sms-spam-v4

April 23, 2019

V4: + LSTM uses the Tokenizert.fit_on_texts(data) then Tokenizert.texts_to_sequences(data) to do the preprocessing + Other models uses the CountVectorizer to do the the preprocessing

Goal of this notebook to test several classifiers on the data set with different features

0.0.1 Let's begin

First of all neccesary imports

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib as mpl
        import matplotlib.pyplot as plt
        import seaborn as sns
        import string
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.model_selection import train_test_split
        from nltk.corpus import stopwords
        from sklearn.preprocessing import LabelEncoder
        %matplotlib inline
```

Let's read the data from csv file

```
In [2]: sms = pd.read_csv('../data/sms-spam.csv',delimiter=',',encoding='latin-1')

        sms.head()
```

```
Out[2]:      v1                                                 v2 Unnamed: 2  \
        0   ham  Go until jurong point, crazy.. Available only ...        NaN
        1   ham                      Ok lar... Joking wif u oni...        NaN
        2  spam  Free entry in 2 a wkly comp to win FA Cup fina...        NaN
        3   ham  U dun say so early hor... U c already then say...        NaN
        4   ham  Nah I don't think he goes to usf, he lives aro...        NaN

          Unnamed: 3 Unnamed: 4
        0        NaN        NaN
        1        NaN        NaN
        2        NaN        NaN
        3        NaN        NaN
        4        NaN        NaN
```

Now drop "unnamed" columns and rename v1 and v2 to "label" and "message"

In [3]:
```
sms = sms.drop(['Unnamed: 2','Unnamed: 3','Unnamed: 4'],axis=1)
sms = sms.rename(columns = {'v1':'label','v2':'message'})
```

Let's look into our data

In [4]:
```
sms.groupby('label').describe()
```

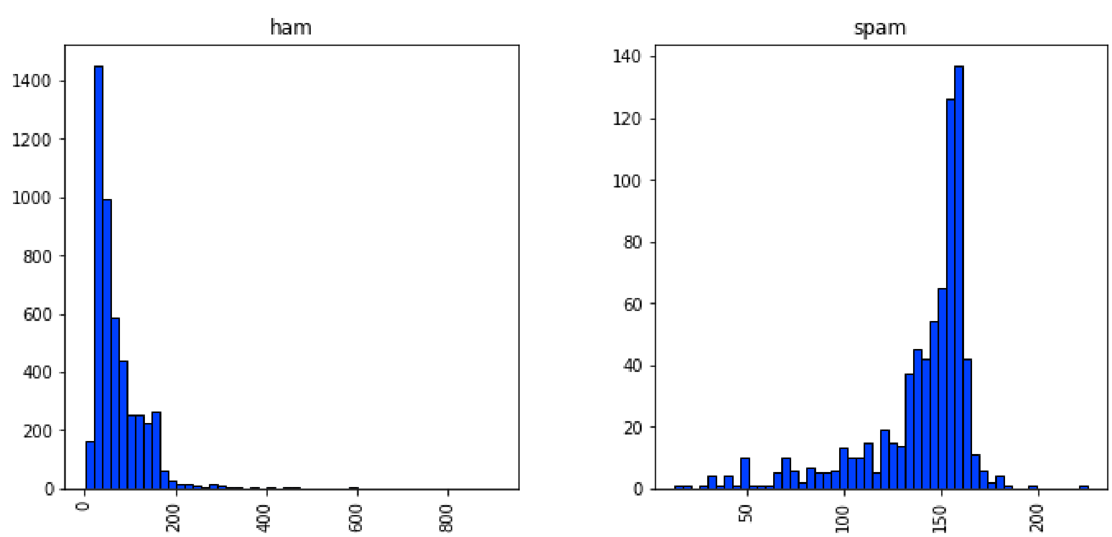
Out[4]:
```
      message
        count unique                                              top freq
label
ham      4825   4516                           Sorry, I'll call later   30
spam      747    653  Please call our customer service representativ...    4
```

Intresting that "Sorry, I'll call later" appears only 30 times here =)
Now let's create new feature "message length" and plot it to see if it's of any interest

In [5]:
```
sms['length'] = sms['message'].apply(len)
sms.head()
```

Out[5]:
```
  label                                            message  length
0   ham  Go until jurong point, crazy.. Available only ...     111
1   ham                      Ok lar... Joking wif u oni...      29
2  spam  Free entry in 2 a wkly comp to win FA Cup fina...     155
3   ham  U dun say so early hor... U c already then say...      49
4   ham  Nah I don't think he goes to usf, he lives aro...      61
```

In [6]:
```
mpl.rcParams['patch.force_edgecolor'] = True
plt.style.use('seaborn-bright')
sms.hist(column='length', by='label', bins=50,figsize=(11,5))
plt.savefig("../img/sms-length-distribution.eps")
plt.show()
```



Looks like the lengthy is the message, more likely it is a spam. Let's not forget this

0.0.2 Text processing and vectorizing our meddages

Let's create new data frame. We'll need a copy later on

