Models_kNN_LDA_QDA_DT_RF_NN_LD

Group 4: Kiet Ly, Mary Monroe, and Shaswati Mukherjee

In [30]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.utils import resample
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score,r2_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import scale
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout

%matplotlib inline

import seaborn as sns
sns.set(style='whitegrid')
pd.set_option('display.width', 1500)
pd.set_option('display.max_columns', 100)

import warnings
warnings.filterwarnings('ignore')
```

Create train/test set for accounts and tweets

Discussion:

The dataset for accounts and tweets are split into train/test ratio of 2/3 and 1/3. In Models_kNN_LDA_QDA_DT_RF notebook we looked at various base models and models using NLP. Here we continue by adding Lexical Diversity Predictors to see if our accuracy improves with all these models. The lexical Diversity features were generated and selected in lexical_diversity NB. These are the additional LD features which we will use to try to improve our model:

Tweets Features
LD-uber_index
LD-yule_s_k
LD-mtld
LD-hdd

In [31]:

```python
combine_df = []
for file_ in ['/Users/smukherjee5/cs109_final_project/cs109a/data/tweets_nlp_1_2_ld.csv','/Users/smukherjee5/cs109_final_project/cs109a/data/tweets_nlp_2_2_ld.csv','/Users/smukherjee5/cs109_final_project/cs109a/data/tweets_nlp_3_2_ld.csv']:
    df = pd.read_csv(file_,index_col=None, header=0,keep_default_na=False)
    combine_df.append(df)
all_tweets = pd.concat(combine_df, axis = 0, ignore_index = True)

all_tweets[['LD-yule_s_k']] = all_tweets[['LD-yule_s_k']].fillna(0)

def convert_float(val):
    try:
        return float(val)
    except ValueError:
        return 0

all_tweets['LD-yule_s_k']=all_tweets['LD-yule_s_k'].apply(lambda x: convert_float(x))
train_base_tweets_df, test_base_tweets_df = train_test_split(all_tweets, test_size=0.33, random_state=42, stratify=all_tweets['user_type'])

print('train tweets shape:',train_base_tweets_df.shape)
print('test tweets shape:',test_base_tweets_df.shape)

all_tweets_df = all_tweets[['retweet_count', 'favorite_count', 'num_hashtags', 'num_urls', 'num_mentions',
                               'user_type', 'sentiment_negative', 'sentiment_neutral', 'sentiment_positive',
                               'ratio_pos', 'ratio_neg', 'ratio_neu', 'token_count', 'url_token_ratio', 'ant',
                               'disgust', 'fear', 'joy', 'sadness', 'surprise', 'trust','jaccard','LD-uber_index','LD-yule_s_k','LD-mtld','LD-hdd']]

train_base_tweets_df, test_base_tweets_df = train_test_split(all_tweets_df, test_size=0.33, random_state=42,
                                                              stratify=all_tweets_df['user_type'])
X_train, y_train = train_base_tweets_df.drop('user_type',axis=1), train_base_tweets_df['user_type']
X_test, y_test = test_base_tweets_df.drop('user_type',axis=1), test_base_tweets_df['user_type']
```

```
train tweets shape: (80574, 60)
test tweets shape: (39686, 60)
```

kNN with NLP and Lexical Density features

In [5]:

```
#scale down to 10% or take forever.
Xs_train, Xs_test = scale(X_train), scale(X_test)

neighbors, train_scores, cvmeans, cvstds, cv_scores = [], [], [], [], []
for n in range(1,11):
    neighbors.append(n)
    knn = KNeighborsClassifier(n_neighbors = n)
    train_scores.append(knn.fit(X_train, y_train).score(X_train, y_train))
    scores = cross_val_score(estimator=knn,X=Xs_train, y=y_train, cv=5)
    cvmeans.append(scores.mean())
    cvstds.append(scores.std())

#Alter data structure for using internal numpy functions
cvmeans = np.array(cvmeans)
cvstds = np.array(cvstds)
#Plot Means and Shade the +-2 SD Interval
plt.plot(neighbors, cvmeans, '*-', label="Mean CV")
plt.fill_between(neighbors, cvmeans - 2*cvstds, cvmeans + 2*cvstds, alpha=0.3)
ylim = plt.ylim()
plt.plot(neighbors, train_scores, '-+', label="Train")
plt.ylim(ylim)
plt.legend()
plt.ylabel("Accuracy")
plt.xlabel("Neighbors")
plt.title('Tweets Mean CV accuracy vs max depth')
plt.xticks(neighbors)
plt.show()
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-5-e73bee2de747> in <module>()
     11     knn = KNeighborsClassifier(n_neighbors = n)
     12     train_scores.append(knn.fit(X_train, y_train).score(X_train, y_train))
---> 13     scores = cross_val_score(estimator=knn,X=Xs_train, y=y_train, cv=5)
     14     cvmeans.append(scores.mean())
     15     cvstds.append(scores.std())

/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_validation.py in cross_val_score(estimator, X, y, groups, scoring, cv, n_jobs, verbose, fit_params, pre_dispatch)
    340                                 n_jobs=n_jobs, verbose=verbose,
    341                                 fit_params=fit_params,
--> 342                                 pre_dispatch=pre_dispatch)
    343     return cv_results['test_score']
    344
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_vali
dation.py in cross_validate(estimator, X, y, groups, scoring, cv, n_
jobs, verbose, fit_params, pre_dispatch, return_train_score)
    204                 fit_params, return_train_score=return_train_scor
e,
    205                 return_times=True)
--> 206         for train, test in cv.split(X, y, groups))
    207
    208     if return_train_score:

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in __call__(self, iterable)
    777                 # was dispatched. In particular this covers the
edge
    778                 # case of Parallel used with an exhausted iterat
or.
--> 779                 while self.dispatch_one_batch(iterator):
    780                     self._iterating = True
    781                 else:

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in dispatch_one_batch(self, iterator)
    623                     return False
    624                 else:
--> 625                     self._dispatch(tasks)
    626                     return True
    627

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in _dispatch(self, batch)
    586         dispatch_timestamp = time.time()
    587         cb = BatchCompletionCallBack(dispatch_timestamp, len
(batch), self)
--> 588         job = self._backend.apply_async(batch, callback=cb)
    589         self._jobs.append(job)
    590

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/_par
allel_backends.py in apply_async(self, func, callback)
    109     def apply_async(self, func, callback=None):
    110         """Schedule a func to be run"""
--> 111         result = ImmediateResult(func)
    112         if callback:
    113             callback(result)

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/_par
allel_backends.py in __init__(self, batch)
    330         # Don't delay the application, to avoid keeping the
input
    331         # arguments in memory
--> 332         self.results = batch()
    333
```

```
    334     def get(self):

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in __call__(self)
    129
    130     def __call__(self):
--> 131         return [func(*args, **kwargs) for func, args, kwargs
in self.items]
    132
    133     def __len__(self):

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in <listcomp>(.0)
    129
    130     def __call__(self):
--> 131         return [func(*args, **kwargs) for func, args, kwargs
in self.items]
    132
    133     def __len__(self):

/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_vali
dation.py in _fit_and_score(estimator, X, y, scorer, train, test, ve
rbose, parameters, fit_params, return_train_score, return_parameters
, return_n_test_samples, return_times, error_score)
    486         fit_time = time.time() - start_time
    487         # _score will return dict if is_multimetric is True
--> 488         test_scores = _score(estimator, X_test, y_test,
scorer, is_multimetric)
    489         score_time = time.time() - start_time - fit_time
    490         if return_train_score:

/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_vali
dation.py in _score(estimator, X_test, y_test, scorer, is_multimetri
c)
    521     """
    522     if is_multimetric:
--> 523         return _multimetric_score(estimator, X_test, y_test,
scorer)
    524     else:
    525         if y_test is None:

/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_vali
dation.py in _multimetric_score(estimator, X_test, y_test, scorers)
    551             score = scorer(estimator, X_test)
    552         else:
--> 553             score = scorer(estimator, X_test, y_test)
    554
    555         if hasattr(score, 'item'):

/anaconda3/lib/python3.6/site-packages/sklearn/metrics/scorer.py in
_passthrough_scorer(estimator, *args, **kwargs)
    242 def _passthrough_scorer(estimator, *args, **kwargs):
    243     """Function that wraps estimator.score"""
```

```
--> 244     return estimator.score(*args, **kwargs)
    245
    246

/anaconda3/lib/python3.6/site-packages/sklearn/base.py in score(self
, X, y, sample_weight)
    347         """
    348         from .metrics import accuracy_score
--> 349         return accuracy_score(y, self.predict(X),
sample_weight=sample_weight)
    350
    351

/anaconda3/lib/python3.6/site-packages/sklearn/neighbors/classificat
ion.py in predict(self, X)
    143         X = check_array(X, accept_sparse='csr')
    144
--> 145         neigh_dist, neigh_ind = self.kneighbors(X)
    146
    147         classes_ = self.classes_

/anaconda3/lib/python3.6/site-packages/sklearn/neighbors/base.py in
kneighbors(self, X, n_neighbors, return_distance)
    383                 delayed(self._tree.query, check_pickle=False
)(
    384                     X[s], n_neighbors, return_distance)
--> 385                 for s in gen_even_slices(X.shape[0], n_jobs)
    386             )
    387             if return_distance:

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in __call__(self, iterable)
    777             # was dispatched. In particular this covers the
edge
    778             # case of Parallel used with an exhausted iterat
or.
--> 779             while self.dispatch_one_batch(iterator):
    780                 self._iterating = True
    781             else:

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in dispatch_one_batch(self, iterator)
    623                 return False
    624             else:
--> 625                 self._dispatch(tasks)
    626                 return True
    627

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in _dispatch(self, batch)
    586         dispatch_timestamp = time.time()
    587         cb = BatchCompletionCallBack(dispatch_timestamp, len
(batch), self)
```

```
--> 588             job = self._backend.apply_async(batch, callback=cb)
    589             self._jobs.append(job)
    590 

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/_par
allel_backends.py in apply_async(self, func, callback)
    109     def apply_async(self, func, callback=None):
    110         """Schedule a func to be run"""
--> 111         result = ImmediateResult(func)
    112         if callback:
    113             callback(result)

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/_par
allel_backends.py in __init__(self, batch)
    330         # Don't delay the application, to avoid keeping the
input
    331         # arguments in memory
--> 332         self.results = batch()
    333 
    334     def get(self):

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in __call__(self)
    129 
    130     def __call__(self):
--> 131         return [func(*args, **kwargs) for func, args, kwargs
in self.items]
    132 
    133     def __len__(self):

/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/para
llel.py in <listcomp>(.0)
    129 
    130     def __call__(self):
--> 131         return [func(*args, **kwargs) for func, args, kwargs
in self.items]
    132 
    133     def __len__(self):

KeyboardInterrupt:
```

LDA/QDA with NLP and Lexical Diversity Features

In [32]:

```
lda = LinearDiscriminantAnalysis().fit(X_train, y_train)
qda = QuadraticDiscriminantAnalysis().fit(X_train, y_train)
print("LDA score: %f, CV score: %f" % (accuracy_score(y_test, lda.predict(X_test
)), cross_val_score(estimator=lda, X=X_test, y=y_test, cv=5).mean()))
print("QDA score: %f, CV score: %f" % (accuracy_score(y_test, qda.predict(X_test
)), cross_val_score(estimator=qda, X=X_test, y=y_test, cv=5).mean()))
```

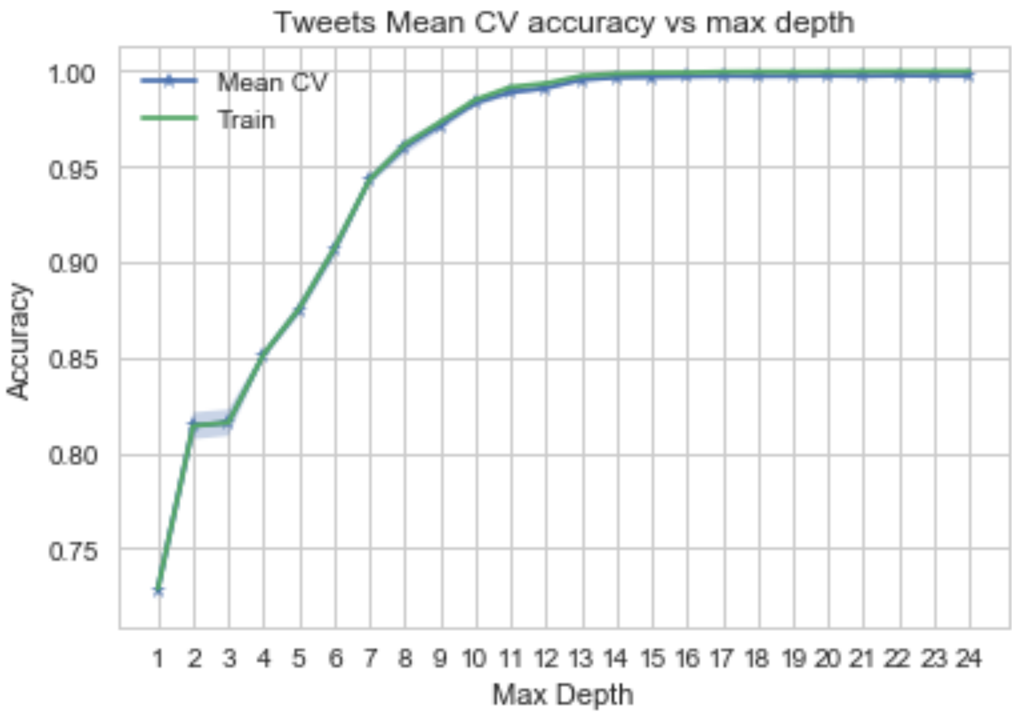
```
LDA score: 0.811369, CV score: 0.811873
QDA score: 0.774228, CV score: 0.735321
```

Decision Tree with NLP and Lexical Diversity features

In [33]:

```
#Perform 5-fold cross validation and store results
depths, train_scores, cvmeans, cvstds, cv_scores = [], [], [], [], []
for depth in range(1,25):
    depths.append(depth)
    dt = DecisionTreeClassifier(max_depth=depth)
    train_scores.append(dt.fit(X_train, y_train).score(X_train, y_train))
    scores = cross_val_score(estimator=dt, X=X_train, y=y_train, cv=5)
    cvmeans.append(scores.mean())
    cvstds.append(scores.std())

#Alter data structure for using internal numpy functions
cvmeans = np.array(cvmeans)
cvstds = np.array(cvstds)
#Plot Means and Shade the +-2 SD Interval
plt.plot(depths, cvmeans, '*-', label="Mean CV")
plt.fill_between(depths, cvmeans - 2*cvstds, cvmeans + 2*cvstds, alpha=0.3)
ylim = plt.ylim()
plt.plot(depths, train_scores, '-+', label="Train")
plt.ylim(ylim)
plt.legend()
plt.ylabel("Accuracy")
plt.xlabel("Max Depth")
plt.title('Tweets Mean CV accuracy vs max depth')
plt.xticks(depths)
plt.show()
```



In [34]:

```
#Choosing the best depth
idx = depths.index(12)
print("Accuracy: Mean={:.3f}, +/- 2 SD: [{:.3f} -- {:.3f}]".format(
    cvmeans[idx], cvmeans[idx] - 2*cvstds[idx], cvmeans[idx] + 2*cvstds[idx]))
```

```
Accuracy: Mean=0.991, +/- 2 SD: [0.990 -- 0.993]
```

In [35]:

```
#Evaluate performance on Test Set
best_cv_depth = 12
fitted_tree = DecisionTreeClassifier(max_depth=best_cv_depth).fit(X_train, y_tra
in)
best_cv_tree_train_score = fitted_tree.score(X_train, y_train)
best_cv_tree_test_score = fitted_tree.score(X_test, y_test)
print(f"The tree of depth {best_cv_depth} achieved an Accuracy of {best_cv_tree_
test_score:.3f} on the test set.")
```

```
The tree of depth 12 achieved an Accuracy of 0.993 on the test set.
```

Random Forest with NLP features and LD

In [36]:

```
#Fit a Random Forest model
fitted_rf = RandomForestClassifier(n_estimators=7, max_depth=13).fit(X_train,y_t
rain)
random_forest_train_score = fitted_rf.score(X_train, y_train)
random_forest_test_score = fitted_rf.score(X_test, y_test)
print(f"The Random Forest scored {random_forest_train_score:.3f} on the training
set.")
print(f"The Random Forest scored {random_forest_test_score:.3f} on the test set.
")
```

```
The Random Forest scored 0.985 on the training set.
The Random Forest scored 0.982 on the test set.
```

Neural Network without NLP

In this section we try to use Keras to build a layered Neural Net. We will use a fully-connected network structure with five layers.

Fully connected layers are defined using the Dense class.

We will use the sigmoid activation function on the first layer,softmax activation in the next, rectifier (‘relu‘) activation function on the next two layers and the sigmoid function in the output layer. We use a sigmoid on the output layer to ensure our network output is between 0 and 1 and easy to map to either a probability of class 1 or snap to a hard classification of either class.

We can piece it all together by adding each layer. The first layer has 100 neurons and expects 5 input variables. The second hidden layer has 300 neurons, the third has 100 and the fourth has 50 neurons,respectively.Finally, the output layer has 1 neuron to predict the class (bot or not).

In [37]:

```
all_tweets_df_no_nlp = all_tweets[['retweet_count', 'favorite_count', 'num_hasht
ags', 'num_urls', 'num_mentions','user_type']].sample(frac=.30)
train_base_tweets_df_no_nlp, test_base_tweets_df_no_nlp = train_test_split(all_t
weets_df_no_nlp, test_size=0.33, random_state=42, stratify=all_tweets_df_no_nlp[
'user_type'])

X_train_no_nlp, y_train_no_nlp = train_base_tweets_df_no_nlp.drop('user_type',ax
is=1), train_base_tweets_df_no_nlp['user_type']
X_test_no_nlp, y_test_no_nlp = test_base_tweets_df_no_nlp.drop('user_type',axis=
1), test_base_tweets_df_no_nlp['user_type']

model = Sequential([
    Dense(100, input_shape=(5,), activation='sigmoid'),
    Dense(300, activation='softmax'),
    Dense(100, activation='relu'),
    Dense(50, activation='relu'),
    Dense(1, activation='sigmoid')
])

model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy']
)
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_21 (Dense)             (None, 100)               600       
_________________________________________________________________
dense_22 (Dense)             (None, 300)               30300     
_________________________________________________________________
dense_23 (Dense)             (None, 100)               30100     
_________________________________________________________________
dense_24 (Dense)             (None, 50)                5050      
_________________________________________________________________
dense_25 (Dense)             (None, 1)                 51        
=================================================================
Total params: 66,101
Trainable params: 66,101
Non-trainable params: 0
_________________________________________________________________
```

In [38]:

```
history=model.fit(X_train_no_nlp, y_train_no_nlp, epochs=200, batch_size=25, val
idation_split = .2)
```

```
Train on 19337 samples, validate on 4835 samples
Epoch 1/200
19337/19337 [==============================] - 2s 126us/step - loss:
0.4859 - acc: 0.7537 - val_loss: 0.4455 - val_acc: 0.7835
```

```
Epoch 2/200
19337/19337 [==============================] - 2s 78us/step - loss:
0.4400 - acc: 0.7851 - val_loss: 0.4402 - val_acc: 0.7876
Epoch 3/200
19337/19337 [==============================] - 2s 78us/step - loss:
0.4366 - acc: 0.7871 - val_loss: 0.4421 - val_acc: 0.7866
Epoch 4/200
19337/19337 [==============================] - 1s 77us/step - loss:
0.4356 - acc: 0.7869 - val_loss: 0.4362 - val_acc: 0.7876
Epoch 5/200
19337/19337 [==============================] - 1s 77us/step - loss:
0.4329 - acc: 0.7921 - val_loss: 0.4344 - val_acc: 0.7876
Epoch 6/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4314 - acc: 0.7895 - val_loss: 0.4336 - val_acc: 0.7868
Epoch 7/200
19337/19337 [==============================] - 2s 80us/step - loss:
0.4307 - acc: 0.7921 - val_loss: 0.4312 - val_acc: 0.7868
Epoch 8/200
19337/19337 [==============================] - 2s 82us/step - loss:
0.4295 - acc: 0.7916 - val_loss: 0.4332 - val_acc: 0.7876
Epoch 9/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4289 - acc: 0.7910 - val_loss: 0.4298 - val_acc: 0.7863
Epoch 10/200
19337/19337 [==============================] - 2s 85us/step - loss:
0.4287 - acc: 0.7913 - val_loss: 0.4302 - val_acc: 0.7863
Epoch 11/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4276 - acc: 0.7926 - val_loss: 0.4292 - val_acc: 0.7876
Epoch 12/200
19337/19337 [==============================] - 2s 82us/step - loss:
0.4270 - acc: 0.7921 - val_loss: 0.4283 - val_acc: 0.7863
Epoch 13/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4267 - acc: 0.7912 - val_loss: 0.4284 - val_acc: 0.7863
Epoch 14/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4266 - acc: 0.7922 - val_loss: 0.4396 - val_acc: 0.7874
Epoch 15/200
19337/19337 [==============================] - 2s 81us/step - loss:
0.4261 - acc: 0.7928 - val_loss: 0.4302 - val_acc: 0.7878
Epoch 16/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4251 - acc: 0.7927 - val_loss: 0.4268 - val_acc: 0.7874
Epoch 17/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4244 - acc: 0.7922 - val_loss: 0.4281 - val_acc: 0.7756
Epoch 18/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4248 - acc: 0.7918 - val_loss: 0.4261 - val_acc: 0.7878
Epoch 19/200
19337/19337 [==============================] - 2s 91us/step - loss:
```

```
0.4241 - acc: 0.7926 - val_loss: 0.4266 - val_acc: 0.7878
Epoch 20/200
19337/19337 [==============================] - 2s 81us/step - loss:
0.4233 - acc: 0.7931 - val_loss: 0.4265 - val_acc: 0.7878
Epoch 21/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4238 - acc: 0.7932 - val_loss: 0.4262 - val_acc: 0.7876
Epoch 22/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4233 - acc: 0.7936 - val_loss: 0.4249 - val_acc: 0.7872
Epoch 23/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4225 - acc: 0.7927 - val_loss: 0.4237 - val_acc: 0.7880
Epoch 24/200
19337/19337 [==============================] - 2s 81us/step - loss:
0.4222 - acc: 0.7936 - val_loss: 0.4227 - val_acc: 0.7876
Epoch 25/200
19337/19337 [==============================] - 2s 81us/step - loss:
0.4219 - acc: 0.7934 - val_loss: 0.4246 - val_acc: 0.7874
Epoch 26/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4219 - acc: 0.7933 - val_loss: 0.4293 - val_acc: 0.7872
Epoch 27/200
19337/19337 [==============================] - 2s 81us/step - loss:
0.4216 - acc: 0.7924 - val_loss: 0.4238 - val_acc: 0.7878
Epoch 28/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4208 - acc: 0.7937 - val_loss: 0.4227 - val_acc: 0.7876
Epoch 29/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4212 - acc: 0.7921 - val_loss: 0.4281 - val_acc: 0.7874
Epoch 30/200
19337/19337 [==============================] - 2s 81us/step - loss:
0.4206 - acc: 0.7929 - val_loss: 0.4212 - val_acc: 0.7876
Epoch 31/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4208 - acc: 0.7929 - val_loss: 0.4213 - val_acc: 0.7878
Epoch 32/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4203 - acc: 0.7934 - val_loss: 0.4215 - val_acc: 0.7874
Epoch 33/200
19337/19337 [==============================] - 2s 79us/step - loss:
0.4203 - acc: 0.7931 - val_loss: 0.4232 - val_acc: 0.7878
Epoch 34/200
19337/19337 [==============================] - 2s 82us/step - loss:
0.4200 - acc: 0.7937 - val_loss: 0.4220 - val_acc: 0.7764
Epoch 35/200
19337/19337 [==============================] - 2s 80us/step - loss:
0.4203 - acc: 0.7930 - val_loss: 0.4256 - val_acc: 0.7874
Epoch 36/200
19337/19337 [==============================] - 2s 82us/step - loss:
0.4197 - acc: 0.7931 - val_loss: 0.4197 - val_acc: 0.7878
Epoch 37/200
```

```
19337/19337 [==============================] - 2s 86us/step - loss:
0.4196 - acc: 0.7940 - val_loss: 0.4249 - val_acc: 0.7872
Epoch 38/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4197 - acc: 0.7937 - val_loss: 0.4301 - val_acc: 0.7768
Epoch 39/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4200 - acc: 0.7928 - val_loss: 0.4206 - val_acc: 0.7874
Epoch 40/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4195 - acc: 0.7936 - val_loss: 0.4218 - val_acc: 0.7874
Epoch 41/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4191 - acc: 0.7930 - val_loss: 0.4204 - val_acc: 0.7876
Epoch 42/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4196 - acc: 0.7929 - val_loss: 0.4206 - val_acc: 0.7872
Epoch 43/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4195 - acc: 0.7932 - val_loss: 0.4197 - val_acc: 0.7878
Epoch 44/200
19337/19337 [==============================] - 2s 82us/step - loss:
0.4194 - acc: 0.7936 - val_loss: 0.4212 - val_acc: 0.7874
Epoch 45/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4194 - acc: 0.7936 - val_loss: 0.4201 - val_acc: 0.7878
Epoch 46/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4192 - acc: 0.7931 - val_loss: 0.4202 - val_acc: 0.7880
Epoch 47/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4189 - acc: 0.7937 - val_loss: 0.4214 - val_acc: 0.7874
Epoch 48/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4191 - acc: 0.7933 - val_loss: 0.4195 - val_acc: 0.7880
Epoch 49/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4185 - acc: 0.7935 - val_loss: 0.4200 - val_acc: 0.7874
Epoch 50/200
19337/19337 [==============================] - 2s 89us/step - loss:
0.4190 - acc: 0.7936 - val_loss: 0.4191 - val_acc: 0.7878
Epoch 51/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4190 - acc: 0.7936 - val_loss: 0.4213 - val_acc: 0.7872
Epoch 52/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4188 - acc: 0.7928 - val_loss: 0.4226 - val_acc: 0.7876
Epoch 53/200
19337/19337 [==============================] - 2s 91us/step - loss:
0.4189 - acc: 0.7929 - val_loss: 0.4219 - val_acc: 0.7872
Epoch 54/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4189 - acc: 0.7931 - val_loss: 0.4212 - val_acc: 0.7880
```

```
Epoch 55/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4188 - acc: 0.7935 - val_loss: 0.4206 - val_acc: 0.7872
Epoch 56/200
19337/19337 [==============================] - 2s 89us/step - loss:
0.4186 - acc: 0.7932 - val_loss: 0.4192 - val_acc: 0.7874
Epoch 57/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4187 - acc: 0.7933 - val_loss: 0.4199 - val_acc: 0.7874
Epoch 58/200
19337/19337 [==============================] - 2s 91us/step - loss:
0.4183 - acc: 0.7940 - val_loss: 0.4192 - val_acc: 0.7878
Epoch 59/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4186 - acc: 0.7938 - val_loss: 0.4185 - val_acc: 0.7876
Epoch 60/200
19337/19337 [==============================] - 2s 89us/step - loss:
0.4189 - acc: 0.7936 - val_loss: 0.4199 - val_acc: 0.7876
Epoch 61/200
19337/19337 [==============================] - 2s 92us/step - loss:
0.4179 - acc: 0.7930 - val_loss: 0.4187 - val_acc: 0.7880
Epoch 62/200
19337/19337 [==============================] - 2s 105us/step - loss:
0.4187 - acc: 0.7937 - val_loss: 0.4203 - val_acc: 0.7872
Epoch 63/200
19337/19337 [==============================] - 2s 111us/step - loss:
0.4183 - acc: 0.7936 - val_loss: 0.4204 - val_acc: 0.7876
Epoch 64/200
19337/19337 [==============================] - 2s 115us/step - loss:
0.4183 - acc: 0.7942 - val_loss: 0.4194 - val_acc: 0.7880
Epoch 65/200
19337/19337 [==============================] - 2s 119us/step - loss:
0.4182 - acc: 0.7938 - val_loss: 0.4191 - val_acc: 0.7874
Epoch 66/200
19337/19337 [==============================] - 2s 119us/step - loss:
0.4186 - acc: 0.7933 - val_loss: 0.4192 - val_acc: 0.7874
Epoch 67/200
19337/19337 [==============================] - 2s 120us/step - loss:
0.4186 - acc: 0.7935 - val_loss: 0.4187 - val_acc: 0.7878
Epoch 68/200
19337/19337 [==============================] - 2s 114us/step - loss:
0.4180 - acc: 0.7936 - val_loss: 0.4211 - val_acc: 0.7876
Epoch 69/200
19337/19337 [==============================] - 2s 107us/step - loss:
0.4183 - acc: 0.7935 - val_loss: 0.4222 - val_acc: 0.7874
Epoch 70/200
19337/19337 [==============================] - 2s 113us/step - loss:
0.4185 - acc: 0.7939 - val_loss: 0.4186 - val_acc: 0.7876
Epoch 71/200
19337/19337 [==============================] - 2s 117us/step - loss:
0.4177 - acc: 0.7939 - val_loss: 0.4210 - val_acc: 0.7880
Epoch 72/200
19337/19337 [==============================] - 2s 119us/step - loss:
```

```
0.4179 - acc: 0.7940 - val_loss: 0.4209 - val_acc: 0.7872
Epoch 73/200
19337/19337 [==============================] - 2s 119us/step - loss:
0.4181 - acc: 0.7943 - val_loss: 0.4193 - val_acc: 0.7878
Epoch 74/200
19337/19337 [==============================] - 3s 131us/step - loss:
0.4180 - acc: 0.7930 - val_loss: 0.4188 - val_acc: 0.7880
Epoch 75/200
19337/19337 [==============================] - 3s 133us/step - loss:
0.4178 - acc: 0.7938 - val_loss: 0.4184 - val_acc: 0.7880
Epoch 76/200
19337/19337 [==============================] - 3s 135us/step - loss:
0.4178 - acc: 0.7938 - val_loss: 0.4204 - val_acc: 0.7874
Epoch 77/200
19337/19337 [==============================] - 3s 133us/step - loss:
0.4176 - acc: 0.7938 - val_loss: 0.4206 - val_acc: 0.7880
Epoch 78/200
19337/19337 [==============================] - 3s 135us/step - loss:
0.4180 - acc: 0.7942 - val_loss: 0.4194 - val_acc: 0.7880
Epoch 79/200
19337/19337 [==============================] - 3s 137us/step - loss:
0.4183 - acc: 0.7943 - val_loss: 0.4225 - val_acc: 0.7880
Epoch 80/200
19337/19337 [==============================] - 3s 156us/step - loss:
0.4177 - acc: 0.7940 - val_loss: 0.4184 - val_acc: 0.7876
Epoch 81/200
19337/19337 [==============================] - 3s 139us/step - loss:
0.4181 - acc: 0.7939 - val_loss: 0.4210 - val_acc: 0.7876
Epoch 82/200
19337/19337 [==============================] - 2s 124us/step - loss:
0.4176 - acc: 0.7938 - val_loss: 0.4185 - val_acc: 0.7878
Epoch 83/200
19337/19337 [==============================] - 3s 132us/step - loss:
0.4177 - acc: 0.7943 - val_loss: 0.4190 - val_acc: 0.7880
Epoch 84/200
19337/19337 [==============================] - 3s 134us/step - loss:
0.4180 - acc: 0.7937 - val_loss: 0.4196 - val_acc: 0.7874
Epoch 85/200
19337/19337 [==============================] - 3s 135us/step - loss:
0.4182 - acc: 0.7938 - val_loss: 0.4187 - val_acc: 0.7876
Epoch 86/200
19337/19337 [==============================] - 2s 127us/step - loss:
0.4176 - acc: 0.7931 - val_loss: 0.4189 - val_acc: 0.7878
Epoch 87/200
19337/19337 [==============================] - 2s 117us/step - loss:
0.4177 - acc: 0.7935 - val_loss: 0.4184 - val_acc: 0.7880
Epoch 88/200
19337/19337 [==============================] - 2s 119us/step - loss:
0.4176 - acc: 0.7940 - val_loss: 0.4186 - val_acc: 0.7878
Epoch 89/200
19337/19337 [==============================] - 2s 127us/step - loss:
0.4174 - acc: 0.7931 - val_loss: 0.4198 - val_acc: 0.7876
Epoch 90/200
```

```
19337/19337 [==============================] - 2s 127us/step - loss:
0.4180 - acc: 0.7937 - val_loss: 0.4188 - val_acc: 0.7878
Epoch 91/200
19337/19337 [==============================] - 3s 130us/step - loss:
0.4178 - acc: 0.7931 - val_loss: 0.4207 - val_acc: 0.7874
Epoch 92/200
19337/19337 [==============================] - 2s 126us/step - loss:
0.4173 - acc: 0.7944 - val_loss: 0.4207 - val_acc: 0.7876
Epoch 93/200
19337/19337 [==============================] - 3s 130us/step - loss:
0.4178 - acc: 0.7938 - val_loss: 0.4218 - val_acc: 0.7878
Epoch 94/200
19337/19337 [==============================] - 3s 135us/step - loss:
0.4175 - acc: 0.7929 - val_loss: 0.4179 - val_acc: 0.7880
Epoch 95/200
19337/19337 [==============================] - 3s 135us/step - loss:
0.4173 - acc: 0.7939 - val_loss: 0.4208 - val_acc: 0.7874
Epoch 96/200
19337/19337 [==============================] - 2s 123us/step - loss:
0.4174 - acc: 0.7929 - val_loss: 0.4184 - val_acc: 0.7878
Epoch 97/200
19337/19337 [==============================] - 2s 125us/step - loss:
0.4172 - acc: 0.7942 - val_loss: 0.4189 - val_acc: 0.7876
Epoch 98/200
19337/19337 [==============================] - 2s 118us/step - loss:
0.4175 - acc: 0.7940 - val_loss: 0.4199 - val_acc: 0.7880
Epoch 99/200
19337/19337 [==============================] - 2s 120us/step - loss:
0.4172 - acc: 0.7939 - val_loss: 0.4189 - val_acc: 0.7874
Epoch 100/200
19337/19337 [==============================] - 2s 125us/step - loss:
0.4172 - acc: 0.7938 - val_loss: 0.4186 - val_acc: 0.7878
Epoch 101/200
19337/19337 [==============================] - 2s 120us/step - loss:
0.4171 - acc: 0.7939 - val_loss: 0.4187 - val_acc: 0.7878
Epoch 102/200
19337/19337 [==============================] - 2s 114us/step - loss:
0.4173 - acc: 0.7938 - val_loss: 0.4189 - val_acc: 0.7874
Epoch 103/200
19337/19337 [==============================] - 2s 113us/step - loss:
0.4177 - acc: 0.7931 - val_loss: 0.4194 - val_acc: 0.7880
Epoch 104/200
19337/19337 [==============================] - 2s 108us/step - loss:
0.4175 - acc: 0.7937 - val_loss: 0.4188 - val_acc: 0.7880
Epoch 105/200
19337/19337 [==============================] - 2s 106us/step - loss:
0.4179 - acc: 0.7940 - val_loss: 0.4200 - val_acc: 0.7876
Epoch 106/200
19337/19337 [==============================] - 2s 108us/step - loss:
0.4174 - acc: 0.7938 - val_loss: 0.4186 - val_acc: 0.7880
Epoch 107/200
19337/19337 [==============================] - 2s 106us/step - loss:
0.4174 - acc: 0.7939 - val_loss: 0.4191 - val_acc: 0.7876
```

```
Epoch 108/200
19337/19337 [==============================] - 2s 106us/step - loss:
0.4177 - acc: 0.7941 - val_loss: 0.4183 - val_acc: 0.7880
Epoch 109/200
19337/19337 [==============================] - 2s 118us/step - loss:
0.4177 - acc: 0.7937 - val_loss: 0.4194 - val_acc: 0.7876
Epoch 110/200
19337/19337 [==============================] - 2s 122us/step - loss:
0.4174 - acc: 0.7937 - val_loss: 0.4195 - val_acc: 0.7874
Epoch 111/200
19337/19337 [==============================] - 2s 121us/step - loss:
0.4173 - acc: 0.7939 - val_loss: 0.4188 - val_acc: 0.7874
Epoch 112/200
19337/19337 [==============================] - 2s 113us/step - loss:
0.4174 - acc: 0.7938 - val_loss: 0.4180 - val_acc: 0.7878
Epoch 113/200
19337/19337 [==============================] - 2s 109us/step - loss:
0.4173 - acc: 0.7942 - val_loss: 0.4179 - val_acc: 0.7874
Epoch 114/200
19337/19337 [==============================] - 2s 119us/step - loss:
0.4174 - acc: 0.7941 - val_loss: 0.4188 - val_acc: 0.7880
Epoch 115/200
19337/19337 [==============================] - 2s 120us/step - loss:
0.4172 - acc: 0.7939 - val_loss: 0.4200 - val_acc: 0.7880
Epoch 116/200
19337/19337 [==============================] - 2s 117us/step - loss:
0.4172 - acc: 0.7936 - val_loss: 0.4181 - val_acc: 0.7880
Epoch 117/200
19337/19337 [==============================] - 2s 107us/step - loss:
0.4169 - acc: 0.7938 - val_loss: 0.4206 - val_acc: 0.7878
Epoch 118/200
19337/19337 [==============================] - 2s 96us/step - loss:
0.4172 - acc: 0.7938 - val_loss: 0.4192 - val_acc: 0.7880
Epoch 119/200
19337/19337 [==============================] - 2s 92us/step - loss:
0.4174 - acc: 0.7939 - val_loss: 0.4194 - val_acc: 0.7880
Epoch 120/200
19337/19337 [==============================] - 2s 91us/step - loss:
0.4170 - acc: 0.7939 - val_loss: 0.4184 - val_acc: 0.7878
Epoch 121/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4170 - acc: 0.7937 - val_loss: 0.4192 - val_acc: 0.7876
Epoch 122/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4173 - acc: 0.7938 - val_loss: 0.4199 - val_acc: 0.7878
Epoch 123/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4175 - acc: 0.7931 - val_loss: 0.4190 - val_acc: 0.7874
Epoch 124/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4171 - acc: 0.7941 - val_loss: 0.4187 - val_acc: 0.7878
Epoch 125/200
19337/19337 [==============================] - 2s 85us/step - loss:
```

```
0.4171 - acc: 0.7941 - val_loss: 0.4193 - val_acc: 0.7880
Epoch 126/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4169 - acc: 0.7940 - val_loss: 0.4180 - val_acc: 0.7874
Epoch 127/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4168 - acc: 0.7941 - val_loss: 0.4191 - val_acc: 0.7876
Epoch 128/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4169 - acc: 0.7941 - val_loss: 0.4224 - val_acc: 0.7880
Epoch 129/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4167 - acc: 0.7939 - val_loss: 0.4188 - val_acc: 0.7878
Epoch 130/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4171 - acc: 0.7939 - val_loss: 0.4195 - val_acc: 0.7874
Epoch 131/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4174 - acc: 0.7937 - val_loss: 0.4189 - val_acc: 0.7874
Epoch 132/200
19337/19337 [==============================] - 2s 94us/step - loss:
0.4171 - acc: 0.7938 - val_loss: 0.4186 - val_acc: 0.7880
Epoch 133/200
19337/19337 [==============================] - 2s 95us/step - loss:
0.4170 - acc: 0.7941 - val_loss: 0.4187 - val_acc: 0.7878
Epoch 134/200
19337/19337 [==============================] - 2s 91us/step - loss:
0.4171 - acc: 0.7941 - val_loss: 0.4183 - val_acc: 0.7876
Epoch 135/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4170 - acc: 0.7938 - val_loss: 0.4191 - val_acc: 0.7878
Epoch 136/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4171 - acc: 0.7940 - val_loss: 0.4184 - val_acc: 0.7880
Epoch 137/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4169 - acc: 0.7938 - val_loss: 0.4210 - val_acc: 0.7880
Epoch 138/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4168 - acc: 0.7939 - val_loss: 0.4200 - val_acc: 0.7876
Epoch 139/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4168 - acc: 0.7939 - val_loss: 0.4185 - val_acc: 0.7876
Epoch 140/200
19337/19337 [==============================] - 2s 85us/step - loss:
0.4169 - acc: 0.7941 - val_loss: 0.4189 - val_acc: 0.7872
Epoch 141/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4170 - acc: 0.7931 - val_loss: 0.4201 - val_acc: 0.7874
Epoch 142/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4167 - acc: 0.7941 - val_loss: 0.4191 - val_acc: 0.7880
Epoch 143/200
```

```
19337/19337 [==============================] - 2s 87us/step - loss:
0.4172 - acc: 0.7938 - val_loss: 0.4187 - val_acc: 0.7880
Epoch 144/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4169 - acc: 0.7936 - val_loss: 0.4191 - val_acc: 0.7880
Epoch 145/200
19337/19337 [==============================] - 2s 85us/step - loss:
0.4167 - acc: 0.7939 - val_loss: 0.4188 - val_acc: 0.7876
Epoch 146/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4168 - acc: 0.7940 - val_loss: 0.4201 - val_acc: 0.7880
Epoch 147/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4168 - acc: 0.7940 - val_loss: 0.4196 - val_acc: 0.7878
Epoch 148/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4169 - acc: 0.7942 - val_loss: 0.4194 - val_acc: 0.7874
Epoch 149/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4169 - acc: 0.7935 - val_loss: 0.4189 - val_acc: 0.7876
Epoch 150/200
19337/19337 [==============================] - 2s 82us/step - loss:
0.4169 - acc: 0.7938 - val_loss: 0.4189 - val_acc: 0.7878
Epoch 151/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4167 - acc: 0.7942 - val_loss: 0.4204 - val_acc: 0.7878
Epoch 152/200
19337/19337 [==============================] - 2s 82us/step - loss:
0.4165 - acc: 0.7942 - val_loss: 0.4199 - val_acc: 0.7878
Epoch 153/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4169 - acc: 0.7939 - val_loss: 0.4187 - val_acc: 0.7878
Epoch 154/200
19337/19337 [==============================] - 2s 84us/step - loss:
0.4170 - acc: 0.7938 - val_loss: 0.4190 - val_acc: 0.7880
Epoch 155/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4168 - acc: 0.7932 - val_loss: 0.4188 - val_acc: 0.7876
Epoch 156/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4165 - acc: 0.7940 - val_loss: 0.4187 - val_acc: 0.7878
Epoch 157/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4167 - acc: 0.7938 - val_loss: 0.4188 - val_acc: 0.7876
Epoch 158/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4165 - acc: 0.7941 - val_loss: 0.4195 - val_acc: 0.7876
Epoch 159/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4171 - acc: 0.7932 - val_loss: 0.4195 - val_acc: 0.7880
Epoch 160/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4169 - acc: 0.7940 - val_loss: 0.4187 - val_acc: 0.7878
```

```
Epoch 161/200
19337/19337 [==============================] - 2s 85us/step - loss:
0.4168 - acc: 0.7939 - val_loss: 0.4204 - val_acc: 0.7878
Epoch 162/200
19337/19337 [==============================] - 2s 92us/step - loss:
0.4168 - acc: 0.7937 - val_loss: 0.4197 - val_acc: 0.7878
Epoch 163/200
19337/19337 [==============================] - 2s 91us/step - loss:
0.4168 - acc: 0.7940 - val_loss: 0.4196 - val_acc: 0.7878
Epoch 164/200
19337/19337 [==============================] - 2s 92us/step - loss:
0.4169 - acc: 0.7939 - val_loss: 0.4186 - val_acc: 0.7876
Epoch 165/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4167 - acc: 0.7939 - val_loss: 0.4195 - val_acc: 0.7878
Epoch 166/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4161 - acc: 0.7939 - val_loss: 0.4190 - val_acc: 0.7876
Epoch 167/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4168 - acc: 0.7937 - val_loss: 0.4188 - val_acc: 0.7880
Epoch 168/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4168 - acc: 0.7943 - val_loss: 0.4195 - val_acc: 0.7878
Epoch 169/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4168 - acc: 0.7940 - val_loss: 0.4185 - val_acc: 0.7874
Epoch 170/200
19337/19337 [==============================] - 2s 89us/step - loss:
0.4169 - acc: 0.7939 - val_loss: 0.4191 - val_acc: 0.7880
Epoch 171/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4167 - acc: 0.7937 - val_loss: 0.4196 - val_acc: 0.7880
Epoch 172/200
19337/19337 [==============================] - 2s 91us/step - loss:
0.4166 - acc: 0.7940 - val_loss: 0.4202 - val_acc: 0.7878
Epoch 173/200
19337/19337 [==============================] - 2s 89us/step - loss:
0.4166 - acc: 0.7939 - val_loss: 0.4189 - val_acc: 0.7876
Epoch 174/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4166 - acc: 0.7939 - val_loss: 0.4209 - val_acc: 0.7876
Epoch 175/200
19337/19337 [==============================] - 2s 88us/step - loss:
0.4166 - acc: 0.7939 - val_loss: 0.4194 - val_acc: 0.7878
Epoch 176/200
19337/19337 [==============================] - 2s 94us/step - loss:
0.4167 - acc: 0.7939 - val_loss: 0.4190 - val_acc: 0.7878
Epoch 177/200
19337/19337 [==============================] - 2s 91us/step - loss:
0.4168 - acc: 0.7936 - val_loss: 0.4192 - val_acc: 0.7880
Epoch 178/200
19337/19337 [==============================] - 2s 91us/step - loss:
```

```
0.4164 - acc: 0.7939 - val_loss: 0.4205 - val_acc: 0.7880
Epoch 179/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4165 - acc: 0.7940 - val_loss: 0.4188 - val_acc: 0.7878
Epoch 180/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4165 - acc: 0.7940 - val_loss: 0.4195 - val_acc: 0.7878
Epoch 181/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4167 - acc: 0.7940 - val_loss: 0.4185 - val_acc: 0.7878
Epoch 182/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4165 - acc: 0.7943 - val_loss: 0.4188 - val_acc: 0.7878
Epoch 183/200
19337/19337 [==============================] - 2s 90us/step - loss:
0.4164 - acc: 0.7940 - val_loss: 0.4215 - val_acc: 0.7880
Epoch 184/200
19337/19337 [==============================] - 2s 94us/step - loss:
0.4166 - acc: 0.7940 - val_loss: 0.4197 - val_acc: 0.7880
Epoch 185/200
19337/19337 [==============================] - 2s 93us/step - loss:
0.4168 - acc: 0.7943 - val_loss: 0.4188 - val_acc: 0.7878
Epoch 186/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4164 - acc: 0.7938 - val_loss: 0.4193 - val_acc: 0.7880
Epoch 187/200
19337/19337 [==============================] - 2s 85us/step - loss:
0.4165 - acc: 0.7941 - val_loss: 0.4185 - val_acc: 0.7878
Epoch 188/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4165 - acc: 0.7940 - val_loss: 0.4192 - val_acc: 0.7876
Epoch 189/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4166 - acc: 0.7940 - val_loss: 0.4196 - val_acc: 0.7878
Epoch 190/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4166 - acc: 0.7939 - val_loss: 0.4188 - val_acc: 0.7878
Epoch 191/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4164 - acc: 0.7939 - val_loss: 0.4193 - val_acc: 0.7876
Epoch 192/200
19337/19337 [==============================] - 2s 83us/step - loss:
0.4164 - acc: 0.7941 - val_loss: 0.4192 - val_acc: 0.7874
Epoch 193/200
19337/19337 [==============================] - 2s 85us/step - loss:
0.4163 - acc: 0.7936 - val_loss: 0.4196 - val_acc: 0.7878
Epoch 194/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4167 - acc: 0.7940 - val_loss: 0.4191 - val_acc: 0.7878
Epoch 195/200
19337/19337 [==============================] - 2s 86us/step - loss:
0.4165 - acc: 0.7939 - val_loss: 0.4186 - val_acc: 0.7878
Epoch 196/200
```

```
19337/19337 [==============================] - 2s 86us/step - loss:
0.4163 - acc: 0.7941 - val_loss: 0.4193 - val_acc: 0.7878
Epoch 197/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4164 - acc: 0.7940 - val_loss: 0.4196 - val_acc: 0.7880
Epoch 198/200
19337/19337 [==============================] - 2s 87us/step - loss:
0.4167 - acc: 0.7938 - val_loss: 0.4181 - val_acc: 0.7878
Epoch 199/200
19337/19337 [==============================] - 2s 94us/step - loss:
0.4165 - acc: 0.7939 - val_loss: 0.4185 - val_acc: 0.7878
Epoch 200/200
19337/19337 [==============================] - 2s 98us/step - loss:
0.4163 - acc: 0.7939 - val_loss: 0.4201 - val_acc: 0.7876
```

In [42]:

```
NN_testScore=model.evaluate(X_test_no_nlp, y_test_no_nlp)
print("\n%s: %.2f%%" % (model.metrics_names[1], NN_testScore[1]*100))
```

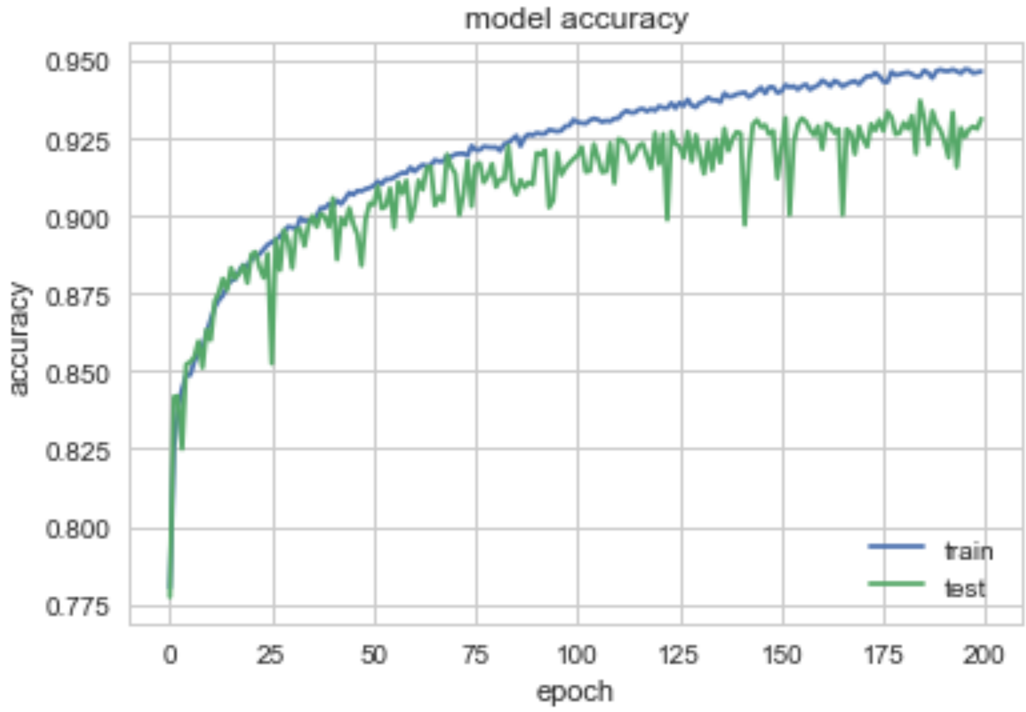
```
11906/11906 [==============================] - 0s 22us/step

acc: 79.02%
```

In [43]:

```
print(history.history.keys())
# summarize history for accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.show()
```

```
dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
```



Lexical Diversity + NLP + Neural Network

Next we use a similar model but by adding in the NLP and Lexical Diversity features to see if we get an improvement in accuracy.

In [44]:

```
model_nlp = Sequential([
    Dense(100, input_shape=(25,), activation='sigmoid'),
    Dense(300, activation='softmax'),
    Dense(100, activation='relu'),
    Dense(50, activation='relu'),
    Dense(1, activation='sigmoid')
])

model_nlp.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accura
cy'])
```

In [72]:

```
history = model_nlp.fit(X_train, y_train, epochs=100, batch_size=32, validation_
split = .2)

print(model_nlp.evaluate(X_test, y_test))

model_json = model_nlp.to_json()

with open("model_ld_"+".json", "w") as json_file:
    json_file.write(model_json)

# serialize weights to HDF5
model_nlp.save_weights("model_ld_"+".h5")

print(history.history.keys())
# summarize history for accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.show()

# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')
plt.show()
plt.savefig("model_ld_"+".jpg")
```

```
Train on 64459 samples, validate on 16115 samples
Epoch 1/100
64459/64459 [==============================] - 1s 12us/step - loss:
0.0164 - acc: 0.9935 - val_loss: 0.4030 - val_acc: 0.9442
Epoch 2/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0132 - acc: 0.9946 - val_loss: 0.4114 - val_acc: 0.9440
Epoch 3/100
64459/64459 [==============================] - 1s 11us/step - loss:
0.0143 - acc: 0.9940 - val_loss: 0.4025 - val_acc: 0.9443
Epoch 4/100
64459/64459 [==============================] - 1s 11us/step - loss:
0.0123 - acc: 0.9949 - val_loss: 0.4032 - val_acc: 0.9444
Epoch 5/100
64459/64459 [==============================] - 1s 11us/step - loss:
0.0114 - acc: 0.9955 - val_loss: 0.4001 - val_acc: 0.9437
Epoch 6/100
```

```
64459/64459 [==============================] - 1s 11us/step - loss:
0.0221 - acc: 0.9917 - val_loss: 0.4207 - val_acc: 0.9441
Epoch 7/100
64459/64459 [==============================] - 1s 11us/step - loss:
0.0262 - acc: 0.9899 - val_loss: 0.4027 - val_acc: 0.9425
Epoch 8/100
64459/64459 [==============================] - 1s 11us/step - loss:
0.0225 - acc: 0.9913 - val_loss: 0.4047 - val_acc: 0.9432
Epoch 9/100
64459/64459 [==============================] - 1s 12us/step - loss:
0.0146 - acc: 0.9942 - val_loss: 0.3969 - val_acc: 0.9462
Epoch 10/100
64459/64459 [==============================] - 1s 13us/step - loss:
0.0155 - acc: 0.9937 - val_loss: 0.4065 - val_acc: 0.9422
Epoch 11/100
64459/64459 [==============================] - 1s 13us/step - loss:
0.0134 - acc: 0.9945 - val_loss: 0.4029 - val_acc: 0.9471
Epoch 12/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0144 - acc: 0.9938 - val_loss: 0.4101 - val_acc: 0.9424
Epoch 13/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0159 - acc: 0.9933 - val_loss: 0.4048 - val_acc: 0.9443
Epoch 14/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0147 - acc: 0.9942 - val_loss: 0.4077 - val_acc: 0.9427
Epoch 15/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0143 - acc: 0.9942 - val_loss: 0.3935 - val_acc: 0.9435
Epoch 16/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0240 - acc: 0.9913 - val_loss: 0.4280 - val_acc: 0.9404
Epoch 17/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0186 - acc: 0.9932 - val_loss: 0.4052 - val_acc: 0.9437
Epoch 18/100
64459/64459 [==============================] - 1s 13us/step - loss:
0.0219 - acc: 0.9915 - val_loss: 0.4003 - val_acc: 0.9421
Epoch 19/100
64459/64459 [==============================] - 1s 13us/step - loss:
0.0129 - acc: 0.9947 - val_loss: 0.3979 - val_acc: 0.9448
Epoch 20/100
64459/64459 [==============================] - 1s 13us/step - loss:
0.0139 - acc: 0.9941 - val_loss: 0.3974 - val_acc: 0.9455
Epoch 21/100
64459/64459 [==============================] - 1s 13us/step - loss:
0.0150 - acc: 0.9939 - val_loss: 0.4098 - val_acc: 0.9445
Epoch 22/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0119 - acc: 0.9952 - val_loss: 0.3964 - val_acc: 0.9466
Epoch 23/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0214 - acc: 0.9914 - val_loss: 0.4321 - val_acc: 0.9403
```

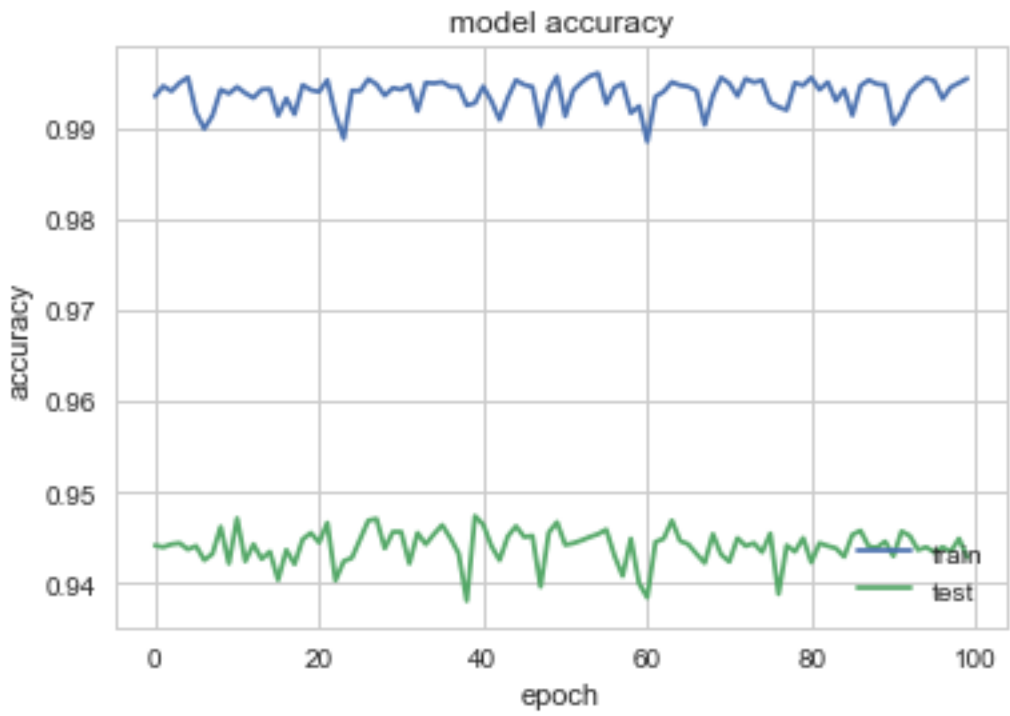
```
Epoch 24/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0293 - acc: 0.9888 - val_loss: 0.4081 - val_acc: 0.9424
Epoch 25/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0151 - acc: 0.9941 - val_loss: 0.4035 - val_acc: 0.9428
Epoch 26/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0145 - acc: 0.9940 - val_loss: 0.3985 - val_acc: 0.9448
Epoch 27/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0116 - acc: 0.9953 - val_loss: 0.3986 - val_acc: 0.9469
Epoch 28/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0136 - acc: 0.9948 - val_loss: 0.4019 - val_acc: 0.9471
Epoch 29/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0160 - acc: 0.9935 - val_loss: 0.4071 - val_acc: 0.9438
Epoch 30/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0148 - acc: 0.9944 - val_loss: 0.4031 - val_acc: 0.9456
Epoch 31/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0145 - acc: 0.9942 - val_loss: 0.4053 - val_acc: 0.9456
Epoch 32/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0132 - acc: 0.9947 - val_loss: 0.4256 - val_acc: 0.9422
Epoch 33/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0200 - acc: 0.9918 - val_loss: 0.4013 - val_acc: 0.9455
Epoch 34/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0127 - acc: 0.9949 - val_loss: 0.4074 - val_acc: 0.9443
Epoch 35/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0126 - acc: 0.9949 - val_loss: 0.4016 - val_acc: 0.9454
Epoch 36/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0119 - acc: 0.9950 - val_loss: 0.4112 - val_acc: 0.9464
Epoch 37/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0141 - acc: 0.9945 - val_loss: 0.4050 - val_acc: 0.9450
Epoch 38/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0144 - acc: 0.9945 - val_loss: 0.4147 - val_acc: 0.9433
Epoch 39/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0176 - acc: 0.9925 - val_loss: 0.4525 - val_acc: 0.9381
Epoch 40/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0183 - acc: 0.9927 - val_loss: 0.4012 - val_acc: 0.9474
Epoch 41/100
64459/64459 [==============================] - 1s 16us/step - loss:
```

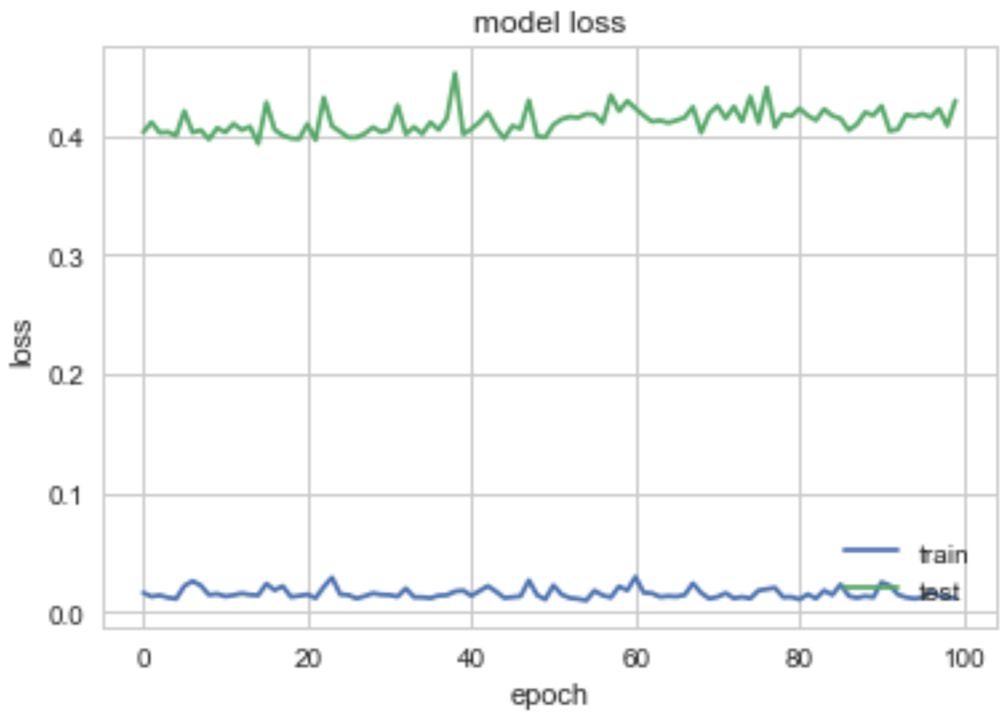
```
0.0138 - acc: 0.9945 - val_loss: 0.4057 - val_acc: 0.9464
Epoch 42/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0180 - acc: 0.9929 - val_loss: 0.4115 - val_acc: 0.9441
Epoch 43/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0221 - acc: 0.9909 - val_loss: 0.4193 - val_acc: 0.9425
Epoch 44/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0174 - acc: 0.9933 - val_loss: 0.4064 - val_acc: 0.9451
Epoch 45/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0121 - acc: 0.9952 - val_loss: 0.3977 - val_acc: 0.9463
Epoch 46/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0128 - acc: 0.9947 - val_loss: 0.4083 - val_acc: 0.9451
Epoch 47/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0135 - acc: 0.9945 - val_loss: 0.4060 - val_acc: 0.9452
Epoch 48/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0268 - acc: 0.9902 - val_loss: 0.4298 - val_acc: 0.9396
Epoch 49/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0145 - acc: 0.9940 - val_loss: 0.3996 - val_acc: 0.9456
Epoch 50/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0108 - acc: 0.9956 - val_loss: 0.3987 - val_acc: 0.9467
Epoch 51/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0227 - acc: 0.9913 - val_loss: 0.4093 - val_acc: 0.9442
Epoch 52/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0148 - acc: 0.9941 - val_loss: 0.4139 - val_acc: 0.9444
Epoch 53/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0120 - acc: 0.9950 - val_loss: 0.4159 - val_acc: 0.9447
Epoch 54/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0113 - acc: 0.9957 - val_loss: 0.4151 - val_acc: 0.9451
Epoch 55/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0100 - acc: 0.9960 - val_loss: 0.4184 - val_acc: 0.9454
Epoch 56/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0182 - acc: 0.9926 - val_loss: 0.4178 - val_acc: 0.9459
Epoch 57/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0142 - acc: 0.9944 - val_loss: 0.4109 - val_acc: 0.9430
Epoch 58/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0125 - acc: 0.9949 - val_loss: 0.4340 - val_acc: 0.9408
Epoch 59/100
```

```
64459/64459 [==============================] - 1s 16us/step - loss:
0.0217 - acc: 0.9916 - val_loss: 0.4207 - val_acc: 0.9449
Epoch 60/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0184 - acc: 0.9924 - val_loss: 0.4292 - val_acc: 0.9400
Epoch 61/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0297 - acc: 0.9885 - val_loss: 0.4229 - val_acc: 0.9384
Epoch 62/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0165 - acc: 0.9934 - val_loss: 0.4171 - val_acc: 0.9445
Epoch 63/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0160 - acc: 0.9940 - val_loss: 0.4119 - val_acc: 0.9449
Epoch 64/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0130 - acc: 0.9950 - val_loss: 0.4128 - val_acc: 0.9469
Epoch 65/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0137 - acc: 0.9947 - val_loss: 0.4109 - val_acc: 0.9446
Epoch 66/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0132 - acc: 0.9945 - val_loss: 0.4129 - val_acc: 0.9443
Epoch 67/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0146 - acc: 0.9941 - val_loss: 0.4153 - val_acc: 0.9432
Epoch 68/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0243 - acc: 0.9903 - val_loss: 0.4242 - val_acc: 0.9422
Epoch 69/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0163 - acc: 0.9935 - val_loss: 0.4026 - val_acc: 0.9454
Epoch 70/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0115 - acc: 0.9955 - val_loss: 0.4187 - val_acc: 0.9432
Epoch 71/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0130 - acc: 0.9949 - val_loss: 0.4252 - val_acc: 0.9424
Epoch 72/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0162 - acc: 0.9935 - val_loss: 0.4146 - val_acc: 0.9450
Epoch 73/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0117 - acc: 0.9954 - val_loss: 0.4245 - val_acc: 0.9441
Epoch 74/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0129 - acc: 0.9950 - val_loss: 0.4121 - val_acc: 0.9444
Epoch 75/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0116 - acc: 0.9952 - val_loss: 0.4328 - val_acc: 0.9434
Epoch 76/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0183 - acc: 0.9928 - val_loss: 0.4109 - val_acc: 0.9455
```

```
Epoch 77/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0195 - acc: 0.9923 - val_loss: 0.4405 - val_acc: 0.9388
Epoch 78/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0206 - acc: 0.9919 - val_loss: 0.4073 - val_acc: 0.9442
Epoch 79/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0127 - acc: 0.9949 - val_loss: 0.4181 - val_acc: 0.9435
Epoch 80/100
64459/64459 [==============================] - 1s 19us/step - loss:
0.0129 - acc: 0.9946 - val_loss: 0.4164 - val_acc: 0.9450
Epoch 81/100
64459/64459 [==============================] - 1s 19us/step - loss:
0.0109 - acc: 0.9955 - val_loss: 0.4229 - val_acc: 0.9423
Epoch 82/100
64459/64459 [==============================] - 1s 18us/step - loss:
0.0151 - acc: 0.9942 - val_loss: 0.4169 - val_acc: 0.9444
Epoch 83/100
64459/64459 [==============================] - 1s 18us/step - loss:
0.0116 - acc: 0.9950 - val_loss: 0.4130 - val_acc: 0.9441
Epoch 84/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0183 - acc: 0.9930 - val_loss: 0.4223 - val_acc: 0.9438
Epoch 85/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0146 - acc: 0.9942 - val_loss: 0.4168 - val_acc: 0.9429
Epoch 86/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0234 - acc: 0.9914 - val_loss: 0.4145 - val_acc: 0.9453
Epoch 87/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0137 - acc: 0.9946 - val_loss: 0.4046 - val_acc: 0.9458
Epoch 88/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0121 - acc: 0.9952 - val_loss: 0.4096 - val_acc: 0.9440
Epoch 89/100
64459/64459 [==============================] - 1s 15us/step - loss:
0.0136 - acc: 0.9948 - val_loss: 0.4197 - val_acc: 0.9439
Epoch 90/100
64459/64459 [==============================] - 1s 14us/step - loss:
0.0126 - acc: 0.9947 - val_loss: 0.4171 - val_acc: 0.9446
Epoch 91/100
64459/64459 [==============================] - 1s 16us/step - loss:
0.0252 - acc: 0.9904 - val_loss: 0.4250 - val_acc: 0.9430
Epoch 92/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0224 - acc: 0.9917 - val_loss: 0.4039 - val_acc: 0.9457
Epoch 93/100
64459/64459 [==============================] - 1s 17us/step - loss:
0.0149 - acc: 0.9938 - val_loss: 0.4055 - val_acc: 0.9452
Epoch 94/100
64459/64459 [==============================] - 1s 18us/step - loss:
```

```
0.0125 - acc: 0.9948 - val_loss: 0.4178 - val_acc: 0.9437
Epoch 95/100
64459/64459 [==============================] - 1s 18us/step - loss:
0.0115 - acc: 0.9955 - val_loss: 0.4160 - val_acc: 0.9440
Epoch 96/100
64459/64459 [==============================] - 1s 19us/step - loss:
0.0123 - acc: 0.9951 - val_loss: 0.4184 - val_acc: 0.9434
Epoch 97/100
64459/64459 [==============================] - 1s 19us/step - loss:
0.0172 - acc: 0.9932 - val_loss: 0.4154 - val_acc: 0.9440
Epoch 98/100
64459/64459 [==============================] - 1s 20us/step - loss:
0.0137 - acc: 0.9944 - val_loss: 0.4225 - val_acc: 0.9435
Epoch 99/100
64459/64459 [==============================] - 1s 19us/step - loss:
0.0130 - acc: 0.9949 - val_loss: 0.4083 - val_acc: 0.9449
Epoch 100/100
64459/64459 [==============================] - 1s 20us/step - loss:
0.0118 - acc: 0.9954 - val_loss: 0.4295 - val_acc: 0.9428
39686/39686 [==============================] - 2s 39us/step
[0.45393353235307565, 0.9405583833089755]
dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
```






```
<Figure size 432x288 with 0 Axes>
```

In [73]:

```
NN_testScore_ld=model_nlp.evaluate(X_test, y_test)
print("\n%s: %.2f%%" % (model_nlp.metrics_names[1], NN_testScore_ld[1]*100))
```

```
39686/39686 [==============================] - 1s 25us/step

acc: 94.06%
```

In [ ]:

```

```