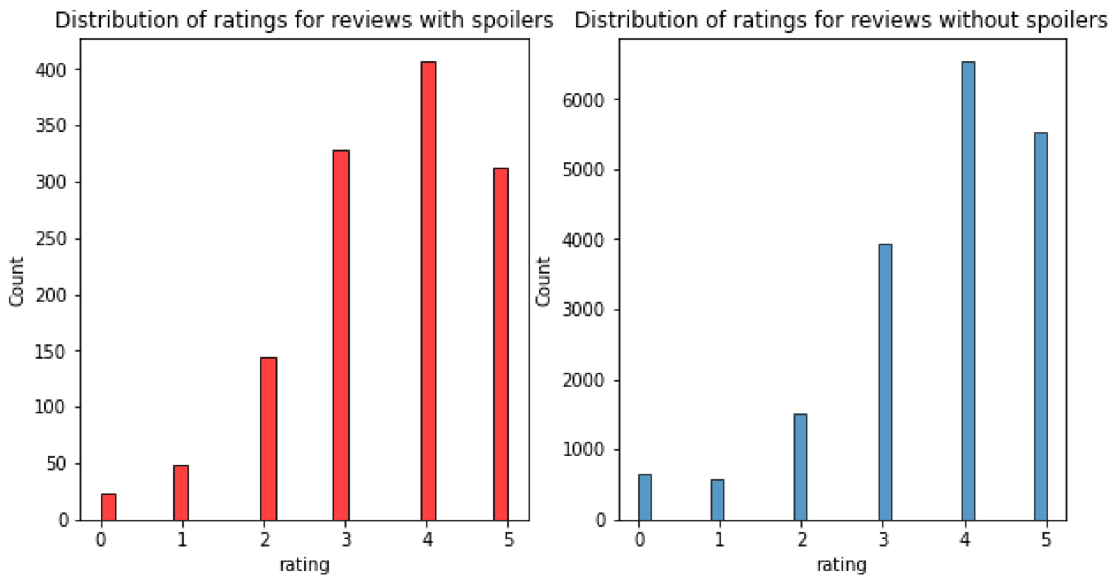


The two distributions are similar, indicating that the number of words per review has little correlation with whether or not a spoiler appears in a review

3.2.2 ratings

```
[ ]: fig, ax = plt.subplots(1,2,figsize=(10,5))

     spoiler_ratings = sns.
      ↪histplot(sub_df[sub_df['has_spoiler']==1]['rating'],ax=ax[0],color='red')
     ax[0].set_title('Distribution of ratings for reviews with spoilers')
     non_spoiler_ratings = sns.
      ↪histplot(sub_df[sub_df['has_spoiler']==0]['rating'],ax=ax[1])
     ax[1].set_title('Distribution of ratings for reviews without spoilers')
```

```
[ ]: Text(0.5, 1.0, 'Distribution of ratings for reviews without spoilers')
```



```
[ ]: (sub_df[sub_df['has_spoiler']==1]['rating']).value_counts()
```

```
[ ]: 4    407
     3    329
     5    313
     2    144
     1     48
     0     23
     Name: rating, dtype: int64
```

```
[ ]: print(((23 / spoiler_total)*100),'percentage of 0 ratings')
     print(((48 / spoiler_total)*100),'percentage of 1 ratings')
     print(((144 / spoiler_total)*100),'percentage of 2 ratings')
     print(((329 / spoiler_total)*100),'percentage of 3 ratings')
     print(((407 / spoiler_total)*100),'percentage of 4 ratings')
     print(((313 / spoiler_total)*100),'percentage of 5 ratings')
```

```
1.8196202531645569 percentage of 0 ratings
3.79746835443038 percentage of 1 ratings
11.39240506329114 percentage of 2 ratings
26.02848101265823 percentage of 3 ratings
32.199367088607595 percentage of 4 ratings
24.7626582278481 percentage of 5 ratings
```

```
[ ]: (sub_df[sub_df['has_spoiler']==0]['rating']).value_counts()
```

```
[ ]: 4    6540
     5    5524
```

```
3    3924
2    1512
0     649
1     587
Name: rating, dtype: int64
```

```
[ ]: print(((649 / non_spoiler_total)*100),'percentage of 0 ratings')
     print(((587 / non_spoiler_total)*100),'percentage of 1 ratings')
     print(((1512 / non_spoiler_total)*100),'percentage of 2 ratings')
     print(((3924 / non_spoiler_total)*100),'percentage of 3 ratings')
     print(((6540 / non_spoiler_total)*100),'percentage of 4 ratings')
     print(((5524 / non_spoiler_total)*100),'percentage of 5 ratings')
```

```
3.463919726729291 percentage of 0 ratings
3.1330059777967554 percentage of 1 ratings
8.07002561912895 percentage of 2 ratings
20.943637916310845 percentage of 3 ratings
34.90606319385141 percentage of 4 ratings
29.48334756618275 percentage of 5 ratings
```

There doesn't seem to be a distinct convincing relationship between the rating of the book and whether or not the review contained a spoiler. The distribution of ratings is similar in the respective histograms and confirmed when looking at the specific percentage breakdowns

3.2.3 Word Cloud

```
[ ]: from nltk.corpus import stopwords
     from nltk.tokenize import word_tokenize

     import nltk
     nltk.download('stopwords')

     stop_words = stopwords.words('english')
     more_stopwords = ['I', 'The', 'And', 'Im', 'But', 'It', 'didnt', 'one',␣
      ↪'would', 'dont', 'could', 'much', 'wasnt', 'doesnt',
                       'cant','also','get','going','still','She']
     stop_words = stop_words + more_stopwords

     def remove_stopwords(token):
         text = [word for word in token if word not in stop_words]
         return text

     sub_df['token'] = sub_df['token'].apply(remove_stopwords)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
[ ]: def create_corpus_df(df, has_spoiler):
         corpus=[]

         for x in df.token[df['has_spoiler']==has_spoiler]:
             for i in x:
                 corpus.append(i)
         return corpus
```

Most Common Words in Spoiler reviews

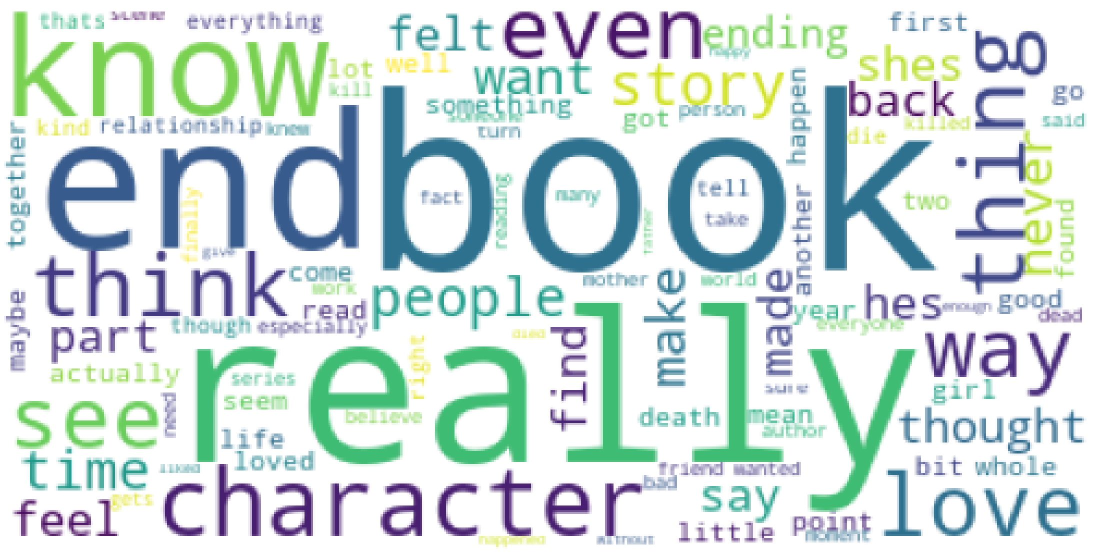
```
[ ]: corpus_spoiler_review = create_corpus_df(sub_df, 1)

     dict = {}
     for word in corpus_spoiler_review:
         dict[word] = dict.get(word, 0) + 1

     top=sorted(dict.items(), key=lambda x:x[1],reverse=True)[:20]
     temp = pd.DataFrame(top)
     temp.columns = ['Common_words','count']
     temp.style.background_gradient(cmap='Blues')
```

```
[ ]: <pandas.io.formats.style.Styler at 0x7f674b1baf10>
```

The most common words that appear in spoiler reviews are book, like, really, end, even know. This was not super insightful, as these words don't convey strong sentiments

```
[ ]: from wordcloud import WordCloud

     wc = WordCloud(
         background_color='white',
         max_words=100
     )

     clean_text = [' '.join(item) for item in sub_df[sub_df.has_spoiler == 1].token]
     wc.generate(' '.join(text for text in clean_text))
     plt.figure(figsize=(9,5))
     plt.title('Top words for spoiler review',
               fontdict={'size': 22,  'verticalalignment': 'bottom'})
     plt.imshow(wc)
     plt.axis("off")
     plt.show()
```

Top words for spoiler review



Most Common words in Non-Spoiler Reviews

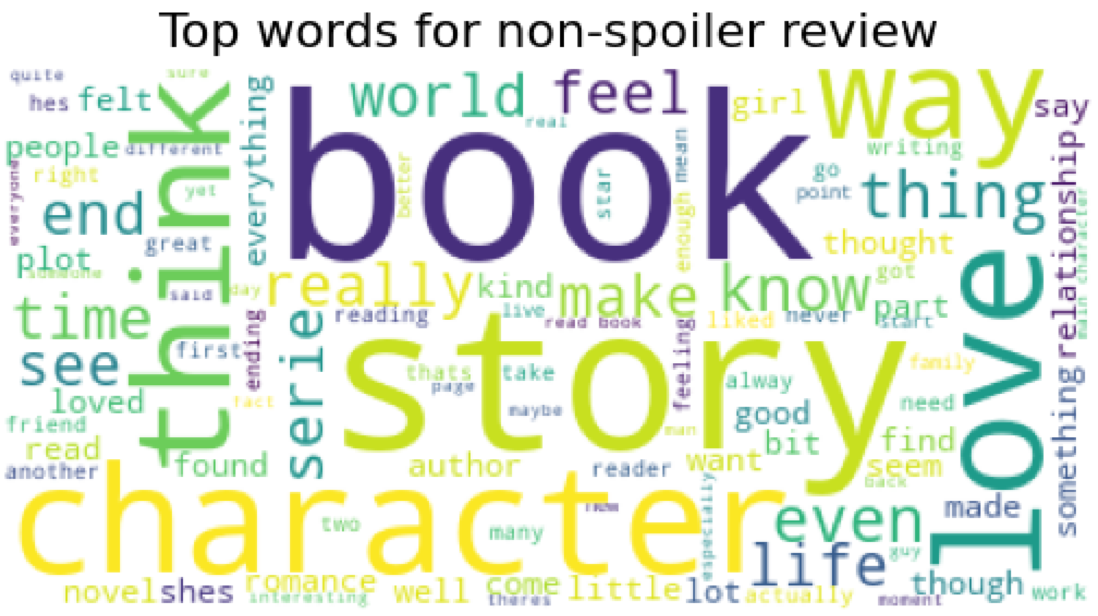
```
[ ]: corpus_spoiler_review = create_corpus_df(sub_df, 0)

dict = {}
for word in corpus_spoiler_review:
    dict[word] = dict.get(word, 0) + 1

top=sorted(dict.items(), key=lambda x:x[1],reverse=True)[:20]
temp = pd.DataFrame(top)
temp.columns = ['Common_words','count']
temp.style.background_gradient(cmap='Purples')
```

```
[ ]: <pandas.io.formats.style.Styler at 0x7f672f7e5650>
```

Similar to the spoiler reviews, the most common words in non-spoiler reviews are book, like, read, story. Again, not super insightful so it would be worth exploring a sentiment analysis for more conclusive insights in the future

```
[ ]: from wordcloud import WordCloud

wc = WordCloud(
    background_color='white',
    max_words=100
)

clean_text = [' '.join(item) for item in sub_df[sub_df.has_spoiler == 0].token]
wc.generate(' '.join(text for text in clean_text))
```

```
plt.figure(figsize=(9,5))
plt.title('Top words for non-spoiler review',
          fontdict={'size': 22,  'verticalalignment': 'bottom'})
plt.imshow(wc)
plt.axis("off")
plt.show()
```



spoiler_model

April 27, 2022

[ ]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.preprocessing import normalize
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_score, recall_score,␣
 ↪f1_score,roc_auc_score, roc_curve
from sklearn.svm import SVC
from imblearn.over_sampling import RandomOverSampler
from nltk.stem import WordNetLemmatizer
from nltk.stem.porter import *
import re
import nltk
import time
from sklearn.utils import shuffle
nltk.download('wordnet')
```

```
[nltk_data] Downloading package wordnet to /root/nltk_data…
[nltk_data]   Unzipping corpora/wordnet.zip.
```

[ ]:
```
True
```

[ ]:
```
# mount gdrive
from google.colab import drive
drive.mount('/gdrive')
```

```
Mounted at /gdrive
```

1 Step1: Loading Data

In the EDA section, we find out that data before 2011 are mostly unlabeled, which means they have little spoiler records. Here we filter out all the records before 2011, and randomly sample 20k records from the filtered data set to form a new data set we deal with.

```
[ ]: # change root to the necessary path
     root = "/gdrive/MyDrive/ads_proj5/ads-spring-2022-prj5-group-4/"
     outputs_dir = root + "output/"
```

```
[ ]: data = pd.read_csv(outputs_dir+'goodreads_reviews_spoiler.csv')
     books_info = pd.read_csv(root+"data/books.csv",on_bad_lines='skip')
```

```
[ ]: books_info = books_info[["bookID","title"]]
     books_info = books_info.rename(columns={"bookID":"book_id"})
```

```
[ ]: data = data.merge(books_info,on="book_id")
     data = data.drop('Unnamed: 0', axis=1)
```

```
[ ]: # has_spoiler(0: this sentence has no spoiler, 1: this sentence has spoiler)
     data = data.drop("has_spoiler",axis=1)
     df = data.rename(columns={"class": "has_spoiler"}, errors="raise")
     df.head(3)
```

```
[ ]:                           review_id  has_spoiler  \
     0  000d87e353329a4f1f938980cef15d5d            0
     1  0f6d9eee40140fa244bd4d11758a4bc3            0
     2  1ab4e3049751a43505cd4cff9383a573            0

                                                   review  book_id  rating  \
     0                             Pure Magic…loved it!!!    16793       5
     1  Having first seen the film adaptation, I'm fin…     16793       3
     2  I was pretty disappointed with this. I have al…     16793       2

         timestamp                           user_id     title
     0  2009-08-01  c3247a4c3cfc1fb4403c758b0ce5b209  Stardust
     1  2014-03-09  f70f0349b2905e9bd73384932988edaf  Stardust
     2  2016-03-03  bb2fe20ae5ca7c09ef6f7e1afa85970c  Stardust
```

```
[ ]: df['year'] = pd.DatetimeIndex(df['timestamp']).year.values
     df = df[df.year>=2011]
```

```
[ ]: sub_df = df.sample(20000,random_state=21)
```

2 Step 2: Review preprocessing :

First of all, we need to preprocess our data. To do so, we remove every stop words, non-alphabetic characters and break sentences on the basis of punctuations. Then we stem and lemmatize our text.

```
[ ]: # process review sentence
     def process_text(review):
         review = review.lower()             # convert to lowercase
```

```
    review = re.sub("[^a-zA-Z#]", " ", review)     # Replace numbers, characters␣
↪with space

    regex = re.compile('(?u)\\b\\w\\w+\\b')        # Break each sentence on the␣
↪basis of punctuations, white spaces
    stemmer = PorterStemmer()
    return " ".join([stemmer.stem(WordNetLemmatizer().lemmatize(token,␣
↪pos='v')) for token in regex.findall(review)])

sub_df['review_process'] = [process_text(review) for review in sub_df['review']]
```

[ ]:
```
sub_df.head(3)
```

[ ]:
```
                              review_id  has_spoiler  \
29753  1b711f779d53794b2e596c1dd5afa34d            0
35291  41a63f400781ad677a304a6e86d0481e            0
66737  9d5c980173341c08d024fe423c198c17            0

                                                   review  book_id  rating  \
29753                                       1st read 8/2010    30183       4
35291  Rating: 3* of five The Publisher Says: Though …    43641       3
66737  And I say, if books could kill… I'm so weak…     5526       5

        timestamp                           user_id  \
29753  2016-10-19  defc1a7606a9645b9b21f77ffaacdb72
35291  2017-08-31  ecf5ccec6487c02f20ae6c7a092dc662
66737  2017-01-10  e867288efaacfb887706751491df4546

                             title  year  \
29753  Marked (House of Night  #1)  2016
35291          Water for Elephants  2017
66737                    Dear John  2017

                                          review_process
29753                                            st read
35291  rat of five the publish say though he may not …
66737  and say if book could kill so weak so emot dra…
```

Now, we need to encode our text data into something that can be used by our baseline model. We encode our data with a bag of words that map a word into it's frequency in the corpus of review.

[ ]:
```
def get_feature_vector(X, min_df=0, stop_words=False, ngram_range=(1,1),␣
↪verbose = True, tokenizer=None, binary=False):
    vect = CountVectorizer(min_df=min_df, stop_words = "english" if stop_words␣
↪else None, ngram_range=ngram_range, tokenizer=tokenizer, binary=binary)
```

```
  vect.fit(X)                                      # Create the␣
↪vocabulary of words for the given reviews dataset

  print("Vocabulary size: {}".format(len(vect.vocabulary_)))

  if verbose:
    feature_names = vect.get_feature_names()
    print("Number of features: {}".format(len(feature_names)))

  bag_of_words = vect.transform(X)                # Transform the reviews into␣
↪feature vector
  bag_of_words_norm = normalize(bag_of_words, norm='l2')  # Normalize the␣
↪feature vectors obtained

  return bag_of_words_norm, vect
```

[ ]:
```
bag_of_words_norm, vect =␣
↪get_feature_vector(sub_df['review_process'],min_df=200,stop_words=True)
```

```
Vocabulary size: 930
Number of features: 930

/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function get_feature_names is deprecated; get_feature_names is
deprecated in 1.0 and will be removed in 1.2. Please use get_feature_names_out
instead.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
features = pd.DataFrame(bag_of_words_norm.toarray(),columns=vect.
↪get_feature_names())
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function get_feature_names is deprecated; get_feature_names is
deprecated in 1.0 and will be removed in 1.2. Please use get_feature_names_out
instead.
  warnings.warn(msg, category=FutureWarning)
```

3 Step3: Baseline Model

We split the data set into train set and test set by 9:1. SVM with linear kernel is our baseline model. For our baseline model, we opted for the SVM. Indeed, it is a classic machine learning algorithm that have good perfomance in classification tasks.

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(features,␣
↪sub_df['has_spoiler'], test_size=0.1, random_state=21,␣
↪stratify=sub_df['has_spoiler'])
```

```
[ ]: # linear SVM
start = time.time()
svm = SVC(kernel="linear",C=1,gamma=1)
svm.probability=True
svm.fit(X_train,y_train)
end = time.time()
print('Training time of SVM:', round(end-start,3), 'seconds')
```

```
Training time of SVM: 151.176 seconds
```

```
[ ]: print("Testing accuracy: " + str(svm.score(X_test, y_test)))
y_pred = svm.predict(X_test)
y_test_pred = svm.decision_function(X_test)
fpr1, tpr1, _ = roc_curve(y_test,  y_test_pred)

print("Precision on test data: " + str(precision_score(y_test, y_pred)))
print("Recall on test data: " + str(recall_score(y_test, y_pred)))
print("f1 score on test data: " + str(f1_score(y_test, y_pred)))
print("AUC on test data: " + str(roc_auc_score(y_test, y_test_pred)))
```

```
Testing accuracy: 0.955
Precision on test data: 0.4
Recall on test data: 0.02247191011235955
f1 score on test data: 0.0425531914893617
AUC on test data: 0.9016074882848559
```

As we can see from those results, the model as a good accuracy but actually failed to predict when there is a spoiler as suggest the low AUC score. This is due to the nature of our data which is imbalanced ! We are close to randomly telling when there is a spoiler or not.

One way to significantly improve ou results is to balance our SVM algorithm.

```
[ ]: # Balanced SVM
# Solution: weighted SVM
ratio = np.sum([y_train==1])/len(y_train)
wsvm = SVC(kernel="linear",C=1,gamma=1,class_weight={1:(1/ratio)})
start = time.time()
wsvm.fit(X_train,y_train)
end = time.time()
print('Training time of Weighted SVM:', round(end-start,3), 'seconds')
```

```
Training time of Weighted SVM: 109.19 seconds
```

```
[ ]: print("Testing accuracy: " + str(wsvm.score(X_test, y_test)))
y_pred = wsvm.predict(X_test)
y_test_pred = wsvm.decision_function(X_test)
fpr2, tpr2, _ = roc_curve(y_test,  y_test_pred)
print("Precision on test data: " + str(precision_score(y_test, y_pred)))
print("Recall on test data: " + str(recall_score(y_test, y_pred)))
print("f1 score on test data: " + str(f1_score(y_test, y_pred)))
print("AUC on test data: " + str(roc_auc_score(y_test, y_test_pred)))
```

```
Testing accuracy: 0.88
Precision on test data: 0.24054982817869416
Recall on test data: 0.7865168539325843
f1 score on test data: 0.368421052631579
AUC on test data: 0.9049882701568095
```

As expected it boost our results significantly! The ROC curve is now relatively far away to the random curve.

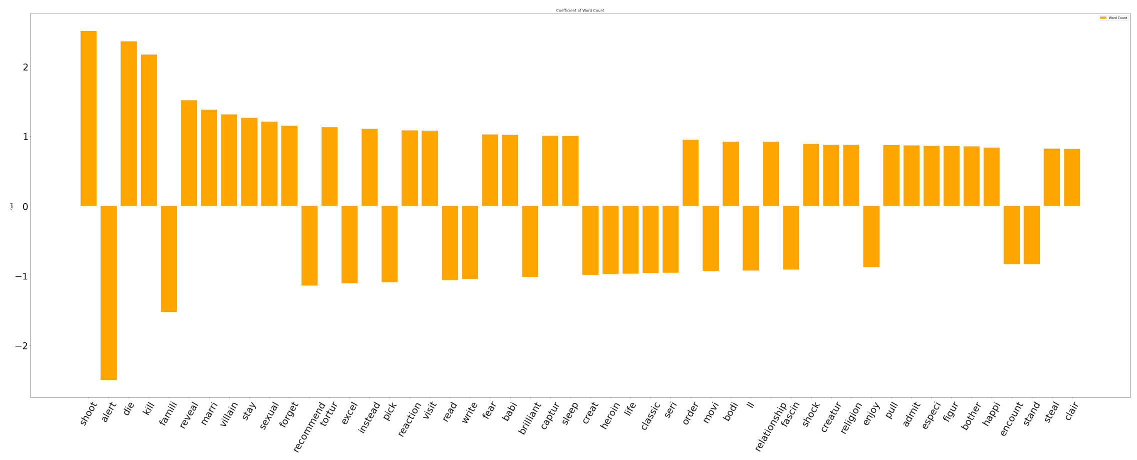
We plot below the most signficant words to predict a spoiler according to our SVM.

[ ]:
```
labels = features.columns
theta_word_count = np.array(svm.coef_.reshape(-1))
result = pd.DataFrame({'words':labels,
                       'coef': theta_word_count})
sort_result = result.sort_values(by='coef', key = lambda x:abs(x),␣
 ↪ascending=False).iloc[0:50]
sort_result.head()
```

[ ]:
```
      words      coef
725   shoot  2.509725
23    alert -2.495762
210     die  2.362985
439    kill  2.173229
282  famili -1.518742
```

[ ]:
```
%matplotlib inline

labels = sort_result.words
theta_word_count = sort_result.coef

x = np.arange(len(labels))  # the label locations
width = 0.35  # the width of the bars

fig, ax = plt.subplots(figsize=(50, 20))
rects1 = ax.bar(list(range(50)), theta_word_count, label='Word Count',␣
 ↪color='orange')
ax.tick_params(axis='both', which='major', labelsize=30)

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Coef')
ax.set_title('Coefficient of Word Count')
ax.set_xticks(x)
plt.setp(ax.get_xticklabels(), rotation=60)
ax.set_xticklabels(labels)
ax.legend()
```

```
fig.tight_layout()

plt.show()
```



4 Step 4: LSTM

In this section, we evaluate the performance of deep neural network for this task and see if they can have a better performance than the weigthed SVM.

As for the SVM, we need to tokenize our text and encode it into something that the LSTM could understand. We make use of the `Tokenizer` from tensorflow that basically maps each word to a unique integer.

```
[ ]: # LSTM
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import LSTM, Activation, Dense, Dropout, Input,␣
 ↪Embedding
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing import sequence
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.callbacks import EarlyStopping
%matplotlib inline

X = sub_df.review_process
Y = sub_df.has_spoiler
le = LabelEncoder()
```

```
Y = le.fit_transform(Y)
Y = Y.reshape(-1,1)

max_words = 6000
max_len = 500
tok = Tokenizer(num_words=max_words)
tok.fit_on_texts(X)
sequences = tok.texts_to_sequences(X)
sequences_matrix = sequence.pad_sequences(sequences,maxlen=max_len)
```

[ ]:
```
features2 = pd.DataFrame(sequences_matrix)
```

Once we have our encoded text, we split it into a training and a test set :

[ ]:
```
X_train2, X_test2, y_train2, y_test2 = train_test_split(features2, Y,␣
↪test_size=0.1, random_state=21)
review_train, review_test = train_test_split(sub_df['review'], test_size=0.1,␣
↪random_state=21)
```

Below we define a basic LSTM network and have a look at its performance and our data set.

[ ]:
```
def my_LSTM():
    inputs = Input(name='inputs',shape=[max_len])
    layer = Embedding(max_words,100,input_length=max_len)(inputs)
    layer = LSTM(64)(layer)
    layer = Dense(256,name='FC1')(layer)
    layer = Activation('relu')(layer)
    layer = Dropout(0.5)(layer)
    layer = Dense(1,name='out_layer')(layer)
    layer = Activation('sigmoid')(layer)
    model = Model(inputs=inputs,outputs=layer)
    return model
```

[ ]:
```
model = my_LSTM()
model.
↪compile(loss='binary_crossentropy',optimizer=Adam(),metrics=['accuracy',tf.
↪keras.metrics.AUC(name="AUC")])
model.summary()
```

```
Model: "model_6"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inputs (InputLayer)         [(None, 500)]             0

 embedding_6 (Embedding)     (None, 500, 100)          600000

 lstm_6 (LSTM)               (None, 64)                42240
 FC1 (Dense)                 (None, 256)               16640

 activation_4 (Activation)   (None, 256)               0

 dropout_6 (Dropout)         (None, 256)               0

 out_layer (Dense)           (None, 1)                 257

 activation_5 (Activation)   (None, 1)                 0

=================================================================
Total params: 659,137
Trainable params: 659,137
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```
start = time.time()
history = model.fit(X_train2,y_train2,batch_size=128,epochs=10,
          validation_split=0.
 ↪1,callbacks=[EarlyStopping(monitor='val_loss',patience=2)])
end = time.time()
print('Training time of LSTM:', round(end-start,3), 'seconds')
```

```
Epoch 1/10
127/127 [==============================] - 16s 104ms/step - loss: 0.2193 -
accuracy: 0.9541 - AUC: 0.5593 - val_loss: 0.1830 - val_accuracy: 0.9467 -
val_AUC: 0.8027
Epoch 2/10
127/127 [==============================] - 11s 85ms/step - loss: 0.1168 -
accuracy: 0.9617 - AUC: 0.8966 - val_loss: 0.1484 - val_accuracy: 0.9539 -
val_AUC: 0.8709
Epoch 3/10
127/127 [==============================] - 11s 84ms/step - loss: 0.0777 -
accuracy: 0.9744 - AUC: 0.9538 - val_loss: 0.1468 - val_accuracy: 0.9606 -
val_AUC: 0.8535
Epoch 4/10
127/127 [==============================] - 11s 84ms/step - loss: 0.0674 -
accuracy: 0.9762 - AUC: 0.9666 - val_loss: 0.1872 - val_accuracy: 0.9561 -
val_AUC: 0.8204
Epoch 5/10
127/127 [==============================] - 11s 83ms/step - loss: 0.0426 -
accuracy: 0.9861 - AUC: 0.9830 - val_loss: 0.1900 - val_accuracy: 0.9500 -
val_AUC: 0.8219
Training time of LSTM: 59.153 seconds
```

[ ]:
```
scores = model.predict(X_test2, verbose=0)
yhat_class2 = [1 if score>0.5 else 0 for score in scores]
fpr3, tpr3, _ = roc_curve(y_test2,  scores)
```

```
print("Testing accuracy: " + str(model.evaluate(X_test2,y_test2)[1]))
print("Precision on test data: " + str(precision_score(y_test2, yhat_class2)))
print("Recall on test data: " + str(recall_score(y_test2, yhat_class2)))
print("f1 score on test data: " + str(f1_score(y_test2, yhat_class2)))
print("AUC on test data: " + str(roc_auc_score(y_test2, scores)))
```

```
63/63 [==============================] - 2s 36ms/step - loss: 0.1863 - accuracy:
0.9520 - AUC: 0.8140
Testing accuracy: 0.9520000219345093
Precision on test data: 0.5294117647058824
Recall on test data: 0.2727272727272727
f1 score on test data: 0.36
AUC on test data: 0.8308067524269523
```

We can see that even though we don't tackle the imbalance problem, we manadge to reach a good level of AUC.

But again, we know that our data is imbalance and that's an issue to tackle. To do so, we make use of oversampling. We augment our data to make sure that we end up with a balanced data set.

```
[ ]: # Balanced LSTM
     # Solution: Oversampling
     oversample = RandomOverSampler(sampling_strategy='minority')
     X_train_o2, y_train_o2 = oversample.fit_resample(X_train2, y_train2)
```

```
[ ]: model_bal = my_LSTM()
     model_bal.
      ↪compile(loss='binary_crossentropy',optimizer=Adam(),metrics=['accuracy'])
```

```
[ ]: start = time.time()
     model_bal.fit(X_train_o2,y_train_o2,batch_size=128,epochs=10,
               validation_split=0.
      ↪1,callbacks=[EarlyStopping(monitor='val_loss',min_delta=0.0001)])
     end = time.time()
     print('Training time of Balanced LSTM:', round(end-start,3), 'seconds')
```

```
Epoch 1/10
242/242 [==============================] - 24s 85ms/step - loss: 0.2485 -
accuracy: 0.8873 - val_loss: 0.0611 - val_accuracy: 0.9893
Epoch 2/10
242/242 [==============================] - 20s 81ms/step - loss: 0.0591 -
accuracy: 0.9826 - val_loss: 0.0296 - val_accuracy: 0.9980
Training time of Balanced LSTM: 44.248 seconds
```

```
[ ]: scores = model_bal.predict(X_test2, verbose=0)
     yhat_class_o2 = np.array([1 if score>0.5 else 0 for score in scores])
     y_test2 = y_test2.flatten()
     fpr4, tpr4, _ = roc_curve(y_test2,  scores)
```

```
print("Testing accuracy: " + str(model_bal.evaluate(X_test2,y_test2)[1]))
print("Precision on test data: " + str(precision_score(y_test2, yhat_class_o2)))
print("Recall on test data: " + str(recall_score(y_test2, yhat_class_o2)))
print("f1 score on test data: " + str(f1_score(y_test2, yhat_class_o2)))
print("AUC on test data: " + str(roc_auc_score(y_test2, scores)))
```

```
63/63 [==============================] - 2s 36ms/step - loss: 0.2780 - accuracy:
0.9480
Testing accuracy: 0.9480000138282776
Precision on test data: 0.4731182795698925
Recall on test data: 0.4444444444444444
f1 score on test data: 0.45833333333333337
AUC on test data: 0.8581820307227986
```

4.0.1 Attention-LSTM with weighted loss:

To boost even more our model, we can use of a Bidirectionnal LSTM and add an attention layer afterward to select the most important words. Also instead of oversampling, we balanced the loss by adding weights :

$$l = w_p \log(\hat{p}) + w_n \log(1 - \hat{p})$$

[ ]:
```
# !wget http://nlp.stanford.edu/data/glove.6B.zip
# !unzip -q glove.6B.zip
import os
import pathlib

path_to_glove_file = os.path.join(
    os.path.expanduser("~"), "/gdrive/MyDrive/ads_proj5/
 ↪ads-spring-2022-prj5-group-4/lib/glove.6B.100d.txt"
)

embeddings_index = {}
with open(path_to_glove_file) as f:
    for line in f:
        word, coefs = line.split(maxsplit=1)
        coefs = np.fromstring(coefs, "f", sep=" ")
        embeddings_index[word] = coefs

# LSTM
from keras import backend as K
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Model
from tensorflow.keras.layers import LSTM, Activation, Dense, Dropout, Input,␣
 ↪Embedding
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing import sequence
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.preprocessing import normalize
%matplotlib inline
max_words = 6000
max_len = 500


X = sub_df.review_process
Y = sub_df.has_spoiler
le = LabelEncoder()
Y = le.fit_transform(Y)
Y = Y.reshape(-1,1)

from tensorflow.keras import layers
from tensorflow.keras.layers import TextVectorization

vectorizer = TextVectorization(max_tokens=max_words,␣
 ↪output_sequence_length=max_len)
text_ds = tf.data.Dataset.from_tensor_slices(X).batch(128)
vectorizer.adapt(text_ds)
voc = vectorizer.get_vocabulary()
word_index = dict(zip(voc, range(len(voc))))
num_tokens = len(voc)
embedding_dim = 100
hits = 0
misses = 0

# Prepare embedding matrix
embedding_matrix = np.zeros((num_tokens, embedding_dim))
for word, i in word_index.items():
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        # Words not found in embedding index will be all-zeros.
        # This includes the representation for "padding" and "OOV"
        embedding_matrix[i] = embedding_vector
        hits += 1
    else:
        misses += 1
print("Converted %d words (%d misses)" % (hits, misses))
tok = Tokenizer(num_words=max_words)
```

```
tok.fit_on_texts(X)
sequences = tok.texts_to_sequences(X)
sequences_matrix = sequence.pad_sequences(sequences,maxlen=max_len)
features = pd.DataFrame(sequences_matrix)
X_train, X_test, y_train, y_test = train_test_split(features, Y, test_size=0.1,␣
↪random_state=21, stratify=Y)
```

```
Converted 4305 words (1695 misses)
```

[ ]:
```
from tensorflow.keras.layers import Layer
from keras import initializers as initializers, regularizers, constraints
from keras.utils.np_utils import to_categorical
from keras.layers import Embedding, Input, Dense, LSTM, GRU, Bidirectional,␣
↪TimeDistributed, Dropout
from keras import backend as K
from keras.models import Model

def dot_product(x, kernel):
    """
    Wrapper for dot product operation, in order to be compatibl/e with both
    Theano and Tensorflow
    Args:
        x (): input
        kernel (): weights
    Returns:
    """
    if K.backend() == 'tensorflow':
        return K.squeeze(K.dot(x, K.expand_dims(kernel)), axis=-1)
    else:
        return K.dot(x, kernel)

class AttentionWithContext(Layer):
    """
    Attention operation, with a context/query vector, for temporal data.
    Supports Masking.
    Follows the work of Yang et al. [https://www.cs.cmu.edu/~diyiy/docs/naacl16.
↪pdf]
    "Hierarchical Attention Networks for Document Classification"
    by using a context vector to assist the attention
    # Input shape
        3D tensor with shape: `(samples, steps, features)`.
    # Output shape
        2D tensor with shape: `(samples, features)`.
    How to use:
    Just put it on top of an RNN Layer (GRU/LSTM/SimpleRNN) with␣
↪return_sequences=True.
    The dimensions are inferred based on the output shape of the RNN.
    Note: The layer has been tested with Keras 2.0.6
    Example:
        model.add(LSTM(64, return_sequences=True))
        model.add(AttentionWithContext())
        # next add a Dense layer (for classification/regression) or whatever...
    """

    def __init__(self,
                 W_regularizer=None, u_regularizer=None, b_regularizer=None,
                 W_constraint=None, u_constraint=None, b_constraint=None,
                 bias=True, **kwargs):

        self.supports_masking = True
        self.init = initializers.get('glorot_uniform')

        self.W_regularizer = regularizers.get(W_regularizer)
        self.u_regularizer = regularizers.get(u_regularizer)
        self.b_regularizer = regularizers.get(b_regularizer)

        self.W_constraint = constraints.get(W_constraint)
        self.u_constraint = constraints.get(u_constraint)
        self.b_constraint = constraints.get(b_constraint)

        self.bias = bias
        super(AttentionWithContext, self).__init__(**kwargs)

    def build(self, input_shape):
        assert len(input_shape) == 3

        self.W = self.add_weight(shape=(input_shape[-1], input_shape[-1],),
                                 initializer=self.init,
                                 name='{}_W'.format(self.name),
                                 regularizer=self.W_regularizer,
                                 constraint=self.W_constraint)
        if self.bias:
            self.b = self.add_weight(shape=(input_shape[-1],),
                                     initializer='zero',
                                     name='{}_b'.format(self.name),
                                     regularizer=self.b_regularizer,
                                     constraint=self.b_constraint)

        self.u = self.add_weight(shape=(input_shape[-1],),
                                 initializer=self.init,
                                 name='{}_u'.format(self.name),
                                 regularizer=self.u_regularizer,
                                 constraint=self.u_constraint)
        super(AttentionWithContext, self).build(input_shape)

    def compute_mask(self, input, input_mask=None):
        # do not pass the mask to the next layers
        return None

    def call(self, x, mask=None):
        uit = dot_product(x, self.W)

        if self.bias:
            uit += self.b

        uit = K.tanh(uit)
        ait = dot_product(uit, self.u)

        a = K.exp(ait)

        # apply mask after the exp. will be re-normalized next
        if mask is not None:
            # Cast the mask to floatX to avoid float64 upcasting in theano
            a *= K.cast(mask, K.floatx())

        # in some cases especially in the early stages of training the sum may␣
↪be almost zero
        # and this results in NaN's. A workaround is to add a very small␣
↪positive number   to the sum.
        # a /= K.cast(K.sum(a, axis=1, keepdims=True), K.floatx())
        a /= K.cast(K.sum(a, axis=1, keepdims=True) + K.epsilon(), K.floatx())

        a = K.expand_dims(a)
        weighted_input = x * a
        return K.sum(weighted_input, axis=1)

    def compute_output_shape(self, input_shape):
        return input_shape[0], input_shape[-1]

def SpoilerLSTM():
    inputs_text = layers.Input(name='inputs',shape=[max_len])
    embbed_input_text = layers.
↪Embedding(max_words,embedding_dim,input_length=max_len,trainable=True,embeddings_initialize
↪initializers.Constant(embedding_matrix))(inputs_text) # Add to initialize␣
↪with GloVe embeddings_initializer=keras.initializers.
↪Constant(embedding_matrix)
    word_lstm =  layers.Bidirectional(layers.
↪LSTM(64,return_sequences=True))(embbed_input_text)
    word_dense = TimeDistributed(Dense(128))(word_lstm)
    attention_layer = AttentionWithContext()(word_dense)
    layer = layers.Dropout(0.5)(attention_layer)
    layer = layers.Dense(1,activation="sigmoid")(layer)
    model = Model(inputs=inputs_text,outputs=layer)
    return model
```

```
[ ]: model = SpoilerLSTM()
     lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(
             0.003,
             decay_steps=100000,
             decay_rate=0.9,
             staircase=True
         )
     model.
      ↪compile(loss='binary_crossentropy',optimizer=Adam(learning_rate=lr_schedule),metrics=['accu
      ↪keras.metrics.AUC(name="AUC")])

     from sklearn.utils import class_weight

     weights = class_weight.compute_class_weight(class_weight='balanced',classes=np.
      ↪unique(y_train),y=np.reshape(y_train,(-1)))
     weights = dict(enumerate(weights))

     checkpoint_filepath = "./doc/tmp/checkpoint_LSTM"
     checkpoint_callback = tf.keras.callbacks.ModelCheckpoint(
             checkpoint_filepath,
             monitor="AUC",
             save_best_only=True,
             save_weights_only=True,
         )

     early_stoping_callback = tf.keras.callbacks.EarlyStopping(monitor='AUC',␣
      ↪patience=2)
```

```
[ ]: start = time.time()
     model.fit(X_train,y_train,batch_size=64,epochs=15, validation_split=0.
      ↪1,callbacks=early_stoping_callback, class_weight=weights)
     end = time.time()
     print('Training time of Modified LSTM:', round(end-start,3), 'seconds')
```

```
Epoch 1/15
254/254 [==============================] - 59s 167ms/step - loss: 0.6418 -
accuracy: 0.5896 - AUC: 0.6876 - val_loss: 0.3596 - val_accuracy: 0.8728 -
val_AUC: 0.9105
Epoch 2/15
254/254 [==============================] - 40s 156ms/step - loss: 0.3709 -
accuracy: 0.8598 - AUC: 0.9128 - val_loss: 0.2645 - val_accuracy: 0.9150 -
val_AUC: 0.9362
Epoch 3/15
```

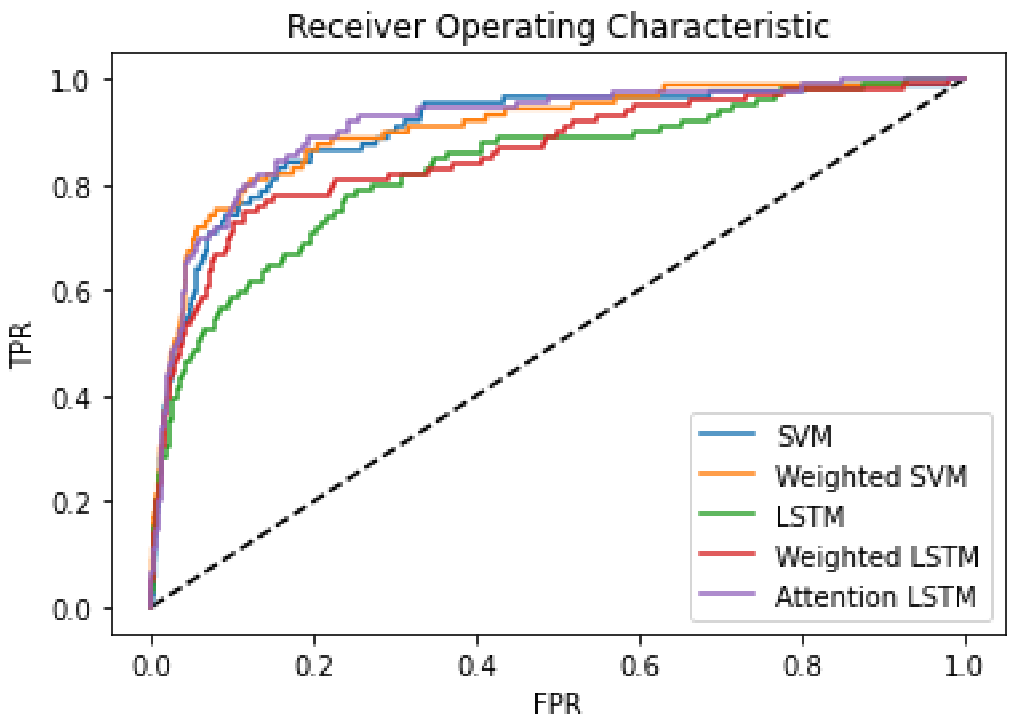
```
254/254 [==============================] - 39s 156ms/step - loss: 0.2075 -
accuracy: 0.9289 - AUC: 0.9704 - val_loss: 0.1870 - val_accuracy: 0.9372 -
val_AUC: 0.9230
Training time of Modified LSTM: 138.208 seconds
```

[ ]:
```
from sklearn.metrics import precision_score, recall_score,␣
↪f1_score,roc_auc_score
# model = SpoilerLSTM()
# model.load_weights(root+"/tmp/checkpoint_LSTM")
scores = model.predict(X_test, verbose=0)
yhat_class = [1 if score>0.5 else 0 for score in scores]
fpr5, tpr5, _ = roc_curve(y_test,  scores)

print("Testing accuracy: " + str(model.evaluate(X_test,y_test)[1]))
print("Precision on test data: " + str(precision_score(y_test, yhat_class)))
print("Recall on test data: " + str(recall_score(y_test, yhat_class)))
print("f1 score on test data: " + str(f1_score(y_test, yhat_class)))
print("AUC on test data: " + str(roc_auc_score(y_test, scores)))
```

```
63/63 [==============================] - 4s 61ms/step - loss: 0.2012 - accuracy:
0.9380 - AUC: 0.9104
Testing accuracy: 0.9380000233650208
Precision on test data: 0.38562091503267976
Recall on test data: 0.6629213483146067
f1 score on test data: 0.48760330578512395
AUC on test data: 0.9116704590219838
```

5 Step 5: Comparison

[ ]:
```
plt.plot([0,1],[0,1], 'k--')
plt.plot(fpr1, tpr1, label= "SVM")
plt.plot(fpr2, tpr2, label= "Weighted SVM")
plt.plot(fpr3, tpr3, label= "LSTM")
plt.plot(fpr4, tpr4, label= "Weighted LSTM")
plt.plot(fpr5, tpr5, label= "Attention LSTM")
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title('Receiver Operating Characteristic')
plt.show()
```


Receiver Operating Characteristic
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0
SVM
Weighted SVM
LSTM
Weighted LSTM
Attention LSTM