```
In [7]: text_feat = sms['message'].copy()
```

Now define our tex precessing function. It will remove any punctuation and stopwords aswell.

```
In [8]: # def text_process(text):

        #     text = text.translate(str.maketrans('', '', string.punctuation))
        #     text = [word for word in text.split() if word.lower() not in stopwords.words('en

        #     return " ".join(text)
```

```
In [9]: # text_feat = text_feat.apply(text_process)
```

```
In [10]: vectorizer = CountVectorizer()
```

```
In [11]: features = vectorizer.fit_transform(text_feat)
```

```
In [12]: labels = LabelEncoder().fit_transform(sms['label'])
         labels = labels.reshape(-1,1)
```

```
In [13]: text_feat.shape
```

```
Out[13]: (5572,)
```

```
In [14]: features.shape
```

```
Out[14]: (5572, 8710)
```

0.0.3 Classifiers and predictions

First of all let's split our features to test and train set

```
In [15]: features_train, features_test, labels_train, labels_test = train_test_split(features,
```

Now let's import bunch of classifiers, initialize them and make a dictionary to itereate through

```
In [16]: from sklearn.linear_model import LogisticRegression
         from sklearn.svm import SVC
         from sklearn.naive_bayes import MultinomialNB
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.ensemble import AdaBoostClassifier
         from sklearn.ensemble import BaggingClassifier
         from sklearn.ensemble import ExtraTreesClassifier
         from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score
```

```
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/ensemble/weight_boosting.py:29
  from numpy.core.umath_tests import inner1d
```

```
In [17]: svc = SVC(kernel='sigmoid', gamma=1.0)
         knc = KNeighborsClassifier(n_neighbors=49)
         mnb = MultinomialNB(alpha=0.2)
         dtc = DecisionTreeClassifier(min_samples_split=7, random_state=111)
         lrc = LogisticRegression(solver='liblinear', penalty='l1')
         rfc = RandomForestClassifier(n_estimators=31, random_state=111)
         abc = AdaBoostClassifier(n_estimators=62, random_state=111)
         bc = BaggingClassifier(n_estimators=9, random_state=111)
         etc = ExtraTreesClassifier(n_estimators=9, random_state=111)
```

```
In [18]: clfs = {'SVC' : svc,'KN' : knc, 'NB': mnb, 'DT': dtc, 'LR': lrc, 'RF': rfc, 'AdaBoost
```

Let's make functions to fit our classifiers and make predictions

```
In [19]: def train_classifier(clf, feature_train, labels_train):
             clf.fit(feature_train, labels_train)
```

```
In [20]: def predict_labels(clf, features):
             return (clf.predict(features))
```

Now iterate through classifiers and save the results

```
In [21]: import time
```

```
In [22]: pred_scores = []
         for k,v in clfs.items():
             since = time.time()

             train_classifier(v, features_train, labels_train)
             time_elapsed = time.time() - since

             pred = predict_labels(v,features_test)
             pred_scores.append((k, [precision_score(labels_test,pred), recall_score(labels_tes
```

```
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/utils/validation.py:578: Data
  y = column_or_1d(y, warn=True)
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/ipykernel/__main__.py:2: DataConversi
  from ipykernel import kernelapp as app
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/metrics/classification.py:113
  'precision', 'predicted', average, warn_for)
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/metrics/classification.py:113
  'precision', 'predicted', average, warn_for)
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/ipykernel/__main__.py:2: DataConversi
  from ipykernel import kernelapp as app
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/utils/validation.py:578: Data
```

