IMDB Movie Sentiment Analasis

In this notebook, we will use the IMDB movie reviews dataset, provided on Kaggle (https://www.kaggle.com/c/word2vec-nlp-tutorial/data (https://www.kaggle.com/c/word2vec-nlp-tutorial/data)), to build a sentiment analysis model using NLP.

Rather than using the Word2Vec model (which provided little to no gains in our score), this time we will be using the Doc2Vec model which will consider the order of words in our review as well, giving us not only each word's average feature vector, but also the whole review's average feature vector as well. Through this, we hope to improve our score.

Importing the Data

In [404]:
```
import numpy as np
import pandas as pd # to read the csv datasets and import them into python
```

In [405]:
```
data_path = "data" # path to the data folder in your directory
# import the labeled and unlabeled training data to train our model
train_1 = pd.read_csv(data_path + "/labeledTrainData.tsv", header=0, delimiter
="\t", quoting=3)
train_2 = pd.read_csv(data_path + "/imdb_master.csv", encoding="latin-1")
```

In [406]:
```
train_2 = train_2.drop(["Unnamed: 0","type","file"],axis=1)
train_2.columns = ["review","sentiment"]
```

In [407]:
```
train_2 = train_2[train_2.sentiment != 'unsup']
train_2['sentiment'] = train_2['sentiment'].map({'pos': 1, 'neg': 0})
```

In [408]:
```
train = pd.concat([train_1, train_2]).reset_index(drop=True)
```

Preprocessing

In [409]:
```
from bs4 import BeautifulSoup # to get rid of the HTML tags in the reviews
import re # to remove punctuations and numericals from the review

from nltk.corpus import stopwords # to remove the stop words in our reviews an
d obtain our tokenizer
from nltk.stem import WordNetLemmatizer # to lemmatize our reviews
from nltk import word_tokenize
import nltk.data
nltk.download()
lemmatizer = WordNetLemmatizer()
stop_words = set(stopwords.words("english"))
```

```
showing info https://raw.githubusercontent.com/nltk/nltk_data/gh-pages/index.
xml
```

In [533]:
```
def preprocess_review(unclean_review):
    """
    Function that takes a single unclean review from the original dataset
    and returns a cleaned and preprocessed version of it.
    Input: string: an uncleaned review from the dataset
    Output: string: cleaned and preprocessed review
    """
    # removes the HTML tags in the review
    untagged_review = BeautifulSoup(unclean_review).get_text()
    # removes everything not in A-Z or a-z and replaces it with a space
    letter_only_review = re.sub("[^a-zA-Z]", " ", untagged_review)
    # converting everything to lowercase
    letter_only_review = letter_only_review.lower()
    # converting everything to tokenized words
    tokenized_review = word_tokenize(letter_only_review)
    # taking only the lemmatized words
    tokens = list(map(lemmatizer.lemmatize, tokenized_review))
    # only accepting the verbs from those lemmatized words to normalize proces
s
    lemmatized_tokens = list(map(lambda x: lemmatizer.lemmatize(x, "v"), token
s))
    # removing all the stop words in the review
    result = [t for t in lemmatized_tokens if not t in stop_words]
    return result
```

Training the Model

In [411]:
```
# clean up the reviews
x_train = []
for i in range(len(train["review"])):
    if i % 10000 == 0:
        print(i)
    x_train.append(preprocess_review(train["review"][i]))

y_train = train.sentiment.values
```

```
0
10000
20000
30000
40000
50000
60000
70000
```

