NLP_assignment 2 Yogesh Kumar (c0852435) In [1]: # Read in and clean data import nltk import numpy as np import pandas as pd import re from sklearn.model selection import train test split import string stopwords = nltk.corpus.stopwords.words('english') path=r'C:/Users/Yogi/Downloads/' messages = pd.read csv(path+'spam.csv', encoding='latin-1') messages = messages.drop(labels = ["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"], axis = 1) messages.columns = ["label", "text"] messages['label'] = np.where(messages['label']=='spam', 1, 0) def clean_text(text): text = "".join([word.lower() for word in text if word not in string.punctuation]) tokens = re.split('\W+', text) text = [word for word in tokens if word not in stopwords] return " ".join(text) messages['clean text'] = messages['text'].apply(lambda x: clean text(x)) messages.head() # Split data into train and test set X_train, X_test, y_train, y_test = train_test_split(messages['clean_text'], messages['label'], test size=0.2) X_train.to_csv(path+'X_train.csv', index=False, header=True) X_test.to_csv(path+'X_test.csv',index=False, header=True) y_train.to_csv(path+'y_train.csv',index=False, header=True) y_test.to_csv(path+'y_test.csv',index=False, header=True) Implementing TF_IDF on Random Forest Classifier In [2]: import pandas as pd from sklearn.feature extraction.text import TfidfVectorizer tfidf vect = TfidfVectorizer(analyzer=clean text) X train tf = tfidf vect.fit transform(X train) X test tf = tfidf vect.transform(X test) print(X train tf) print(tfidf vect.get feature names()) print(X test tf.shape) 0.1305215467349456 (0, 12)(0, 20)0.23365117051855516 0.07811019208852882 (0, 11)(0, 28) 0.08522129078428922 0.19403961573899664 (0, 17)0.0966270093375372 (0, 18)(0, 30) 0.16015821047986506 (0, 23)0.19436439289921897 (0, 14)0.0956659857770686 0.1624279213243988 (0, 24) 0.1015433601160494 (0, 31) 0.1356621471009756 (0, 16)(0, 15)0.2997464826664797 0.16228036373342095 (0, 19)0.424115627507151 (0, 0)0.25321492731224543 (0, 29)0.3475688278006075 (0, 21) (0, 25) 0.4786268869111465 0.17400706897799065 (0, 22)0.04302915389069457 (1, 26)0.09276490402987163 (1, 7)0.1728998119165411 (1, 6)(1, 9)0.08369949552655141 0.491689998291232 (1, 1)0.11488561434643722 (1, 13)(4455, 30) 0.38450713632640726 (4455, 23) 0.07777153175973134 0.22967448327981874 (4455, 14) (4455, 24) 0.32496354022255647 (4455, 31) 0.08126161935792414 0.32569709372624284 (4455**,** 16) 0.29984585587972634 (4455, 15) (4455, 19) 0.1948009963216655 (4455, 0) 0.5091074785221629 0.06754636645033862 (4455, 29) 0.09271574807430057 (4455, 21) (4455, 25) 0.06383807510767087 0.2088777078390567 (4455, 22) (4456, 33) 0.26078134134777164 0.2993581878103964 (4456, 12) (4456, 20) 0.5358915270001587 0.19545961421875488 (4456, 28) (4456, 17) 0.22252014776154772 0.18366573508959125 (4456, 30) (4456, 24) 0.3725371740822554 (4456, 15) 0.17187117012143327 0.18609937140532734 (4456**,** 19) 0.16212200060530585 (4456, 0) (4456, 21) 0.2657226004251656 (4456, 25) 0.36591883635891814 [' ', '0', '1', '2', '3', '4', '5', '6', '7', '8', '9', 'a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l', 'm', 'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x', 'y', 'z', 'a', 'á', 'â', 'ä', 'å', 'è', 'ì', 'ï', 'ð', 'ò', 'ó', 'ô', 'ō', 'ö', 'û'] (1115, 53)In [3]: from sklearn.ensemble import RandomForestClassifier model = RandomForestClassifier(n estimators=100, criterion='entropy', random state =0) In [4]: model.fit(X train tf, y train) pred=model.predict(X test tf) from sklearn.metrics import precision score, recall score, confusion matrix, classification report, accuracy sc from sklearn.model selection import cross val score acc1=accuracy score(y test,pred) prel=precision score(y test,pred) print("Accuracy Score :",acc1) print("Precision Score :",pre1) import seaborn as sns sns.heatmap(confusion matrix(y test,pred),annot=True, cmap='summer', cbar=False, linewidths=3, linecolor='r', s print(classification report(y test,pred)) Accuracy Score : 0.9757847533632287 Precision Score : 0.9699248120300752 precision recall f1-score 1.00 0 0.98 0.99 963 0.91 0.97 0.85 accuracy 0.98 1115 0.97 0.92 0.95 1115 0.98 0.98 weighted avg 959 fake Implementing Word2vec on Random Forest Classifier In [5]: ! pip install gensim import gensim from gensim.models import Word2Vec w2v model = gensim.models.Word2Vec(X train, vector size=100, window=5, min count=2) words = set(w2v model.wv.index to key) X train vect = np.array([np.array([w2v model.wv[i] for i in ls if i in words]) for ls in X train]) X test vect = np.array([np.array([w2v model.wv[i] for i in ls if i in words]) for ls in X test]) Requirement already satisfied: gensim in c:\users\yogi\anaconda3\lib\site-packages (4.2.0) Requirement already satisfied: smart-open>=1.8.1 in c:\users\yogi\anaconda3\lib\site-packages (from gensim) (6. Requirement already satisfied: numpy>=1.17.0 in c:\users\yogi\anaconda3\lib\site-packages (from gensim) (1.20. Requirement already satisfied: Cython==0.29.28 in c:\users\yogi\anaconda3\lib\site-packages (from gensim) (0.2 9.28)Requirement already satisfied: scipy>=0.18.1 in c:\users\yogi\anaconda3\lib\site-packages (from gensim) (1.7.1) C:\Users\Yogi\AppData\Local\Temp/ipykernel 37152/1448500749.py:10: VisibleDeprecationWarning: Creating an ndarr ay from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray. X train vect = np.array([np.array([w2v model.wv[i] for i in ls if i in words]) C:\Users\Yogi\AppData\Local\Temp/ipykernel 37152/1448500749.py:12: VisibleDeprecationWarning: Creating an ndarr ay from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray. X test vect = np.array([np.array([w2v model.wv[i] for i in ls if i in words]) In [6]: #print(X train vect[0:10]) #print(X test vect[0:10]) X train vect avg = [] for v in X train vect: if v.size: X train vect avg.append(v.mean(axis=0)) X train vect avg.append(np.zeros(100, dtype=float)) X test vect avg = [] for v in X test vect: if v.size: X test vect avg.append(v.mean(axis=0)) X test vect avg.append(np.zeros(100, dtype=float)) print(X train vect.shape) (4457,)In [7]: model rf = RandomForestClassifier() model_rf.fit(X_train_vect_avg,y_train.values.ravel()) pred=model_rf.predict(X_test_vect_avg) print(len(X train vect avg)) print(y train.values.ravel().shape) from sklearn.metrics import precision score, recall score, confusion matrix, classification report, accuracy sc from sklearn.model selection import cross val score acc2=accuracy score(y test,pred) pre2=precision score(y test,pred) print("Accuracy Score :",acc2) print("Precision Score :",pre2) import seaborn as sns sns.heatmap(confusion matrix(y test,pred),annot=True, cmap='CMRmap', cbar=False, linewidths=3, linecolor='r', s print(classification report(y test,pred)) 4457 (4457,)Accuracy Score : 0.9730941704035875 Precision Score : 0.9552238805970149 precision recall f1-score support 0.98 0.99 0.98 963 0.96 0.84 0.90 152 0.97 1115 accuracy 0.97 0.92 0.94 1115 macro avq weighted avg 0.97 0.97 0.97 1115 957 24 128 fake real Implementing doc2vec on Random Forest Classifier In [8]: tagged docs = [gensim.models.doc2vec.TaggedDocument(v, [i]) for i, v in enumerate(X train)] tagged docs[0] d2v model = gensim.models.Doc2Vec(tagged docs, vector size=100, window=5, min count=2) print(X train[0:10]) X train doc=[] for i in X train: X train doc.append(i.split(" ")) print(X train doc[0:10]) print(X test[0:10]) X test doc=[] for i in X_test: X_test_doc.append(i.split(" ")) print(X_test_doc[0:10]) 3372 looks like found something smoke great job 2819 interflora åòits late order interflora flowers... sad story man last week bday wife didnt wish p... 2258 gotta collect da car 6 lei 1889 2122 know result 2937 hey ive booked pilates yoga lesson already haha 978 hey pay salary de ltgt 3402 good night dear sleepwellamptake care 2230 hey thk juz go accordin wat discussed yest lor... 502 check nuerologist Name: clean text, dtype: object [['looks', 'like', 'found', 'something', 'smoke', 'great', 'job'], ['interflora', 'åòits', 'late', 'order', 'in terflora', 'flowers', 'christmas', 'call', '0800', '505060', 'place', 'order', 'midnight', 'tomorrow'], ['sad', 'story', 'man', 'last', 'week', 'bday', 'wife', 'didnt', 'wish', 'parents', 'forgot', 'n', 'kids', 'went', 'wor k', 'even', 'colleagues', 'wish'], ['gotta', 'collect', 'da', 'car', '6', 'lei'], ['know', 'result'], ['hey', 'ive', 'booked', 'pilates', 'yoga', 'lesson', 'already', 'haha'], ['hey', 'pay', 'salary', 'de', 'ltgt', ''], ['good', 'night', 'dear', 'sleepwellamptake', 'care'], ['hey', 'thk', 'juz', 'go', 'accordin', 'wat', 'discusse d', 'yest', 'lor', 'except', 'kb', 'sun', 'cos', 'theres', 'nt', 'much', 'lesson', 'go', 'attend', 'kb', 'sa t'], ['check', 'nuerologist']] 3077 okay thought expert hi dear call urgnt dont know whats problem don... 1625 2355 hello love went day alright think sweet send j... 1122 okok okthenwhats ur todays plan 1939 people dogging area call 09090204448 join like... 855 talk sexy make new friends fall love worlds di... 2500 remember ask alex pizza 5372 ok problem u frm wats matter 4275 please send auntys number walked hour 2 c u doesnåõt show care wont u be... 1048 Name: clean text, dtype: object [['okay', 'thought', 'expert'], ['hi', 'dear', 'call', 'urgnt', 'dont', 'know', 'whats', 'problem', 'dont', 'wa nt', 'work', 'problem', 'least', 'tell', 'wating', 'reply'], ['hello', 'love', 'went', 'day', 'alright', 'thin k', 'sweet', 'send', 'jolt', 'heart', 'remind', 'love', 'hear', 'screamed', 'across', 'sea', 'world', 'hear', 'ahmad', 'al', 'hallaq', 'loved', 'owned', 'possessive', 'passionate', 'kiss'], ['okok', 'okthenwhats', 'ur', 'todays', 'plan'], ['people', 'dogging', 'area', 'call', '09090204448', 'join', 'like', 'minded', 'guys', 'arra nge', '1', 'theres', '1', 'evening', 'aå', '150', 'minapn', 'ls278bb'], ['talk', 'sexy', 'make', 'new', 'friend s', 'fall', 'love', 'worlds', 'discreet', 'text', 'dating', 'service', 'text', 'vip', '83110', 'see', 'could', 'meet'], ['remember', 'ask', 'alex', 'pizza'], ['ok', 'problem', 'u', 'frm', 'wats', 'matter'], ['please', 'sen d', 'auntys', 'number'], ['walked', 'hour', '2', 'c', 'u', 'doesnåõt', 'show', 'care', 'wont', 'u', 'believe', 'im', 'serious']] In [9]: X train doc vect = np.array([d2v model.infer vector(i) for i in X train doc]) X_test_doc_vect = np.array([d2v_model.infer_vector(i) for i in X_test_doc]) print(X train doc vect[0:10]) X_train_doc_vect.shape print(X test doc vect[0:10]) X_test_doc_vect.shape [[-1.97096705e-03 1.89116603e-04 1.79397408e-03 3.21650156e-03 -1.46501960e-04 -4.86364868e-03 -4.69636079e-03 -3.78340040e-03-3.67069780e-03 -2.48226710e-03 -2.55713821e-03 4.99928882e-031.45393785e-03 2.49507488e-03 -8.46061084e-05 1.94053049e-04 -2.24484736e-03 -2.98719225e-03 -1.11764995e-03 9.15783632e-045.61350571e-05 -2.47923145e-03 -4.22814535e-03 3.37808905e-03 -3.72007908e-03 -1.03709043e-03 -2.93633156e-03 1.26775028e-03 4.27068351e-03 -1.86327007e-03 -2.60812049e-05 1.33782264e-03 2.73997779e-04 -1.25242467e-03 -2.45185802e-04 2.73799663e-03 -3.74487112e-03 -3.61587713e-03 -1.93792314e-03 -1.31568883e-031.00927532e-03 -4.34413878e-03 -4.64724423e-03 -3.27371527e-03 1.73319574e-03 -1.56345638e-03 -4.06962034e-04 3.15540441e-04 -1.19444553e-03 3.85201280e-03 1.28663599e-03 8.16088344e-04 -1.99977588e-03 -6.78795550e-05 8.40884459e-04 4.44133859e-033.19875544e-03 4.99354722e-03 3.08746821e-03 -1.38380169e-03 2.69842218e-03 2.02928190e-04 4.55617253e-03 -4.31599608e-03 2.12017301e-04 1.12942874e-03 -2.02006544e-03 -7.19274860e-04 2.71455175e-03 2.34174542e-03 2.16660742e-03 -4.41146316e-03 -3.60637973e-03 -3.19188298e-03 5.50605648e-04 -4.24018688e-03-3.21501610e-03 2.75668432e-03 -3.80394282e-03 4.51803859e-03 3.08856834e-03 2.92636757e-03 4.29136446e-03 3.78820952e-03 -2.28936947e-03 -2.11889157e-03 -1.60276773e-03 -4.13687294e-03 2.45422847e-03 -1.58591929e-03 -1.99517701e-03 -2.24435629e-04 7.97715795e-04 2.43963534e-03 -3.11900978e-03 -4.57696337e-03 3.55282542e-03 2.64127087e-03 4.60635824e-03 8.36285355e-04] [4.48413379e-03 2.44626397e-04 3.54981539e-03 -2.70133372e-03 3.98495788e-04 2.73300940e-03 2.65656295e-03 3.28538008e-03 2.68956600e-03 5.59385400e-04 -2.25706049e-03 9.59072728e-04 1.53078558e-03 2.67903320e-03 -2.57783540e-04 3.11671267e-03 -4.07306291e-03 4.43579489e-03 -1.17100810e-03 9.52193164e-04 1.96281541e-03 4.26336052e-03 1.93470949e-03 2.98191677e-03 2.87507894e-03 9.76170879e-04 -2.88352044e-03 3.21545545e-03 -3.46912863e-03 2.40935269e-03 -4.48730728e-03 3.91324982e-03 1.75873877e-03 4.26968513e-03 -1.31236797e-03 -3.13599175e-03 -2.73311860e-03 -4.39819461e-03 6.75788498e-04 8.16345200e-05-2.28925981e-03 -4.98499442e-03 -3.76006449e-03 -1.49675133e-035.80207095e-04 4.08831099e-03 1.82866934e-03 4.93304664e-03 -3.51736974e-03 1.58695702e-03 -8.12330225e-04 -2.38086190e-03 -4.82690339e-05 4.91506234e-03 3.83886811e-03 2.15272899e-04 -3.57381883e-03 2.35990225e-03 -2.33425526e-03 -4.35061473e-03 -3.59224528e-03 -1.67626445e-03 4.30664467e-03 -2.80259480e-03 -1.67705445e-03 -3.14151775e-03 -3.81832127e-04 5.76865103e-04 -1.20366097e-03 -3.53604276e-03 1.74811843e-03 3.12279235e-03 -4.29844437e-03 3.98078607e-03 -3.93536920e-03 -3.08903167e-04 -1.43758650e-03 3.12288874e-03 3.52566014e-03 -9.82839148e-04 2.76797422e-04 3.34875216e-03 -4.40385100e-03 3.32460529e-03 -2.58580752e-04 2.62086280e-03 2.07542768e-03 3.74424038e-03 3.03011248e-03 -3.17586237e-03 -1.37094315e-03 2.98606465e-03 3.98311438e-03 -4.39885352e-03 3.22064763e-04 -3.93010536e-03 -2.44358298e-03 1.07752020e-03 1.43448648e-03 3.19932867e-03] [-1.50326053e-02 2.33720485e-02 4.27093245e-02 -8.67371820e-03 7.62364944e-04 -8.38285591e-03 1.75248012e-02 3.87595929e-02 -3.34964581e-02 -2.33036559e-02 1.23848682e-02 -2.45889686e-02 -2.31660865e-02 -1.63986087e-02 2.74699666e-02 -1.07484013e-02 2.91726645e-02 2.51875687e-02 -2.12938096e-02 -6.05102330e-02 2.52604000e-02 -1.05914902e-02 5.48903719e-02 -4.09843512e-02 -4.91047427e-02 3.47440019e-02 -4.91700508e-03 -1.36402398e-02 -4.14595567e-03 1.68750789e-02 2.69708340e-03 -2.20290273e-02 6.97579607e-03 1.70566812e-02 -1.46828629e-02 6.16768561e-03 -2.78133806e-02 1.04409987e-02 -1.54850194e-02 -3.50269419e-03 6.62003532e-02 8.48833937e-03 -5.52371750e-03 3.34543176e-02 -8.95058736e-03 7.87579454e-03 -1.37616298e-04 -2.60825530e-02 5.61093539e-03 1.62323210e-02 5.00275940e-03 -4.19090353e-02 1.56034222e-02 -1.16800042e-02 -2.71011554e-02 1.83153385e-03 2.82120355e-03 -1.64997764e-03 2.57056896e-02 -2.16343440e-02 -1.02113904e-02 7.60074938e-03 3.93435322e-02 -1.95588712e-02 -2.12915484e-02 4.90818806e-02 3.12895887e-02 4.00264859e-02 -1.05817998e-02 -1.78802572e-02 4.26569395e-03 2.44223811e-02 1.34106958e-02 4.46485840e-02 2.01959070e-02 2.80952770e-02 4.94695269e-02 -4.48416872e-03 -2.29242779e-02 -2.82812249e-02 -3.88493165e-02 2.21420005e-02 1.47683015e-02 1.27959643e-02 4.85856319e-03 -1.26856696e-02 2.68890411e-02 -9.07115079e-03 -3.04388329e-02 -2.61153579e-02 1.73969306e-02 1.54818920e-02 -4.98219253e-03 1.76928192e-02 1.83494315e-02 2.52679158e-02 3.42054330e-02 4.70492104e-03 1.32856742e-02 3.21734771e-02] [-2.23177038e-02 3.77678052e-02 5.26131429e-02 1.12298783e-02 5.64516708e-03 -3.40459570e-02 2.32256297e-02 7.24501684e-02 -5.21231592e-02 -6.70583099e-02 2.56086849e-02 -5.61455637e-02 -1.87617354e-02 -1.22663993e-02 5.67685142e-02 -2.19040941e-02 4.76449840e-02 1.17707793e-02 -3.31403837e-02 -1.10223822e-01 2.89300345e-02 -1.87962279e-02 7.27758184e-02 -3.75068486e-02 -4.69661132e-02 3.80857661e-02 -4.38448936e-02 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2.58372203e-02 3.95044452e-03 3.30288406e-03 6.12850301e-02 3.37075368e-02 3.69956531e-02 -5.67345088e-03 3.01545747e-02 3.23488340e-02] [2.24040332e-03 3.51834949e-03 4.27228911e-03 -2.00713193e-03 2.54825479e-03 -2.74868496e-03 2.60700705e-03 2.47270288e-03 -1.10419397e-03 9.34707525e-04 5.57270658e-04 7.75072549e-04 -2.60955514e-03 -1.75806310e-03 -3.28579522e-03 -4.83133784e-03 2.49853916e-03 1.80147949e-03 -1.14010100e-03 -2.91802455e-03 -2.66682752e-03 -3.57033126e-03 1.74591062e-03 -1.91042724e-04 2.11944454e-03 -1.94972602e-03 2.73387367e-03 -1.49896473e-03 3.03765526e-03 -6.61560916e-05 1.86432246e-03 -3.09289573e-03 -2.20013922e-03 4.84825484e-03 1.88259664e-03 2.24893144e-03 3.08364560e-03 4.42651054e-03 -4.28421423e-03 -3.29099782e-03 1.89079519e-03 -7.52588501e-04 -1.20179739e-03 2.06941017e-03 4.93740197e-03 -1.87331589e-03 -4.80535813e-03 -2.74573080e-03 4.33808332e-03 4.56310809e-03 -2.21250486e-03 -7.79321766e-04 5.06541110e-04 2.48121028e-03 3.61084589e-03 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-3.69295944e-03 -2.77226884e-03 4.76110168e-03 3.30484984e-03 -3.07668815e-03 -2.82747205e-03 -2.35885386e-06 2.14157766e-03 -3.09846969e-03 3.43135465e-03 4.05517872e-03 -3.72108049e-03 -2.26280987e-04 -1.36749272e-03 1.46303652e-03 2.09397194e-03 -3.99389165e-03 -1.92634168e-03 -3.08158644e-035.37258398e-04 -1.01363359e-04 3.19746602e-03 3.75241879e-03 7.49543309e-04 -1.69249950e-03 -4.52794088e-03 -4.31931717e-03 $-3.50058684 \\ e-03 \\ -2.85936473 \\ e-03 \\ -1.28515775 \\ e-03 \\ 4.52402839 \\ e-03$ 3.16024548e-03 2.09408812e-03 7.36106012e-04 4.91945678e-03] [-1.14243710e-02 4.08698246e-02 7.59659559e-02 -2.23000459e-02 -2.02016048e-02 -2.81370636e-02 1.74839888e-02 6.35988638e-02 -5.24329431e-02 -6.96849898e-02 1.57731511e-02 -4.10088636e-02 -3.39860842e-02 -4.11406271e-02 6.60655200e-02 -1.44113451e-02 4.27038707e-02 3.74182090e-02 -2.84840781e-02 -9.56150368e-02 4.14373465e-02 -1.83257814e-02 5.95930330e-02 -6.04322627e-02 -6.85705915e-02 4.19557504e-02 -1.85567327e-02 -2.23696157e-02 -1.92271341e-02 1.13440948e-02 1.58242304e-02 -3.93442884e-02 2.27016844e-02 2.52873451e-03 -1.49477962e-02 2.00738274e-02 -2.43375413e-02 2.42335517e-02 -3.19421254e-02 -1.33402301e-02 8.94114748e-02 1.59770325e-02 -1.07836127e-02 5.92442602e-02 -1.23081803e-02 -7.51141878e-03 -1.30087445e-02 -3.64692919e-02 3.18519701e-03 3.70854214e-02 8.18810053e-03 -5.05383462e-02 1.13018733e-02 -3.53291780e-02 -4.98894416e-02 3.49357491e-03 1.03191677e-02 -3.89416260e-03 4.60515954e-02 -4.54453416e-02 -2.08020192e-02 2.25796290e-02 6.56830892e-02 -2.68713944e-02 -3.09991445e-02 9.58280861e-02 4.29001153e-02 4.65281382e-02 -1.99445207e-02 -3.48530896e-02 1.61293391e-02 4.27644327e-02 1.67636462e-02 6.94420561e-02 4.06254418e-02 7.19528496e-02 7.54765645e-02 -9.59256198e-03 -4.39969786e-02 -3.22896652e-02 -8.13663006e-02 1.88639164e-02 3.19711268e-02 1.88643858e-02 3.42357741e-03 -2.11408809e-02 4.39295694e-02 -7.45151984e-03 -4.09549996e-02 -2.12903153e-02 3.12322434e-02 3.93284932e-02 -2.55133188e-03 4.32699956e-02 4.50843126e-02 4.91437502e-02 5.18986993e-02 1.74695998e-03 1.37147391e-02 5.25171086e-02]] (1115, 100)Out[9]: In [10]: model doc rf = RandomForestClassifier() model_doc_rf.fit(X_train_doc_vect,y_train.values.ravel()) pred_doc_rf=model_doc_rf.predict(X_test_doc_vect) In [11]: print(pred doc rf.shape) print(y test.shape) acc3=accuracy score(y test,pred doc rf) pre3=precision score(y test,pred doc rf) print("Accuracy Score :",acc3) print("Precision Score :",pre3) import seaborn as sns sns.heatmap(confusion matrix(y test,pred doc rf),annot=True, cmap='Blues', cbar=False, linewidths=3, linecolor= print(classification report(y test,pred doc rf))

!pip install -U from keras.prepr	rocessing.text import Tokenizer # simple pre-process function from genesis celan and to rocessing.sequence import pad_sequences enizer()
<pre>X_test_seq = tok X_train_seq[0] X_train_seq_padd X_test_seq_padde X_train_seq_padd import keras.bac from keras.layer</pre>	
possible recall = return r def precision_m(true_pos predicte precisio return p # Construct a si model = Sequenti model.add(Embedd model.add(LSTM(3)	<pre>sitives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1))) e_positives = K.sum(K.round(K.clip(y_true, 0, 1))) = true_positives / (possible_positives + K.epsilon()) recall (y_true, y_pred): sitives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1))) ed_positives = K.sum(K.round(K.clip(y_pred, 0, 1))) on = true_positives / (predicted_positives + K.epsilon()) precision imple RNN model ial() ding(len(tokenizer.index_word)+1, 32)) 32, dropout=0, recurrent_dropout=0))</pre>
<pre>model.add(Dense(model.summary() model.compile(op</pre>	oss='binary_crossentropy', etrics=['accuracy', precision_m, recall_m])
<pre>import matplotli for i in ['accur acc = histor val_acc = hi epochs = ran plt.figure() plt.plot(epo plt.plot(epo plt.title('R plt.legend() plt.show()</pre>	<pre>racy', 'precision_m', 'recall_m']: ry.history[i] istory.history['val_{{}'.format(i)}] nge(1, len(acc) + 1)) ochs, acc, label='Training Accuracy') ochs, val_acc, label='Validation Accuracy') Results for {{}'.format(i)}) ady satisfied: keras in c:\users\yogi\anaconda3\lib\site-packages (2.9.0)</pre>
Layer (type) embedding (Embed lstm (LSTM) dense (Dense) dense_1 (Dense)	Output Shape Param #
140/140 [====================================	======================================
9857 - recall_m: 401 Epoch 8/10 140/140 [====================================	======================================
1.00 - 0.98 - 0.96 - 0.94 -	Results for accuracy Training Accuracy Validation Accuracy
0.9 - 0.8 - 0.7 - 0.6 - 0.5	Results for precision_m Training Accuracy Validation Accuracy
1.0 - 0.9 - 0.8 - 0.7 - 0.6 - 0.5 - 0.4 -	Results for recall_m Training Accuracy Validation Accuracy
print (f"The accu The accuracy and ctively. The accuracy and pectively. The accuracy and pectively.	4 6 8 10
Conclusion ve can conclude that and ease of use. It is e	n: TF_IDF is best technique TF_IDF is best algorithm as we can see accuracy is more than other models. The advantage of TF-IDF is its sine easy to compute, has low computational cost, and is an easy starting point for similarity computation. TF-IDF he frequency of words to determine how relevant those words are to a particular document. This is a relatively