```
  y = column_or_1d(y, warn=True)
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/utils/validation.py:578: DataC
  y = column_or_1d(y, warn=True)
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/ipykernel/__main__.py:2: DataConversio
  from ipykernel import kernelapp as app
```

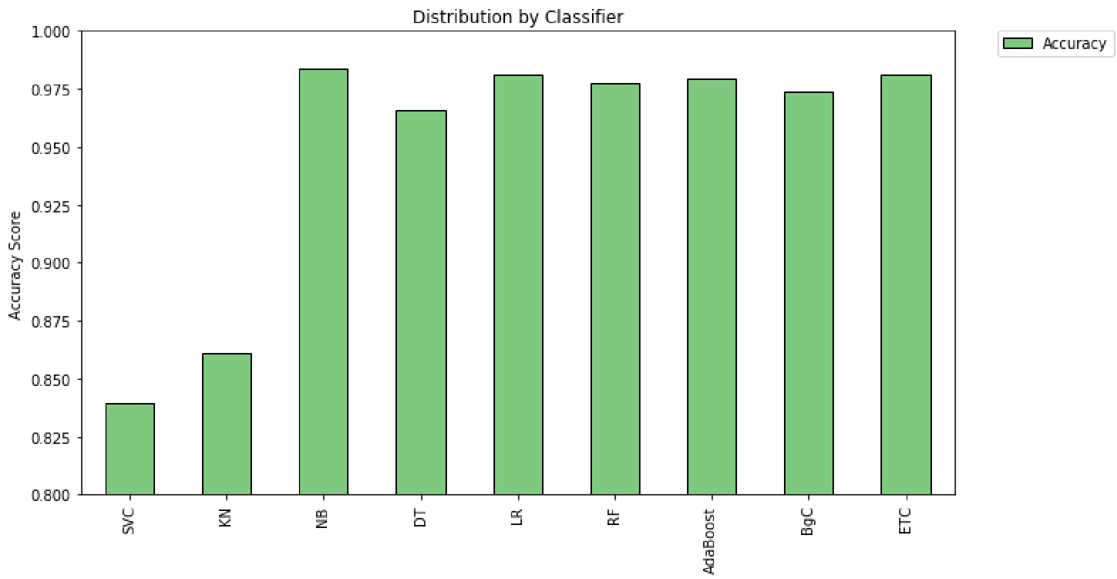
```
In [23]: # pred_scores
```

```
In [24]: df = pd.DataFrame.from_items(pred_scores,orient='index', columns=['Precision', 'Recall
         df
```

Out[24]:

	Precision	Recall	Accuracy	F1	Training Time (s)
SVC	0.408163	0.344828	0.839713	0.373832	0m 0.4723s
KN	0.000000	0.000000	0.861244	0.000000	0m 0.0010s
NB	0.914980	0.974138	0.983852	0.943633	0m 0.0019s
DT	0.882096	0.870690	0.965909	0.876356	0m 0.1238s
LR	0.967290	0.892241	0.980861	0.928251	0m 0.0153s
RF	1.000000	0.836207	0.977273	0.910798	0m 0.9301s
AdaBoost	0.962441	0.883621	0.979067	0.921348	0m 2.1926s
BgC	0.915929	0.892241	0.973684	0.903930	0m 0.7393s
ETC	0.990196	0.870690	0.980861	0.926606	0m 0.6012s

```
In [26]: df.plot(kind='bar', y="Accuracy", ylim=(0.8,1.0), figsize=(11,6), align='center', colo
         plt.xticks(np.arange(9), df.index)
         plt.ylabel('Accuracy Score')
         plt.title('Distribution by Classifier')
         plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
         plt.savefig("../img/sms-acc-basemodel-v4.eps")
         plt.show()
```



Looks like ensemble classifiers are not doing as good as expected.

0.0.4 Voting classifier

We are using ensemble algorithms here, but what about ensemble of ensembles? Will it beat NB?

```
In [27]: from sklearn.ensemble import VotingClassifier

In [28]: eclf = VotingClassifier(estimators=[('BgC', bc), ('ETC', etc), ('RF', rfc), ('Ada', al

In [29]: eclf.fit(features_train,labels_train)
```

```
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/preprocessing/label.py:95: Da
  y = column_or_1d(y, warn=True)
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/preprocessing/label.py:128: Da
  y = column_or_1d(y, warn=True)
```

```
Out[29]: VotingClassifier(estimators=[('BgC', BaggingClassifier(base_estimator=None, bootstrap=
                  bootstrap_features=False, max_features=1.0, max_samples=1.0,
                  n_estimators=9, n_jobs=1, oob_score=False, random_state=111,
                  verbose=0, warm_start=False)), ('ETC', ExtraTreesClassifier(bootstrap=False,
                   learning_rate=1.0, n_estimators=62, random_state=111))],
                  flatten_transform=None, n_jobs=1, voting='soft', weights=None)
```

```
In [30]: pred = eclf.predict(features_test)
```

```
/Users/alex/anaconda/envs/gc/lib/python3.6/site-packages/sklearn/preprocessing/label.py:151: De
  if diff:
```

```
In [31]: print(precision_score(labels_test,pred), recall_score(labels_test,pred), accuracy_sco
```

```
0.9951219512195122 0.8793103448275862 0.9826555023923444 0.9336384439359268
```

Better but nope.

0.0.5 RNN

Define the RNN structure.

```
In [32]: from keras.models import Model
         from keras.layers import LSTM, Activation, Dense, Dropout, Input, Embedding
         from keras.optimizers import RMSprop
         from keras.preprocessing.text import Tokenizer
         from keras.preprocessing import sequence
         from keras.utils import to_categorical
         from keras.callbacks import EarlyStopping
         from keras.callbacks import Callback
```

```
Using TensorFlow backend.
```

0.0.6 Process the data

- Tokenize the data and convert the text to sequences.
- Add padding to ensure that all the sequences have the same shape.
- There are many ways of taking the *max_len* and here an arbitrary length of 500 is chosen. (From the Fig, almost all the sentences have the length < 200)

In [33]:
```
features_lstm = text_feat
labels_lstm = labels
```

In [34]:
```
max_words = 1000
max_len = 200 # n_features
tok = Tokenizer(num_words=max_words)
tok.fit_on_texts(features_lstm)
sequences = tok.texts_to_sequences(features_lstm)
features_lstm = sequence.pad_sequences(sequences,maxlen=max_len)
```

In [35]:
```
features_lstm.shape
```

Out[35]:
```
(5572, 200)
```

In [36]:
```
labels_lstm.shape
```

Out[36]:
```
(5572, 1)
```

In [37]:
```
features_lstm_train, features_lstm_test, labels_lstm_train, labels_lstm_test = train_t
```

In [38]:
```
def RNN():
    inputs = Input(name='inputs',shape=[max_len])
    layer = Embedding(max_words,50,input_length=max_len)(inputs)
    layer = LSTM(64)(layer)
    layer = Dense(256,name='FC1')(layer)
    layer = Activation('relu')(layer)
    layer = Dropout(0.5)(layer)
    layer = Dense(1,name='out_layer')(layer)
    layer = Activation('sigmoid')(layer)
    model = Model(inputs=inputs,outputs=layer)
    return model
```

Call the function and compile the model.

In [39]:
```
model = RNN()
model.summary()
model.compile(loss='binary_crossentropy',optimizer=RMSprop(),metrics=['accuracy'])
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
inputs (InputLayer)          (None, 200)               0
_________________________________________________________________
```

```
embedding_1 (Embedding)      (None, 200, 50)           50000
_________________________________________________________________
lstm_1 (LSTM)                (None, 64)                29440
_________________________________________________________________
FC1 (Dense)                  (None, 256)               16640
_________________________________________________________________
activation_1 (Activation)    (None, 256)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
out_layer (Dense)            (None, 1)                 257
_________________________________________________________________
activation_2 (Activation)    (None, 1)                 0
=================================================================
Total params: 96,337
Trainable params: 96,337
Non-trainable params: 0
_________________________________________________________________
```

```
In [40]: since = time.time()


         model.fit(features_lstm_train, labels_lstm_train, epochs=10, batch_size=128,validatio
                              callbacks=[EarlyStopping(monitor='val_loss',min_delta=0.0001)])

         time_elapsed = time.time() - since
```

```
Train on 3120 samples, validate on 780 samples
Epoch 1/10
3120/3120 [==============================] - 7s 2ms/step - loss: 0.3692 - acc: 0.8561 - val_los
Epoch 2/10
3120/3120 [==============================] - 7s 2ms/step - loss: 0.1216 - acc: 0.9673 - val_los
Epoch 3/10
3120/3120 [==============================] - 6s 2ms/step - loss: 0.0544 - acc: 0.9859 - val_los
Epoch 4/10
3120/3120 [==============================] - 6s 2ms/step - loss: 0.0332 - acc: 0.9897 - val_los
Epoch 5/10
3120/3120 [==============================] - 6s 2ms/step - loss: 0.0289 - acc: 0.9926 - val_los
```

```
In [41]: print('Training complete in {:.0f}m {:.4f}s'.format(
                 time_elapsed // 60, time_elapsed % 60))
```

```
Training complete in 0m 32.2483s
```

```
In [42]: pred = (np.asarray(model.predict(features_lstm_test, batch_size=128))).round()

In [43]: pred_scores.append(("LSTM", [precision_score(labels_lstm_test,pred), recall_score(labe
```

0.0.7 gcForest

```
In [44]: import sys
         sys.path.append("..")
         from gcforest.gcforest import GCForest
         from gcforest.utils.config_utils import load_json

In [45]: def get_toy_config():
             config = {}
             ca_config = {}
             ca_config["random_state"] = 111
             ca_config["max_layers"] = 10
             ca_config["early_stopping_rounds"] = 3
             ca_config["n_classes"] = 2
             ca_config["estimators"] = []
             ca_config["estimators"].append({"n_folds": 5, "type": "RandomForestClassifier", "r
             ca_config["estimators"].append({"n_folds": 5, "type": "MultinomialNB", "alpha": 0

             config["cascade"] = ca_config
             return config

In [46]: config = get_toy_config()
         gc = GCForest(config)

         # features_train  ndarraylabels_train  (n_samples, )(n_samples, 1)
         features_train = features_train.toarray()
         labels_train = labels_train.reshape(-1)

         since = time.time()
         gc.fit_transform(features_train, labels_train)

         time_elapsed = time.time() - since

         # gc.fit_transform(features_train, labels_train, features_test, labels_test)

[ 2019-04-23 22:11:30,254][cascade_classifier.fit_transform] X_groups_train.shape=[(3900, 8710)
[ 2019-04-23 22:11:30,476][cascade_classifier.fit_transform] group_dims=[8710]
[ 2019-04-23 22:11:30,476][cascade_classifier.fit_transform] group_starts=[0]
[ 2019-04-23 22:11:30,477][cascade_classifier.fit_transform] group_ends=[8710]
[ 2019-04-23 22:11:30,478][cascade_classifier.fit_transform] X_train.shape=(3900, 8710),X_test
[ 2019-04-23 22:11:30,672][cascade_classifier.fit_transform] [layer=0] look_indexs=[0], X_cur_
[ 2019-04-23 22:11:33,452][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_0 - 5_
[ 2019-04-23 22:11:36,074][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_0 - 5_
[ 2019-04-23 22:11:38,781][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_0 - 5_
[ 2019-04-23 22:11:41,485][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_0 - 5_
[ 2019-04-23 22:11:44,105][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_0 - 5_
[ 2019-04-23 22:11:44,106][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_0 - 5_
[ 2019-04-23 22:11:44,333][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_1 - 5_
[ 2019-04-23 22:11:44,561][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_1 - 5_
```

```
[ 2019-04-23 22:11:44,776][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_1 - 5_
[ 2019-04-23 22:11:44,992][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_1 - 5_
[ 2019-04-23 22:11:45,215][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_1 - 5_
[ 2019-04-23 22:11:45,216][kfold_wrapper.log_eval_metrics] Accuracy(layer_0 - estimator_1 - 5_
[ 2019-04-23 22:11:45,217][cascade_classifier.calc_accuracy] Accuracy(layer_0 - train.classifi
[ 2019-04-23 22:11:45,405][cascade_classifier.fit_transform] [layer=1] look_indexs=[0], X_cur_
[ 2019-04-23 22:11:47,148][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_0 - 5_
[ 2019-04-23 22:11:49,038][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_0 - 5_
[ 2019-04-23 22:11:50,823][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_0 - 5_
[ 2019-04-23 22:11:52,611][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_0 - 5_
[ 2019-04-23 22:11:54,487][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_0 - 5_
[ 2019-04-23 22:11:54,488][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_0 - 5_
[ 2019-04-23 22:11:54,709][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_1 - 5_
[ 2019-04-23 22:11:54,927][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_1 - 5_
[ 2019-04-23 22:11:55,149][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_1 - 5_
[ 2019-04-23 22:11:55,378][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_1 - 5_
[ 2019-04-23 22:11:55,595][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_1 - 5_
[ 2019-04-23 22:11:55,597][kfold_wrapper.log_eval_metrics] Accuracy(layer_1 - estimator_1 - 5_
[ 2019-04-23 22:11:55,597][cascade_classifier.calc_accuracy] Accuracy(layer_1 - train.classifi
[ 2019-04-23 22:11:55,786][cascade_classifier.fit_transform] [layer=2] look_indexs=[0], X_cur_
[ 2019-04-23 22:11:57,476][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_0 - 5_
[ 2019-04-23 22:11:59,375][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_0 - 5_
[ 2019-04-23 22:12:01,260][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_0 - 5_
[ 2019-04-23 22:12:03,045][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_0 - 5_
[ 2019-04-23 22:12:04,932][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_0 - 5_
[ 2019-04-23 22:12:04,933][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_0 - 5_
[ 2019-04-23 22:12:05,164][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_1 - 5_
[ 2019-04-23 22:12:05,384][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_1 - 5_
[ 2019-04-23 22:12:05,617][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_1 - 5_
[ 2019-04-23 22:12:05,835][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_1 - 5_
[ 2019-04-23 22:12:06,057][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_1 - 5_
[ 2019-04-23 22:12:06,058][kfold_wrapper.log_eval_metrics] Accuracy(layer_2 - estimator_1 - 5_
[ 2019-04-23 22:12:06,059][cascade_classifier.calc_accuracy] Accuracy(layer_2 - train.classifi
[ 2019-04-23 22:12:06,263][cascade_classifier.fit_transform] [layer=3] look_indexs=[0], X_cur_
[ 2019-04-23 22:12:08,408][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_0 - 5_
[ 2019-04-23 22:12:10,204][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_0 - 5_
[ 2019-04-23 22:12:12,090][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_0 - 5_
[ 2019-04-23 22:12:13,971][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_0 - 5_
[ 2019-04-23 22:12:15,743][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_0 - 5_
[ 2019-04-23 22:12:15,744][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_0 - 5_
[ 2019-04-23 22:12:15,977][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_1 - 5_
[ 2019-04-23 22:12:16,196][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_1 - 5_
[ 2019-04-23 22:12:16,413][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_1 - 5_
[ 2019-04-23 22:12:16,641][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_1 - 5_
[ 2019-04-23 22:12:16,857][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_1 - 5_
[ 2019-04-23 22:12:16,858][kfold_wrapper.log_eval_metrics] Accuracy(layer_3 - estimator_1 - 5_
[ 2019-04-23 22:12:16,860][cascade_classifier.calc_accuracy] Accuracy(layer_3 - train.classifi
[ 2019-04-23 22:12:16,861][cascade_classifier.fit_transform] [Result][Optimal Level Detected]
```

In [47]:
```
print('Training complete in {:.0f}m {:.4f}s'.format(
            time_elapsed // 60, time_elapsed % 60))
```

```
Training complete in 0m 46.6826s
```

In [48]:
```
pred = predict_labels(gc,features_test.toarray())
pred_scores.append(("DCF", [precision_score(labels_test,pred), recall_score(labels_tes
```

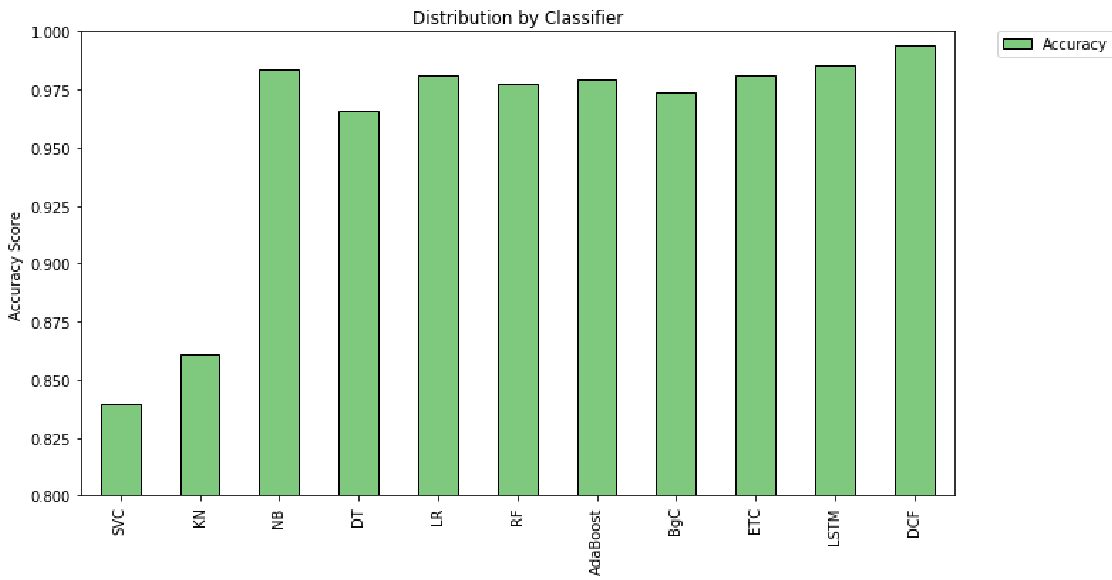
```
[ 2019-04-23 22:12:16,989][cascade_classifier.transform] X_groups_test.shape=[(1672, 8710)]
[ 2019-04-23 22:12:17,103][cascade_classifier.transform] group_dims=[8710]
[ 2019-04-23 22:12:17,104][cascade_classifier.transform] X_test.shape=(1672, 8710)
[ 2019-04-23 22:12:17,179][cascade_classifier.transform] [layer=0] look_indexs=[0], X_cur_test
```

In [49]:
```
df = pd.DataFrame.from_items(pred_scores,orient='index', columns=['Precision', 'Recal
df
```

Out[49]:

	Precision	Recall	Accuracy	F1	Training Time (s)
SVC	0.408163	0.344828	0.839713	0.373832	0m 0.4723s
KN	0.000000	0.000000	0.861244	0.000000	0m 0.0010s
NB	0.914980	0.974138	0.983852	0.943633	0m 0.0019s
DT	0.882096	0.870690	0.965909	0.876356	0m 0.1238s
LR	0.967290	0.892241	0.980861	0.928251	0m 0.0153s
RF	1.000000	0.836207	0.977273	0.910798	0m 0.9301s
AdaBoost	0.962441	0.883621	0.979067	0.921348	0m 2.1926s
BgC	0.915929	0.892241	0.973684	0.903930	0m 0.7393s
ETC	0.990196	0.870690	0.980861	0.926606	0m 0.6012s
LSTM	0.980769	0.910714	0.985646	0.944444	0m 32.2483s
DCF	0.982609	0.974138	0.994019	0.978355	0m 46.6826s

In [52]:
```
df.plot(kind='bar', y="Accuracy", ylim=(0.8,1.0), figsize=(11,6), align='center', colo
plt.xticks(np.arange(11), df.index)
plt.ylabel('Accuracy Score')
plt.title('Distribution by Classifier')
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
plt.savefig("../img/sms-acc-v4.eps")
plt.show()
```



In [53]:
```
import pickle
# dump
with open("../pkl/sms-gc-v4.pkl", "wb") as f:
    pickle.dump(gc, f, pickle.HIGHEST_PROTOCOL)

# # load
# with open("../pkl/2018_gc.pkl", "rb") as f:
#     gc = pickle.load(f)
```

0.0.8 Final verdict - gcForest is your friend in spam detection.

In [ ]:

In [ ]: