Bag of Words Model with Naive Bayes:

In [1]: **import** pandas **as** pd

- from bs4 import BeautifulSoup
- from sklearn.model_selection import train_test_split
 from sklearn.preprocessing import LabelEncoder
- from nltk.stem import WordNetLemmatizer
- $\label{eq:constraint} \textit{from sklearn.feature_extraction.text} ~ \textit{import CountVectorizer, TfidfVectorizer}$
- from sklearn.naive_bayes import MultinomialNB
 from sklearn.model_selection import GridSearchCV
- from sklearn.metrics import accuracy_score
- from sklearn.metrics import classification_report

In [2]: data = pd.read_csv('IMDB Dataset.csv')
 data.head()

Out[2]:

 review
 sentiment

 0
 One of the other reviewers has mentioned that ...
 positive

1	A wonderful little production. The	positive

2 I thought this was a wonderful way to spend ti... positive

3 Basically there's a family where a little boy ... negative

4 Petter Mattei's "Love in the Time of Money" is... positive

Basic Statistics

In [3]:	<pre>print("Number of rows: ", data.shape[0]) print("Number of columns: ", data.shape[1])</pre>
	Number of rows: 50000 Number of columns: 2
In [4]:	<pre>data.info()</pre>
	<class 'pandas.core.frame.dataframe'=""> RangeIndex: 50000 entries, 0 to 49999 Data columns (total 2 columns): # Column Non-Null Count Dtype</class>
	0 review 50000 non-null object 1 sentiment 50000 non-null object dtypes: object(2) memory usage: 781.4+ KB
In [5]:	<pre>data.sentiment.value_counts()</pre>
Out[5]:	positive 25000 negative 25000 Name: sentiment, dtype: int64

from the above, we can confirm that the data is equally partioned.

Data Cleaning and preprocessing

In [6]: data['review'][1]

Out[6]: 'A wonderful little production.

The filming technique is very unassuming- very old-time-BBC fashion and gives a comforting, and sometimes discomfo rting, sense of realism to the entire piece.
the actors are extremely well chosen- Michael Sheen not only "has got all the polari" but he has all the voices down pat too! You can truly see the seamless editing guided by the references to Williams\' diary entries, not only is it well worth the watching b ut it is a terrificly written and performed piece. A masterful production about one of the great master\'s of comedy and his life.

The realism rea lly comes home with the little things: the fantasy of the guard which, rather than use the traditional \'dream\' techniques remains solid then disappears. It plays on our knowledge and our senses, particularly with the scenes concerning Orton and Halliwell and the sets (particularly of their flat with Halliwell\'s murals decorating every surface) are terribly well done.'

In the above data we can see \

\ break tags. We need to remove them before using this data.

In [7]: cleantext = BeautifulSoup(data["review"][1], 'lxml').text

We need to remove the slash

In [8]: import re

cleantext = re.sub(r'[^\w\s]', '', cleantext)
cleantext

Out[8]: 'A wonderful little production The filming technique is very unassuming very oldtimeBBC fashion and gives a comforting and sometimes discomforting sense of re alism to the entire piece The actors are extremely well chosen Michael Sheen not only has got all the polari but he has all the voices down pat too You can tr uly see the seamless editing guided by the references to Williams diary entries not only is it well worth the watching but it is a terrificly written and perf ormed piece A masterful production about one of the great masters of comedy and his life The realism really comes home with the little things the fantasy of t he guard which rather than use the traditional dream techniques remains solid then disappears It plays on our knowledge and our senses particularly with the s cenes concerning Orton and Halliwell and the sets particularly of their flat with Halliwells murals decorating every surface are terribly well done'

- In [9]: import nltk
- from nltk.corpus import stopwords

In [10]: nltk.download('stopwords')

stopwords.words('english') [nltk_data] Error loading stopwords: <urlopen error [WinError 10060] A</pre> connection attempt failed because the connected party [nltk_data] [nltk_data] did not properly respond after a period of time, or [nltk_data] established connection failed because connected host [nltk_data] has failed to respond> ['i', 'me', Out[10]: 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you',

"you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not'

	'not',
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	'wouldn',
	"wouldn't"]
In [11]:	<pre>token = cleantext.lower().split()</pre>
	<pre>stopword = set(stopwords.words('english'))</pre>
	<pre>token_list = [word for word in token if word.lower() not in stopword]</pre>
In [12]:	" ".join(token_list)
Out[12]:	'wonderful little production filming technique unassuming oldtimebbc fashion gives comforting sometimes discomforting sense realism entire piece actors extrem
	ely well chosen michael sheen got polari voices pat truly see seamless editing guided references williams diary entries well worth watching terrificly written
	performed piece masterful production one great masters comedy life realism really comes home little things fantasy guard rather use traditional dream techniqu es remains solid disappears plays knowledge senses particularly scenes concerning orton halliwell sets particularly flat halliwells murals decorating every su
	rface terribly well done'
	·
In [13]:	<pre>lemmatizer = WordNetLemmatizer()</pre>
Ta [44].	lemmetizer lemmetize(" " icin(teken liet))
	<pre>lemmatize(" ".join(token_list))</pre>
	'wonderful little production filming technique unassuming oldtimebbc fashion gives comforting sometimes discomforting sense realism entire piece actors extrem
	ely well chosen michael sheen got polari voices pat truly see seamless editing guided references williams diary entries well worth watching terrificly written
	performed piece masterful production one great masters comedy life realism really comes home little things fantasy guard rather use traditional dream techniqu es remains solid disappears plays knowledge senses particularly scenes concerning orton halliwell sets particularly flat halliwells murals decorating every su
	rface terribly well done'
In [15]:	data.keys()
Out[15]:	Index(['review', 'sentiment'], dtype='object')
In [16]:	from tqdm import tqdm
	<pre>def data_cleaner(data):</pre>
	clean_data = [] for review in tqdm(data):
	cleantext = BeautifulSoup(review, "lxml").text
	$cleantext = re_sub(r'[^\w\s]', '', cleantext)$
	<pre>cleantext = [token for token in cleantext.lower().split() if token not in stopword]</pre>
	<pre>cleantext = lemmatizer.lemmatize(" ".join(cleantext)) clean_data.append(cleantext.strip())</pre>
	return clean_data
In []:	<pre>clean_data = data_cleaner(data.review.values)</pre>
In [18]:	clean_data[0]
00+[40]	'one reviewers mentioned watching 1 oz episode youll hooked right exactly happened methe first thing struck oz brutality unflinching scenes violence set right
	word go trust show faint hearted timid show pulls punches regards drugs sex violence hardcore classic use wordit called oz nickname given oswald maximum secur ity state penitentary focuses mainly emerald city experimental section prison cells glass fronts face inwards privacy high agenda em city home manyaryans musl ims gangstas latinos christians italians irish moreso scuffles death stares dodgy dealings shady agreements never far awayi would say main appeal show due fac

Word go trust show faint hearted timid show pulls punches regards drugs sex violence hardcore classic use wordit called of hickname given oswald maximum secur ity state penitentary focuses mainly emerald city experimental section prison cells glass fronts face inwards privacy high agenda em city home manyaryans musl ims gangstas latinos christians italians irish moreso scuffles death stares dodgy dealings shady agreements never far awayi would say main appeal show due fac t goes shows wouldnt dare forget pretty pictures painted mainstream audiences forget charm forget romanceoz doesnt mess around first episode ever saw struck n asty surreal couldnt say ready watched developed taste oz got accustomed high levels graphic violence violence injustice crooked guards wholl sold nickel inma tes wholl kill order get away well mannered middle class inmates turned prison bitches due lack street skills prison experience watching oz may become comfort able uncomfortable viewingthats get touch darker side'

In [19]: X_train, X_test, y_train, y_test = train_test_split(data, data.sentiment, test_size=0.2, random_state=42, stratify=data.sentiment)

Train test split

2 2	In [19]:	X_train, X_test, y_train, y_test = train_test_split(data, data.sentiment, test_size=0.2, random_state=42, stratify=data.sentiment)
in print (C. 1000, L. 1000, C. 10000, C. 1000, C. 10000, C. 10000, C. 10000, C. 10000, C. 1000, C. 1000, C	In [20]:	<pre>y_train = le.fit_transform(y_train) le_test = LabelEncoder()</pre>
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	In []:	<pre>clean_data_train_data = data_cleaner(X_train.review.values)</pre>
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Interface and a function of the set of the	Out[23]:	review sentiment cleaned_text
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H1 Intercent projected transmitter intervent i		20154 I can't believe that I let myself into this mo negative cant believe let movie accomplish favor friend
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1/1 yet = Control (Control (Contro) (C	In []:	X_test['cleaned_text'] = clean_data_test_data
1 Wo = wo.Txi(L_TXi).Cuested_text) Int (200, USED (1000, USED) (1000,		Vectorizer
In Train	In [25]:	
1 print((rail_x,box,shape)) 1 print((rail_x,box,shape)) 1 print((rail_x,box,shape)) 1 print((rail_x,box,shape)) 1 print(rail_x,box,shape)) 1 print(rail_x,box,s		<pre>train_x_bow = vec.transform(X_train.cleaned_text)</pre>
Implant(retr		<pre>test_x_bow = vec.transform(X_test.cleaned_text)</pre>
<pre>[10000, 102100] Naive Bayes with Hyperparameter Tuning [10100] classifier = MultinomialMR() [1010] classifier = MultinomialMR() [1010</pre>	In [26]:	
<pre>in [21] classifier = Multinom.180() [10 [22] classifier = Multinom.180() [10 [22] alsha_runges = {"alpha": [0.083, 0.01, 0.1, 1, 10.0, 100]; [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy', ows6, return_train_score=true) [11 [2] prid_sourch = fridSourch(viclassifier, param_prid=ulpha_ranges, scoring='accuracy is 0.000 [12 [2] pridit= = classifier.predict(test_kbox) [13 [2] pridit= = classifier.predict(test_kbox] [14 [2] pridit= = classifier.predict(test_kbox] [15 [2] pridit== classifie</pre>		
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<pre>in [] orid_search = GridSearchCV(classifier, param_grid=alpha_ranges, scoring='accuracy', cv=3, return_train_score=True) prid_wearch.fit(train_tow, y_train) in [30] alpha = [0.001, 0.01, 0.1, 1.0.0, 100] train_score_fit_accuracy_isrange_fit_alpha_ranges, scoring='accuracy', cv=3, return_train_score=True) in [30] alpha = [0.001, 0.01, 0.1, 1.0.0, 100] train_score_fit_accuracy_is_range_fit_alpha_ranges, scoring='accuracy', cv=3, return_train_score=True) in [30] alpha = [0.001, 0.01, 0.1, 1.0.0, 100] train_score_fit_accuracy_isrange_fit_alpha_ranges, score_fit_accuracy', cv=3, return_train_score=True) in [30] alpha = [0.001, 0.01, 0.1, 1.0.0, 100] in [31] grid_search.ov_results['std_fit_accuracy_is_core'] iclassifier = #ultinomialms(alpha=1) iclassifier = #ultinomialms(al</pre>	In [27]:	<pre>classifier = MultinomialNB()</pre>
prid.seerch.fit(train_x.box, y.train) In [30] idph= [0.001, 0.01, 0.1, 1, 1, 0.0, 100] train_std = grid_seerch.cy.results.['std[train_score'] train_std = grid_seerch.cy.results.['std[train_score'] trest at e grid_seerch.cy.results.['std[train_score'] trest at e grid_seerch.cy.results.['std[train_score'] In []: grid_seerch.cy.results.['std[train_score'] trest at e grid_seerch.cy.results.['std[train_score'] In []: classifier = MultinomialN8(alph=1) classifier : full(train_x.bow, y.train) In []: classifier.predict(tost_x.bow) In []: prid_classifier.predict(tost_x.bow) In [33]: predict = classifier.predict(tost_x.bow) In [34]: print("Accuracy is ", classification report(y test, predict)) Accuracy is 0.850 0.85 0.85 In [35]: print("Accuracy is ", classification report(y test, predict)) Accuracy is 0.85 0.85 10000 in [36]: print("Accuracy is ", classification report(y test, predict)) Accuracy is 0.85 0.85 10000 in [37]: PriDF Model with Naive Bayes: In [38]: // Vectorizer f= trainform(X_train_cleaned_text) X_train_tid = trid = vectorizer (Teriform(X_train_cleaned_text) X_train_tid = trid = vectorizer (Teriform(X_train_cleaned_text) X_train_tid = trid = vectorizer (Teriform(X_train_cleaned_text) X_train_tid = trid = vectorizer interiform(X_train_cleaned_text) </th <th>In [28]:</th> <th>alpha_ranges = {"alpha": [0.001, 0.01, 0.1, 1, 10.0, 100]}</th>	In [28]:	alpha_ranges = {"alpha": [0.001, 0.01, 0.1, 1, 10.0, 100]}
<pre>trian_acc = prid_search.cv_results['emen_train_score'] test_acc = prid_search.cv_results['emen_test_score'] test_score = Nullnows[alw(alwall)] test_acc = classifier.predict(test_x_bow) test_acc = classifier.predict(test_x_bow) test_acc = classifier.predict(test_x_bow) test_acc = prid_* classifier.predict(test_x_bow) test_acc = prid_* classifier.predict(y_test, predict)) Accuracy is 0.85 0.86 0.86 0.86 0.86 0.86 0.86 0.86 0.86</pre>	In []:	
<pre>test_std = grid_search.ev_results_['std_test_score'] in []; grid_search.best_estimator_ in []; grid_search.best_estimator_ in []; classifier = MultinomialN8(alphe=1) classifier = MultinomialN8(alphe=1) classifier = fult(train_x_bow, y_train) in [30]; predict = classifier.predict(test_x_bow) in [34]; print("Accuracy is ", accuracy_score(y_test, predict)) Accuracy is 0.8699 in [35]; print("Accuracy is ", classification_report(y_test, predict)) Accuracy is 0.8699 in [35]; print("Accuracy is ", classification_report(y_test, predict)) Accuracy is 0.86 0.86 0.86 0.86 0.86 10000</pre>	In [30]:	<pre>train_acc = grid_search.cv_results_['mean_train_score']</pre>
<pre>In []: classifier = MultinomialNB(alpha=1) classifier .fit((train_kbow, y_train) In [33]: predict = classifier.predict(test_kbow) In [33]: print("Accuracy is ", accuracy.score(y_test, predict)) Accuracy is 0.8599 In [35]: print("Accuracy is ", classification_report(y_test, predict)) Accuracy is 0.859 precision recall fi-score support 0 0.85 0.88 0.86 5000 accuracy a 0.86 0.86 10000 accuracy 0.86 0.86 10000 TF-IDF Model with Naive Bayes: In [36]: # Vectorize the text using TF-IDF model tfidf_vectorizer (1) X_test_tfidf = tfidf_vectorizer.transform(X_train.cleaned_text) X_test_tfidf = tfidf_vectorizer.transform(X_test.cleaned_text) X_test_tfidf = tfidf_vectorizer.transform(X_test.cleaned_text) # Train a Naive Bayes classifier on the TF-IDF features # TF-IDF formate() </pre>		
<pre>classifier.fit(train_x_bow, y_train) In [33]: predict = classifier.predict(test_x_bow) In [34]: print("Accuracy is ", accuracy_score(y_test, predict)) Accuracy is 0.8599 In [35]: print("Accuracy is ", classification_report(y_test, predict)) Accuracy is precision recall fi-score support 0 0.85 0.88 0.86 5000 accuracy 0 0.86 0.86 10000 TFF-IDF Model with Naive Bayes: In [36]: # Vectorize the text using TF-IDF model tfidf_vectorizer = Thidfwectorizer() X_test_tfidf = thidf_vectorizer() X_test_tfidf = thidf_v</pre>	In []:	grid_search.best_estimator_
<pre>In [34] print("Accuracy is ", accuracy_score(y_test, predict)) Accuracy is 0.8599 In [35] print("Accuracy is ", classification_report(y_test, predict)) Accuracy is precision recall fi-score support 0 0.85 0.88 0.86 5000 accuracy 0.86 0.86 10000 accuracy 0.86 0.86 10000 accuracy 0.86 0.86 10000 TF-IDF Model with Naive Bayes: In [36]: # Vectorize the text using TF-IDF model triaf_vectorizer = Tfidfyectorizer() X_train_tfidf = tfidf_vectorizer.fit_transform(X_train.cleaned_text) X_test_tfidf = tfidf_vectorizer.transform(X_test.cleaned_text) # Train a Naive Bayes classifier on the TF-IDF features p_classifier_tfidf = withinomialNB()</pre>	In []:	
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<pre>In [35]: print("Accuracy is ", classification_report(y_test, predict)) Accuracy is precision recall f1-score support 0 0.85 0.88 0.86 5000 1 0.87 0.84 0.86 5000 accuracy 0.86 0.86 10000 accuracy 0.86 0.86 0.86 10000 TF-IDF Model with Naive Bayes: In [36]: # Vectorize the text using TF-IDF model tfidf_vectorizer = TfidfVectorizer() X_train_tfidf = tfidf_vectorizer.transform(X_train.cleaned_text)) X_test_tfidf = tfidf_vectorizer.transform(X_train.cleaned_text) # Train a Naive Bayes classifier on the TF-IDF features mb_classifier_tfidf = MultinomialNB()</pre>	In [34]:	
Accuracy is precision recall f1-score support 0 0.85 0.88 0.86 5000 1 0.87 0.84 0.86 5000 accuracy 0.86 0.86 10000 weighted avg 0.86 0.86 10000 TF-IDF Model with Naive Bayes: In [36]: # Vectorize the text using TF-IDF model tfidf_vectorizer = Tfidfvectorizer() X_test_tfidf = tfidf_vectorizer.transform(X_train.cleaned_text) X_test_tfidf = tfidf_vectorizer.transform(X_test.cleaned_text) # Train a Naive Bayes classifier on the TF-IDF features mb_classifier_tfidf = MultinomialNB()		·
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<pre>1 0.87 0.84 0.86 5000 accuracy</pre>		
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<pre>nb_classifier_tfidf = MultinomialNB()</pre>		X_test_tfidf = tfidf_vectorizer.transform(X_test.cleaned_text)
		<pre>nb_classifier_tfidf = MultinomialNB()</pre>

Predict and calculate accuracy
predictions_tfidf = nb_classifier_tfidf.predict(X_test_tfidf)
accuracy_tfidf = accuracy_score(y_test, predictions_tfidf)
print("Accuracy using TF-IDF model:", accuracy_tfidf)