In [412]:
```
from sklearn.model_selection import train_test_split
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.layers import Dense , Input , LSTM , Embedding, Dropout , Activatio
n, GRU, Flatten
from keras.layers import Bidirectional, GlobalMaxPool1D
from keras.models import Model, Sequential
from keras.layers import Convolution1D
from keras import initializers, regularizers, constraints, optimizers, layers

max_features = 5000 # we will keep the 5000 most freq words for our model
tokenizer = Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(x_train)
train_tokens = tokenizer.texts_to_sequences(x_train)

max_length = 130
x_train = pad_sequences(train_tokens, maxlen=max_length)

x_train, x_test, y_train, y_test = train_test_split(x_train, y_train, test_siz
e = 0.1, shuffle=True)
embedding_size = 128
model = Sequential()
model.add(Embedding(max_features, embedding_size))
model.add(Bidirectional(LSTM(32, return_sequences = True)))
model.add(GlobalMaxPool1D())
model.add(Dense(20, activation="relu"))
model.add(Dropout(0.05))
model.add(Dense(1, activation="sigmoid"))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accurac
y'])

batch_size = 100
epochs = 8
history = model.fit(x=x_train, y=y_train, validation_data=(x_test, y_test),
          batch_size=batch_size, epochs=epochs)
```

```
C:\Users\yasoo\Anaconda3\envs\walmart1\lib\site-packages\tensorflow_core\pyth
on\framework\indexed_slices.py:433: UserWarning: Converting sparse IndexedSli
ces to a dense Tensor of unknown shape. This may consume a large amount of me
mory.
  "Converting sparse IndexedSlices to a dense Tensor of unknown shape. "

Train on 67500 samples, validate on 7500 samples
Epoch 1/8
67500/67500 [==============================] - 111s 2ms/step - loss: 0.3199 -
accuracy: 0.8636 - val_loss: 0.2497 - val_accuracy: 0.9003
Epoch 2/8
67500/67500 [==============================] - 113s 2ms/step - loss: 0.2103 -
accuracy: 0.9207 - val_loss: 0.2285 - val_accuracy: 0.9123
Epoch 3/8
67500/67500 [==============================] - 117s 2ms/step - loss: 0.1586 -
accuracy: 0.9443 - val_loss: 0.2161 - val_accuracy: 0.9228
Epoch 4/8
67500/67500 [==============================] - 116s 2ms/step - loss: 0.1177 -
accuracy: 0.9603 - val_loss: 0.2189 - val_accuracy: 0.9296
Epoch 5/8
67500/67500 [==============================] - 116s 2ms/step - loss: 0.0820 -
accuracy: 0.9739 - val_loss: 0.2325 - val_accuracy: 0.9335
Epoch 6/8
67500/67500 [==============================] - 119s 2ms/step - loss: 0.0584 -
accuracy: 0.9828 - val_loss: 0.2360 - val_accuracy: 0.9349
Epoch 7/8
67500/67500 [==============================] - 118s 2ms/step - loss: 0.0422 -
accuracy: 0.9876 - val_loss: 0.2843 - val_accuracy: 0.9364
Epoch 8/8
67500/67500 [==============================] - 119s 2ms/step - loss: 0.0332 -
accuracy: 0.9899 - val_loss: 0.2969 - val_accuracy: 0.9348
```

Output Model Results

In [413]:
```
# import the test data to evaluate our model
result_data = pd.read_csv(data_path + "/testData.tsv", header=0, delimiter="\t
", quoting=3)
```

In [414]:
```
result_data["review"] = result_data.review.apply(lambda x: preprocess_review(x
))
```

In [415]:
```
result_data["sentiment"] = result_data["id"].map(lambda x: 1 if int(x.strip(
'"').split("_")[1]) >= 5 else 0)
```

In [416]:
```
y_result = result_data["sentiment"]
reviews = result_data["review"]
tokenized = tokenizer.texts_to_sequences(reviews)
x_result = pad_sequences(tokenized, maxlen=max_length)
```

In [417]:
```
predictions = model.predict(x_result)
```

In [418]:
```
y_result_pred = (predictions > 0.5)
```

In [419]:
```
# to obtain the area under ROC score
from sklearn.metrics import f1_score, confusion_matrix
print('F1-score: {0}'.format(f1_score(y_result_pred, y_result)))
print('Confusion matrix:')
confusion_matrix(y_result_pred, y_result)
```

```
F1-score: 0.9769425777634704
Confusion matrix:
```

Out[419]:
```
array([[12288,   361],
       [  212, 12139]], dtype=int64)
```

In [420]:
```
y_result_pred = y_result_pred.astype(int)
```

In [421]:
```
y_result_pred = [item for items in y_result_pred for item in items]
```

In [422]:
```
output = pd.DataFrame(data={"id":test_data["id"], "sentiment":y_result_pred} )
output.to_csv( "cnn_model.csv", index=False, quoting=3 )
```

In [423]:
```
output
```

Out[423]:

	id	sentiment
0	"12311_10"	1
1	"8348_2"	0
2	"5828_4"	0
3	"7186_2"	0
4	"12128_7"	1
...	...	...
24995	"2155_10"	1
24996	"59_10"	1
24997	"2531_1"	0
24998	"7772_8"	1
24999	"11465_10"	1

25000 rows × 2 columns

In [ ]:

Visualizing the Model

In this part, we will visualize the confusion matrix and the model accuracy/loss curves, using guidance from [here (https://www.kaggle.com/alexcherniuk/imdb-review-word2vec-bilstm-99-acc)](https://www.kaggle.com/alexcherniuk/imdb-review-word2vec-bilstm-99-acc)

In [424]:

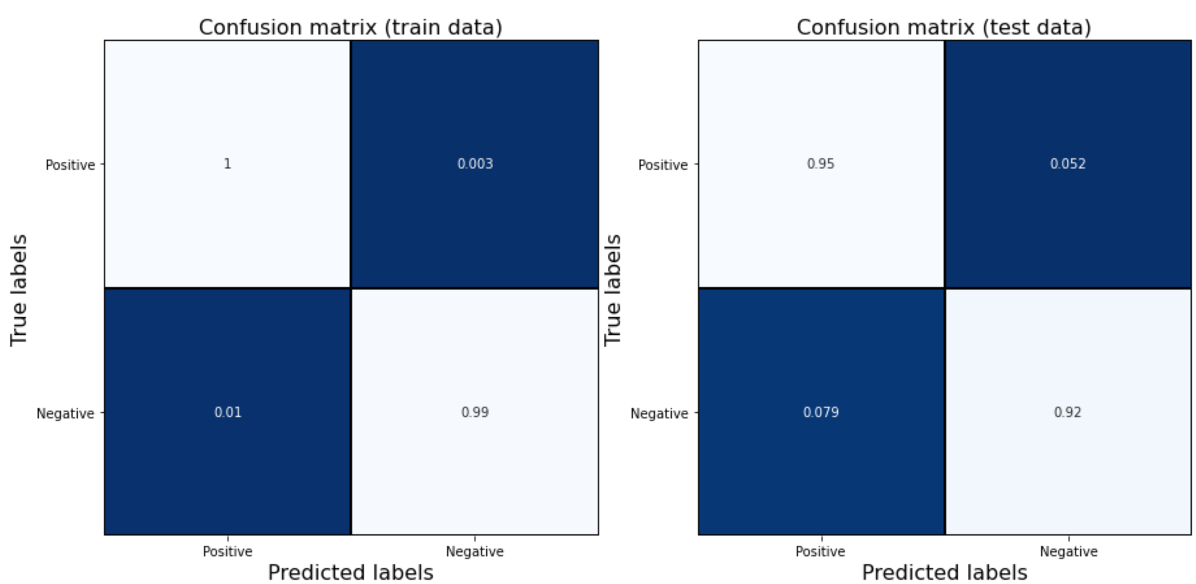
```
y_train_predictions = model.predict_classes(x_train)
y_test_predictions = model.predict_classes(x_test)
```

In [425]:

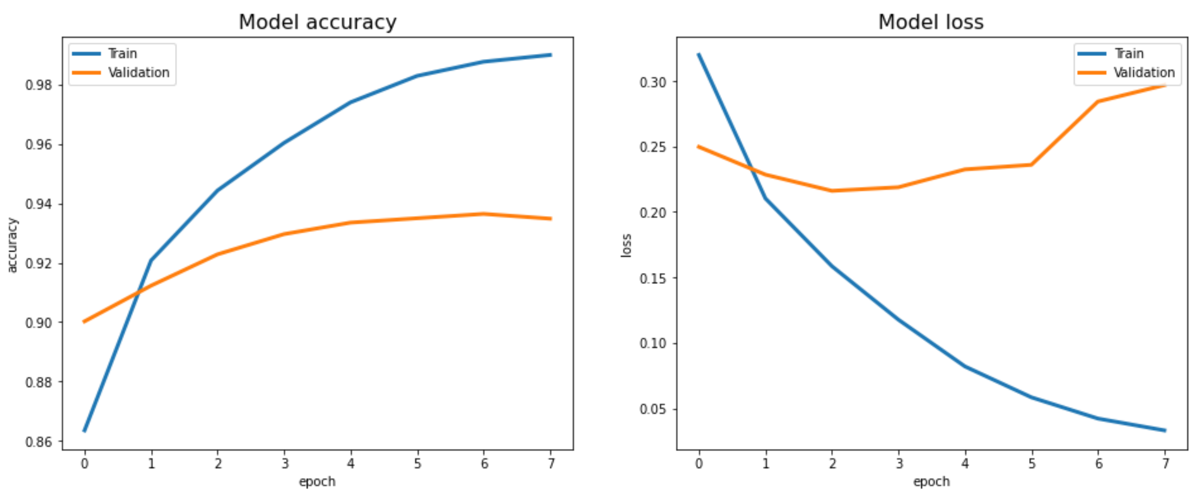
```
# library to plot the confusion matrix and our curves
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, confusion_matrix
import seaborn as sb


# function to plot the confusion matrix
def plot_confusion_matrix(y_true, y_pred, ax, class_names, vmax=None,
                          normed=True, title='Confusion matrix'):
    matrix = confusion_matrix(y_true,y_pred)
    if normed:
        matrix = matrix.astype('float') / matrix.sum(axis=1)[:, np.newaxis]
    sb.heatmap(matrix, annot=True, square=True, ax=ax,
               cmap=plt.cm.Blues_r, cbar=False, linecolor='black',
               linewidths=1, xticklabels=class_names)
    ax.set_title(title, y=1, fontsize=16)
    ax.set_ylabel('True labels', fontsize=16)
    ax.set_xlabel('Predicted labels', y=1, fontsize=16)
    ax.set_yticklabels(class_names, rotation=0)
```

In [426]:

```
fig, (axis1, axis2) = plt.subplots(nrows=1, ncols=2, figsize=(15, 15))
plot_confusion_matrix(y_train, y_train_predictions, ax=axis1,
                      title='Confusion matrix (train data)',
                      class_names=['Positive', 'Negative'])
plot_confusion_matrix(y_test, y_test_predictions, ax=axis2,
                      title='Confusion matrix (test data)',
                      class_names=['Positive', 'Negative'])
```



In [427]:
```
fig, (axis1, axis2) = plt.subplots(nrows=1, ncols=2, figsize=(16,6))

# summarize history for accuracy
axis1.plot(history.history['accuracy'], label='Train', linewidth=3)
axis1.plot(history.history['val_accuracy'], label='Validation', linewidth=3)
axis1.set_title('Model accuracy', fontsize=16)
axis1.set_ylabel('accuracy')
axis1.set_xlabel('epoch')
axis1.legend(loc='upper left')

# summarize history for loss
axis2.plot(history.history['loss'], label='Train', linewidth=3)
axis2.plot(history.history['val_loss'], label='Validation', linewidth=3)
axis2.set_title('Model loss', fontsize=16)
axis2.set_ylabel('loss')
axis2.set_xlabel('epoch')
axis2.legend(loc='upper right')
plt.show()
```



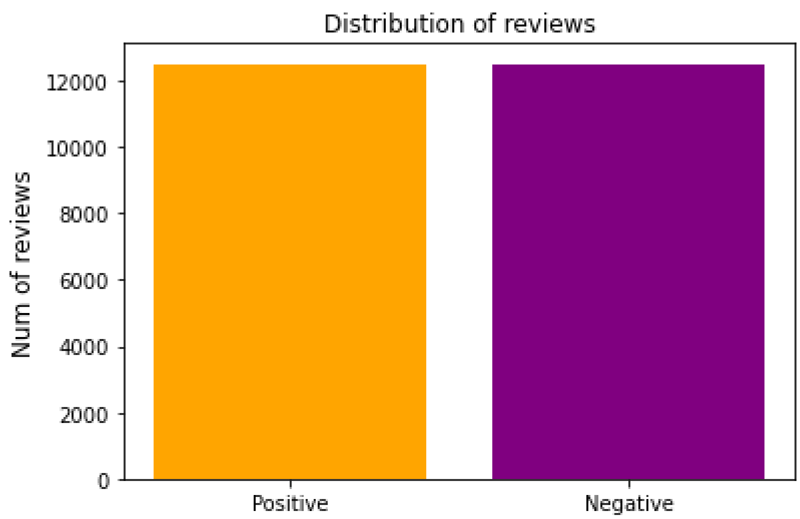
In [ ]:

Analysis

1) How many movie reviews are positive and how many are negative in labeledTrainData.tsv? Do we have balance between the classes?

In [453]:
```
positive = train_1[train_1.sentiment == 1]
negative = train_1[train_1.sentiment == 0]
x = ["Positive", "Negative"]
y = [len(positive), len(negative)]
plt.bar(x, y, color=["orange", "purple"])
plt.title("Distribution of reviews")
plt.ylabel("Num of reviews", fontsize=12)
```

Out[453]: Text(0, 0.5, 'Num of reviews')



As we can observe, both the positive and negative reviews are equally balanced (12,500 each) in the labeledTrainData.tsv

2) What is the average length of all the cleaned up reviews (string length)?

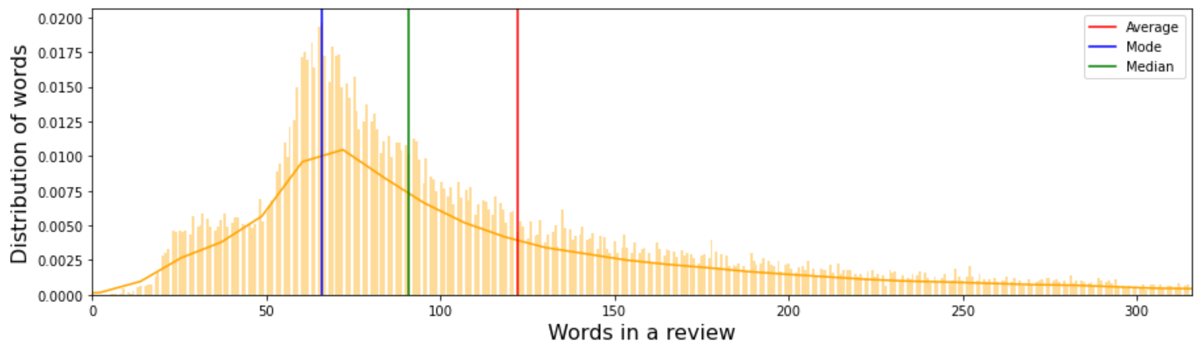
In [562]:
```
def clean_frame(dataframe):
    cleaned_reviews = []
    i = 0
    for review in dataframe["review"]:
        if i % 10000 == 0:
            print(i)
        cleaned_reviews.append(preprocess_review(review))
        i += 1
    return cleaned_reviews
```

In [ ]:
```
cleaned_reviews = clean_frame(train_1)
```

In [536]:
```
import scipy, statistics
review_lengths = []
for review in cleaned_reviews:
    review_lengths.append(len(review))
average = np.mean(review_lengths)
mode = statistics.mode(review_lengths)
median = np.median(review_lengths)
```

In [547]:
```
fig, ax = plt.subplots(figsize=(15, 4))
sb.distplot(review_lengths, bins=2000, ax=ax, color="orange")
ax.set_xlim(left=0, right=np.percentile(review_lengths, 95))
ax.set_xlabel("Words in a review", fontsize=16)
ax.set_ylabel("Distribution of words", fontsize=16)
plt.axvline(x=average, ymin=0, ymax=1, label="Average", color="red")
plt.axvline(x=mode, ymin=0, ymax=1, label="Mode", color="blue")
plt.axvline(x=median, ymin=0, ymax=1, label="Median", color="green")
plt.legend()
print("Average: {}, Mode: {}, Median: {}".format(average, mode, median))
```

```
Average: 122.18704, Mode: 66, Median: 91.0
```



What does the word cloud for positive review words look like? Negative review words?

In [563]:
```
positive["review"]
```

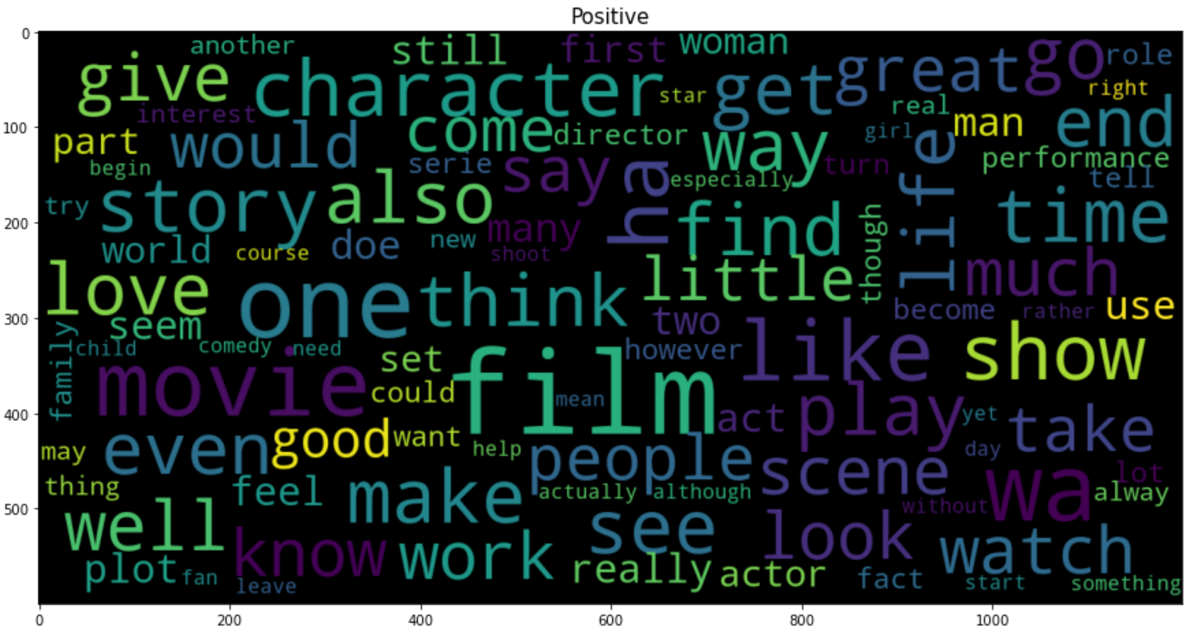
Out[563]:
```
0        "With all this stuff going down at the moment ...
1        "\"The Classic War of the Worlds\" by Timothy ...
4        "Superbly trashy and wondrously unpretentious ...
5        "I dont know why people think this is such a b...
9        "<br /><br />This movie is full of references....
                               ...
24987    "First off, I'd like to make a correction on a...
24988    "While originally reluctant to jump on the ban...
24989    "I heard about this movie when watching VH1's ...
24990    "I've never been huge on IMAX films. They're c...
24999    "I saw this movie as a child and it broke my h...
Name: review, Length: 12500, dtype: object
```

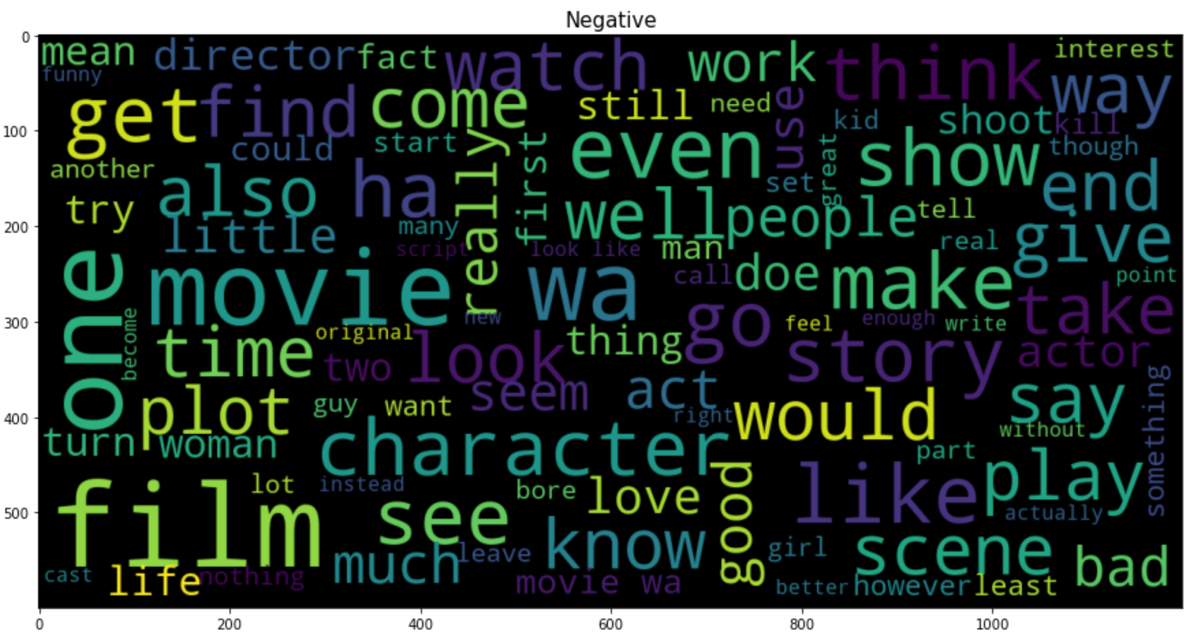
In [584]:
```
clean_positive = clean_frame(positive)
clean_negative = clean_frame(negative)
```

```
0
10000
0
10000
```

In [586]:
```
pos_word_list = ""
for review in clean_positive:
    pos_word_list += " ".join(review)

neg_word_list = ""
for review in clean_negative:
    neg_word_list += " ".join(review)
```

In [589]:
```
from wordcloud import WordCloud

def generate_wordcloud(words, heading):
    """
    Function that generates a word cloud for us using the words we supply to i
t
    """
    # instantialize the word cloud
    wordcloud = WordCloud(stopwords=stop_words, max_words=100, max_font_size=4
0, scale=3).generate(words)
    # generate the figure
    fig =plt.figure(figsize=(15, 15))
    plt.title(heading, fontsize=15)
    plt.imshow(wordcloud)
    plt.show()


generate_wordcloud(pos_word_list, "Positive")
generate_wordcloud(neg_word_list, "Negative")
```


Positive
another still first woman role
give character get great go
star right interest real
part would come director way girl man end
begin serie say ha especially turn performance tell
try story also find life time
world course doe new many shoot though
love one think little much
seem two become rather use
family child comedy need however
like show set
movie film could mean
act play yet take
may even good want help
people scene day lot
thing feel make actually although wa alway
well see without
know work look watch
plot fan leave really actor fact start something


Negative
mean director fact watch work think interest
funny way
get find come still need use kid shoot kill
could start even great though
another show
also ha really first set end
try well people tell
little many give
script look like man real
movie one wa call doe make point
new enough write take
original feel
become time two look thing go story actor
seem act
guy want plot right would say
turn woman character part without something
lot instead bore love like play
film see good actually
leave know girl scene bad
cast life nothing much movie wa better however least

In [ ]: