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. tr	om sklearn.feature_selection import chi2 port numpy as np = 5 r current_class in list(le.classes_):
fro imp N =	<pre>current_class_id = le.transform([current_class])[0] features_chi2 = chi2(features_description, labels == current_class_id) indices = np.argsort(features_chi2[0]) feature_names = np.array(tfidf_desc.get_feature_names())[indices] unigrams = [v for v in feature_names if len(v.split(' ')) == 1] bigrams = [v for v in feature_names if len(v.split(' ')) == 2] print("# '{}':".format(current_class)) print("Most correlated unigrams:") print('-' *30) print("Most correlated bigrams:") print('-' *30) print('. {}'.format('\n. '.join(bigrams[-N:]))) print('. {}'.format('\n. '.join(bigrams[-N:]))) print("\n")</pre>
Most . of . pa . mu . ar . th Most . ca . cl	usic rt heatre t correlated bigrams: apitol theatre
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fro fro fro fro	om sklearn.model_selection import train_test_split om sklearn.naive_bayes import MultinomialNB om sklearn import linear_model om sklearn.ensemble import AdaBoostClassifier crain, X_test, y_train, y_test = train_test_split(data.iloc[:, 1:3], data['Category'], random_state = 0)
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3072 713 3598 1680 819	travel hong kong heres hong kong vlog stay overnight airport vi train.head() 4 5 8 1 9 5
fro fro fro fro fro	waive Bayes = MultinomialNB().fit(features, y_train) om keras.preprocessing.text import Tokenizer om keras.preprocessing.sequence import pad_sequences om keras.models import Sequential om keras.layers import Dense, Embedding, LSTM, SpatialDropout1D om sklearn.naive_bayes import MultinomialNB om keras.utils.np_utils import to_categorical The maximum number of words to be used. (most frequent) (CNB_WORDS = 20000
# M MAX # T EMB # C tit des dat	<pre>C_NB_WORDS = 20000 Max number of words in each complaint. (_SEQUENCE_LENGTH = 50 This is fixed. BEDDING_DIM = 100 Combining titles and descriptions into a single sentence tles = data['Title'].values Scriptions = data['Description'].values ta_for_lstms = [] i in range(len(titles)): temp_list = [titles[i], descriptions[i]] data_for_lstms.append(' '.join(temp_list))</pre>
tok wor pri # C X = X = pri	<pre>kenizer = Tokenizer(num_words=MAX_NB_WORDS, filters='!"#\$%&()*+,/:;<=>?@[\]^_`{ }~', lower=True) kenizer.fit_on_texts(data_for_lstms) rd_index = tokenizer.word_index int('Found %s unique tokens.' % len(word_index)) Convert the data to padded sequences tokenizer.texts_to_sequences(data_for_lstms) pad_sequences(X, maxlen=MAX_SEQUENCE_LENGTH) int('Shape of data tensor:', X.shape)</pre> Cone-hot Encode labels
pri # S X_t Foun Shap Shap Pe	<pre>crain, X_test, y_train, y_test = train_test_split(data.iloc[:, 1:3], data['Category'], random_state = 0)</pre>
#Na fro imp imp fro imp	<pre>test_title_features = tfidf_title.transform(X_test['Title']).toarray() test_desc_features = tfidf_desc.transform(X_test['Description']).toarray() st_features = np.concatenate([X_test_title_features, X_test_desc_features], axis=1) aive Bayes om sklearn import metrics oort matplotlib.pyplot as plt oort seaborn as sns om sklearn.metrics import confusion_matrix oort scikitplot as skplt</pre>
X_t tes # N y_p y_p pri con fig sns plt plt plt plt skp plt	<pre>cest_title_features = tfidf_title.transform(X_test['Description']).toarray() cest_desc_features = tfidf_desc.transform(X_test['Description']).toarray() sts_features = np.concatenate([X_test_title_features, X_test_desc_features], axis=1) daive Bayes oroda = nb.predict(test_features) orobas = nb.predict_proba(test_features) int(metrics.classification_report(y_test, y_pred, target_names=list(le.classes_))) inf_mat = confusion_matrix(y_test, y_pred)</pre>
	precision recall f1-score support art and music
	Confusion Matrix - Naive Bayes art and music - 396
Actual	history - 5 1 397 4 8 3 -250 manufacturing - 2 1 0 394 1 0 -150
sci	travel - 11 4 1 3 1 386 Language Property of the pool
walli wa	Predicted Users\91981\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:86: FutureWarning: Function plot_precision_recall_curve is deprecated; be removed in v0.5.0. Please use scikitplot.metrics.plot_precision_recall instead. arnings.warn(msg, category=FutureWarning) Precision-Recall Curve - Naive Bayes
0.0 0.0 0.0 0.0	Precision-recall curve of class 0 (area = 0.976) Precision-recall curve of class 1 (area = 0.989) Precision-recall curve of class 2 (area = 0.992) Precision-recall curve of class 3 (area = 0.989) Precision-recall curve of class 4 (area = 0.987) Precision-recall curve of class 5 (area = 0.992) micro-average Precision-recall curve (area = 0.988)
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