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In [1]: from sklearn import model_selection, preprocessing, linear_model, naive_bayes, model sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer from sklearn import decomposition, ensemble
    import pandas, xgboost, numpy, textblob, string from keras.preprocessing import text, sequence from keras import layers, models, optimizers
```

c:\users\mglewis\appdata\local\programs\python\python36\lib\site-packages\sklea rn\ensemble\weight_boosting.py:29: DeprecationWarning: numpy.core.umath_tests i s an internal NumPy module and should not be imported. It will be removed in a future NumPy release.

from numpy.core.umath_tests import inner1d
Using TensorFlow backend.

```
In [2]: # Load the dataset
    data = open("corpus", encoding="utf8")
    labels, texts = [], []
    for i, line in enumerate(list(data)):
        content = line.split()
        labels.append(content[0])
        texts.append(" ".join(content[1:]))

# create a dataframe using texts and lables
    trainDF = pandas.DataFrame()
    trainDF['text'] = texts
    trainDF['label'] = labels
```

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In [3]: # split the dataset into training and validation datasets
    train_x, valid_x, train_y, valid_y = model_selection.train_test_split(trainDF['to
    # Label encode the target variable
    encoder = preprocessing.LabelEncoder()
    train_y = encoder.fit_transform(train_y)
    valid_y = encoder.fit_transform(valid_y)
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In [4]: # create a count vectorizer object
    count_vect = CountVectorizer(analyzer='word', token_pattern=r'\w{1,}')
    count_vect.fit(trainDF['text'])

# transform the training and validation data using count vectorizer object
    xtrain_count = count_vect.transform(train_x)
    xvalid_count = count_vect.transform(valid_x)
```

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In [5]: # word level tf-idf
        tfidf_vect = TfidfVectorizer(analyzer='word', token_pattern=r'\w{1,}', max_featu
        tfidf vect.fit(trainDF['text'])
        xtrain tfidf = tfidf vect.transform(train x)
        xvalid tfidf = tfidf vect.transform(valid x)
        # ngram level tf-idf
        tfidf vect ngram = TfidfVectorizer(analyzer='word', token pattern=r'\w{1,}', ngr
        tfidf vect ngram.fit(trainDF['text'])
        xtrain_tfidf_ngram = tfidf_vect_ngram.transform(train_x)
        xvalid tfidf ngram = tfidf vect ngram.transform(valid x)
        # characters level tf-idf
        tfidf vect ngram chars = TfidfVectorizer(analyzer='char', token pattern=r'\w{1,}
        tfidf vect ngram chars.fit(trainDF['text'])
        xtrain_tfidf_ngram_chars = tfidf_vect_ngram_chars.transform(train_x)
        xvalid tfidf ngram chars = tfidf vect ngram chars.transform(valid x)
In [8]: | # Load the pre-trained word-embedding vectors
        embeddings index = {}
        for i, line in enumerate(open('wiki-news-300d-1M.vec', encoding="utf8")):
            values = line.split()
            embeddings index[values[0]] = numpy.asarray(values[1:], dtype='float32')
        # create a tokenizer
        token = text.Tokenizer()
        token.fit on texts(trainDF['text'])
        word index = token.word index
        # convert text to sequence of tokens and pad them to ensure equal length vectors
        train_seq_x = sequence.pad_sequences(token.texts_to_sequences(train_x), maxlen=7
        valid seq x = sequence.pad sequences(token.texts to sequences(valid x), maxlen=70
        # create token-embedding mapping
        embedding matrix = numpy.zeros((len(word index) + 1, 300))
        for word, i in word index.items():
            embedding_vector = embeddings_index.get(word)
            if embedding_vector is not None:
                embedding matrix[i] = embedding vector
        trainDF['char count'] = trainDF['text'].apply(len)
        trainDF['word count'] = trainDF['text'].apply(lambda x: len(x.split()))
        trainDF['word_density'] = trainDF['char_count'] / (trainDF['word_count']+1)
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trainDF['punctuation_count'] = trainDF['text'].apply(lambda x: len("".join(_ for
trainDF['title_word_count'] = trainDF['text'].apply(lambda x: len([wrd for wrd interpretation of the count']);
trainDF['upper case word count'] = trainDF['text'].apply(lambda x: len([wrd for v
```

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In [11]:
         import nltk
          nltk.download('averaged perceptron tagger')
         pos family = {
              'noun' : ['NN','NNS','NNP','NNPS'],
              'pron' : ['PRP','PRP$','WP','WP$'],
              'verb' : ['VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ'],
              'adj' : ['JJ','JJR','JJS'],
              'adv' : ['RB', 'RBR', 'RBS', 'WRB']
          }
         # function to check and get the part of speech tag count of a words in a given se
         def check_pos_tag(x, flag):
              cnt = 0
              try:
                  wiki = textblob.TextBlob(x)
                  for tup in wiki.tags:
                      ppo = list(tup)[1]
                      if ppo in pos_family[flag]:
                          cnt += 1
              except:
                  pass
              return cnt
         trainDF['noun_count'] = trainDF['text'].apply(lambda x: check_pos_tag(x, 'noun')
         trainDF['verb_count'] = trainDF['text'].apply(lambda x: check_pos_tag(x, 'verb')
         trainDF['adj_count'] = trainDF['text'].apply(lambda x: check_pos_tag(x, 'adj'))
          trainDF['adv count'] = trainDF['text'].apply(lambda x: check pos tag(x, 'adv'))
         trainDF['pron_count'] = trainDF['text'].apply(lambda x: check_pos_tag(x, 'pron')
         [nltk data] Downloading package averaged perceptron tagger to
                          C:\Users\mglewis\AppData\Roaming\nltk data...
         [nltk data]
         [nltk data]
                        Unzipping taggers\averaged perceptron tagger.zip.
In [12]: | # train a LDA Model
         lda model = decomposition.LatentDirichletAllocation(n components=20, learning me
         X_topics = lda_model.fit_transform(xtrain_count)
         topic word = lda model.components
         vocab = count vect.get feature names()
         # view the topic models
         n \text{ top words} = 10
         topic_summaries = []
         for i, topic dist in enumerate(topic word):
              topic_words = numpy.array(vocab)[numpy.argsort(topic_dist)][:-(n_top_words+1
              topic summaries.append(' '.join(topic words))
```

```
In [13]: def train model(classifier, feature vector train, label, feature vector valid, i
                                         # fit the training dataset on the classifier
                                         classifier.fit(feature vector train, label)
                                         # predict the labels on validation dataset
                                         predictions = classifier.predict(feature_vector_valid)
                                        if is neural net:
                                                     predictions = predictions.argmax(axis=-1)
                                         return metrics.accuracy score(predictions, valid y)
In [15]: | # Naive Bayes on Count Vectors
                             accuracy = train model(naive bayes.MultinomialNB(), xtrain count, train y, xvalid
                             print("NB, Count Vectors: ", accuracy)
                             # Naive Bayes on Word Level TF IDF Vectors
                             accuracy = train model(naive bayes.MultinomialNB(), xtrain tfidf, train y, xvalid
                             print("NB, WordLevel TF-IDF: ", accuracy)
                             # Naive Bayes on Ngram Level TF IDF Vectors
                             accuracy = train model(naive bayes.MultinomialNB(), xtrain tfidf ngram, train y,
                             print("NB, N-Gram Vectors: ", accuracy)
                             # Naive Bayes on Character Level TF IDF Vectors
                             accuracy = train_model(naive_bayes.MultinomialNB(), xtrain_tfidf_ngram_chars, train_tfidf_ngram_chars, train_tfidf_n
                             print("NB, CharLevel Vectors: ", accuracy)
                            NB, Count Vectors: 0.834
                            NB, WordLevel TF-IDF: 0.8396
                            NB, N-Gram Vectors: 0.8428
                            NB, CharLevel Vectors: 0.8064
In [16]:
                           # Linear Classifier on Count Vectors
                             accuracy = train model(linear model.LogisticRegression(), xtrain count, train y,
                             print("LR, Count Vectors: ", accuracy)
                             # Linear Classifier on Word Level TF IDF Vectors
                             accuracy = train model(linear model.LogisticRegression(), xtrain tfidf, train y,
                             print("LR, WordLevel TF-IDF: ", accuracy)
                             # Linear Classifier on Ngram Level TF IDF Vectors
                             accuracy = train_model(linear_model.LogisticRegression(), xtrain_tfidf_ngram, train_tfidf_ngram, train_
                             print("LR, N-Gram Vectors: ", accuracy)
                             # Linear Classifier on Character Level TF IDF Vectors
                             accuracy = train_model(linear_model.LogisticRegression(), xtrain_tfidf_ngram_chai
                             print("LR, CharLevel Vectors: ", accuracy)
                            LR, Count Vectors: 0.8564
                            LR, WordLevel TF-IDF: 0.866
                            LR, N-Gram Vectors: 0.8364
                            LR, CharLevel Vectors: 0.8368
```

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In [17]: # SVM on Ngram Level TF IDF Vectors
    accuracy = train_model(svm.SVC(), xtrain_tfidf_ngram, train_y, xvalid_tfidf_ngram
    print("SVM, N-Gram Vectors: ", accuracy)

SVM, N-Gram Vectors: 0.5148
In [ ]:
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