Sentinel

July 15, 2017

1 Sentinel - Fact-Checking Facebook Politics Pages — Analysis

In [1]:
```
# time
import time
from datetime import datetime, timedelta
# load and save data
import pickle
import os
from os.path import expanduser
# manipulate data
import pandas as pd
import numpy as np
# plot data
%matplotlib inline
import matplotlib.pyplot as plt
# sklearn
from sklearn.cross_validation import train_test_split
#from sklearn.model_selection import cross_val_score

from sklearn.cross_validation import cross_val_score
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.grid_search import GridSearchCV
```

In [2]:
```
posts = pd.read_csv("../data/facebook-fact-check.csv")
data = pd.read_csv("../data/Dataset13000+.csv")
```

2 Data Exploration

In [3]:
```
posts.head(2)
```

Out[3]:
```
         account_id           post_id    Category               Page  \
0  184096565021911  1035057923259100  mainstream  ABC News Politics
1  184096565021911  1035269309904628  mainstream  ABC News Politics

                                            Post URL Date Published Post Type  \
0  https://www.facebook.com/ABCNewsPolitics/posts...     2016-09-19     video
1  https://www.facebook.com/ABCNewsPolitics/posts...     2016-09-19      link

               Rating Debate  share_count  reaction_count  comment_count
0  no factual content    NaN          NaN           146.0           15.0
1         mostly true    NaN          1.0            33.0           34.0
```

In [4]: posts.shape

Out[4]: (2282, 12)

In [5]: posts.columns

Out[5]: Index([u'account_id', u'post_id', u'Category', u'Page', u'Post URL',
       u'Date Published', u'Post Type', u'Rating', u'Debate', u'share_count',
       u'reaction_count', u'comment_count'],
      dtype='object')

In [6]: data.head()

Out[6]:
```
   type  caps_text  text_len  excl_text  anger  anticipation  disgust  fear  \
0     1        6.0     890.0        0.0      2             2        0     1
1     1        0.0    1150.0        0.0      2             2        1     1
2     1        1.0    2601.0        0.0      1             7        0     2
3     1       12.0    2560.0        0.0      1             5        1     2
4     1        1.0    1582.0        0.0      0            10        1     1

   joy  sadness  surprise  trust  negative  positive
0    2        1         1      4         2         6
1    4        3         2      4         3         9
2    6        3         3     12         5        15
3    3        6         1     10         6        14
4    5        0         3      8         2        18
```

In [7]:
```
# Label balancing
data_count = data.groupby(by=[u'type'], as_index=True)\
.agg({u'type' : 'count'})\
.rename(columns={u'type' : 'N'})\
.sort_values("N",ascending = False)
data_count
```

Out[7]:
```
                N
type
bs          10900
1            1313
bias          443
conspiracy    430
hate          243
satire        146
state         120
junksci       102
fake           19
```

In [8]:
```
# Label balancing
posts_count = posts.groupby(by=[u'Rating'], as_index=True)\
.agg({u'Rating' : 'count'})\
.rename(columns={u'Rating' : 'N'})\
.sort_values("N",ascending = False)
posts_count
```

Out[8]:
```
                              N
Rating
mostly true                1669
```

```
        no factual content          264
        mixture of true and false   245
        mostly false                104
```

```
In [9]: np.sum(np.sum(posts.isnull()))
```

```
Out[9]: 2058
```

```
In [10]: np.sum(np.sum(posts.loc[:,u'Debate'].isnull()))
```

```
Out[10]: 1984
```

```
In [11]: np.sum(np.sum(posts.loc[:,u'share_count'].isnull()))
```

```
Out[11]: 70
```

```
In [12]: np.sum(np.sum(posts.loc[:,u'reaction_count'].isnull()))
```

```
Out[12]: 2
```

```
In [13]: np.sum(np.sum(posts.loc[:,u'comment_count'].isnull()))
```

```
Out[13]: 2
```

```
In [14]: posts.dropna().shape
```

```
Out[14]: (292, 12)
```

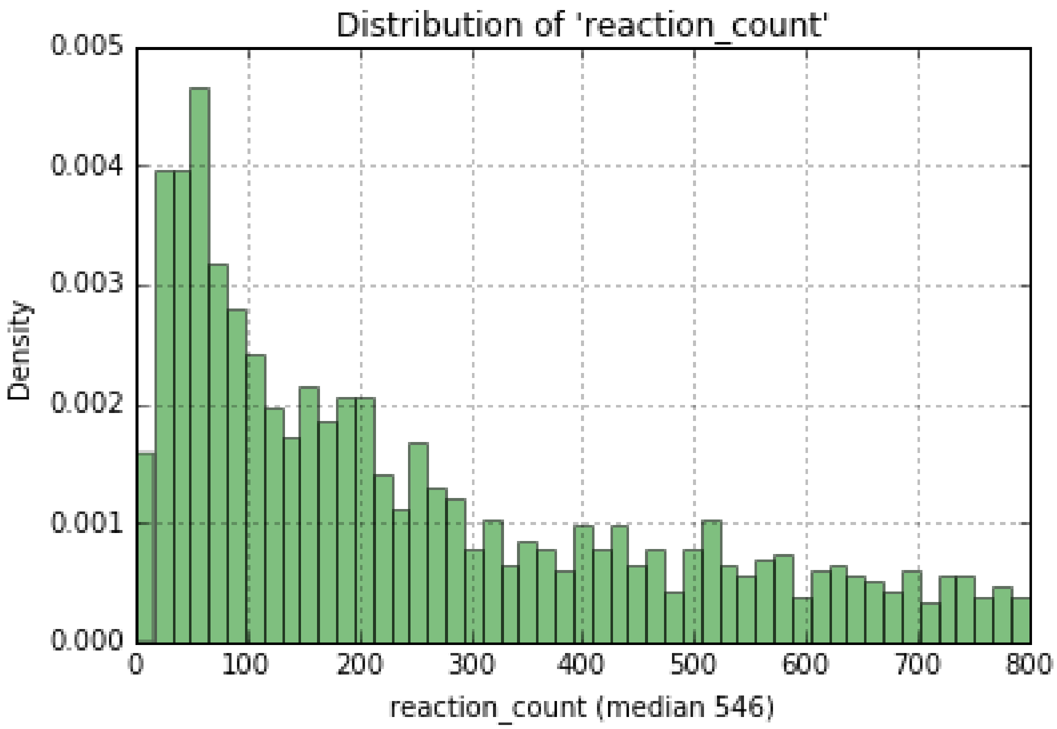
```
In [15]: posts.describe()
```

Out[15]:

	account_id	post_id	share_count	reaction_count	comment_count
count	2.282000e+03	2.282000e+03	2.212000e+03	2280.000000	2280.000000
mean	1.867111e+14	3.299586e+15	4.044816e+03	5364.284649	516.102193
std	1.393826e+14	3.808724e+15	2.983192e+04	19126.544561	3569.355445
min	6.231759e+10	5.510967e+14	1.000000e+00	2.000000	0.000000
25%	1.145179e+14	1.247441e+15	2.400000e+01	149.000000	37.000000
50%	1.840966e+14	1.290536e+15	9.600000e+01	545.500000	131.500000
75%	3.469371e+14	1.540752e+15	7.390000e+02	2416.750000	390.250000
max	4.401065e+14	1.015386e+16	1.088995e+06	456458.000000	159047.000000

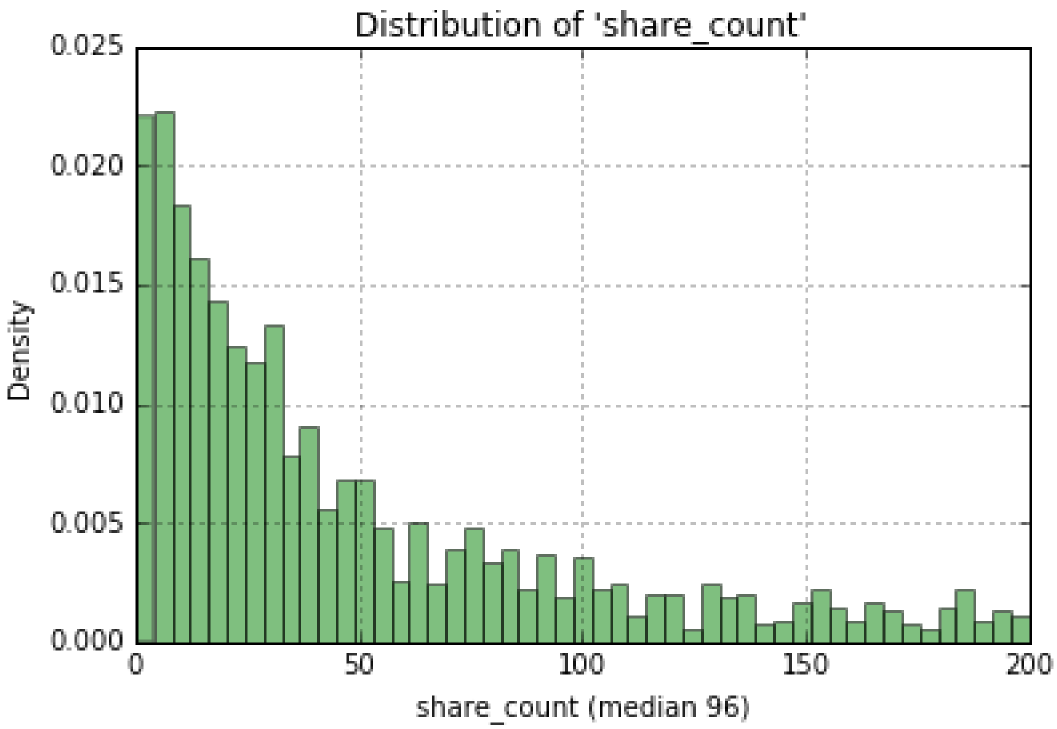
```
In [16]: median = np.median(posts.loc[:,u'reaction_count'].dropna())
         startTime = time.time()
         fig=plt.figure()
         plt.title(u"Distribution of 'reaction_count'")
         plt.ylabel(u'Density')
         plt.xlabel("reaction_count (median {:0.0f})".format(median))
         bins = np.linspace(0, 800, 50)
         plt.hist(posts[u'reaction_count'], bins, normed=True, facecolor='g', alpha=0.5)
         plt.grid()
         print("...done in %0.1f s...." % (time.time() - startTime))
```

```
...done in 0.4 s...
```



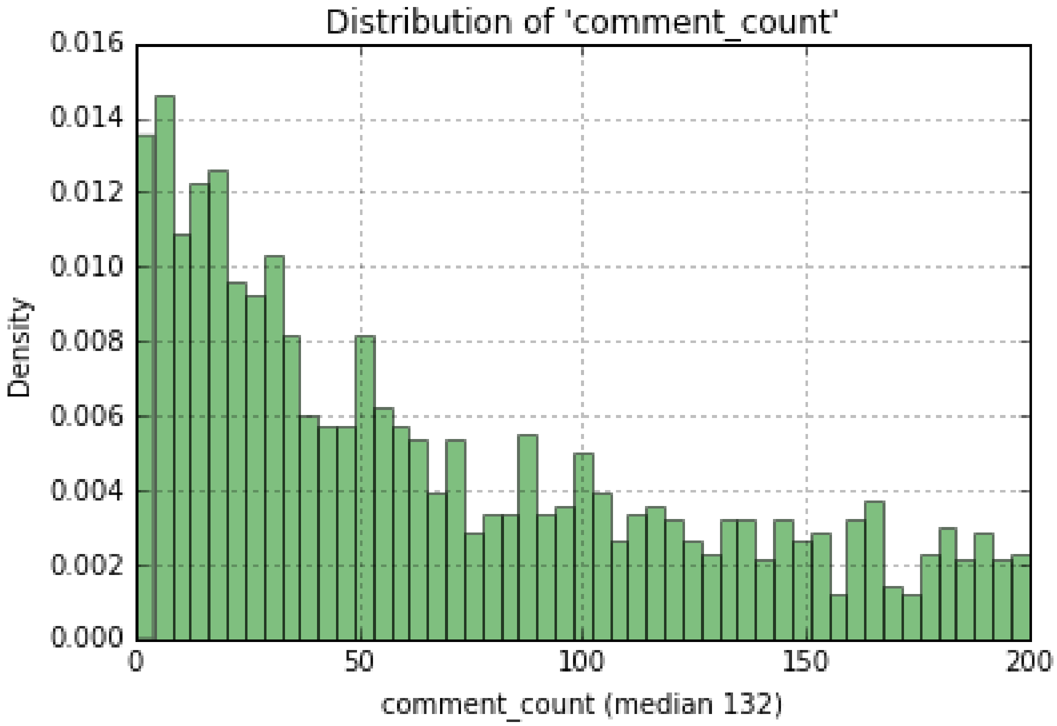
In [17]:
```
median = np.median(posts.loc[:,u'share_count'].dropna())
startTime = time.time()
fig=plt.figure()
plt.title(u"Distribution of 'share_count'")
plt.ylabel(u'Density')
plt.xlabel("share_count (median {:0.0f})".format(median))
bins = np.linspace(0, 200, 50)
plt.hist(posts[u'share_count'], bins, normed=True, facecolor='g', alpha=0.5)
plt.grid()
print("...done in %0.1f s...." % (time.time() - startTime))
```

```
...done in 0.4 s...
```




```
In [18]: median = np.median(posts.loc[:,u'comment_count'].dropna())
         startTime = time.time()
         fig=plt.figure()
         plt.title(u"Distribution of 'comment_count'")
         plt.ylabel(u'Density')
         plt.xlabel("comment_count (median {:0.0f})".format(median))
         bins = np.linspace(0, 200, 50)
         plt.hist(posts[u'comment_count'], bins, normed=True, facecolor='g', alpha=0.5)
         plt.grid()
         print("...done in %0.1f s...." % (time.time() - startTime))
```

```
...done in 0.3 s...
```



3 Preparing data

In [19]:
```
# Supression of row with "no factual content"
data = posts.loc[posts[u'Rating']<>"no factual content",:]
# Buildind new label with 2 categories 0 & 1 (1 meaning potential fake...)
data["label"] = 1
data.loc[data[u'Rating']=='mostly true','label'] = 0
# dropping other columns
data = data.loc[:,[u'share_count',u'reaction_count', u'comment_count', u'label']]
print("Number of remaining occurences with at least 1 Nan :%i " % np.sum(np.sum(data.isnull()))
# Supression of row having at least one null value
data = data.dropna()
print("Shape of non null data"),
print data.shape
# Label balancing
balancing = data.groupby(by=[u'label'], as_index=True)\
.agg({u'label' : 'count'})\
.rename(columns={u'label' : 'N'})\
.sort_values("N",ascending = False)
balancing
```

```
Number of remaining occurences with at least 1 Nan :45
Shape of non null data (1977, 4)
```

```
/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing
//anaconda/lib/python2.7/site-packages/pandas/core/indexing.py:461: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing
  self.obj[item] = s
```

Out[19]:

label	N
0	1633
1	344

rebalancing of categories will be needed during training...

```
In [20]: X = data.loc[:,[u'share_count', u'reaction_count', u'comment_count']]
         y = data.loc[:,[u'label']]
```

```
In [21]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

```
In [22]: # data normalisation
         scaler = StandardScaler().fit(X_train)
         X_train = scaler.transform(X_train)
         X_test = scaler.transform(X_test)
         print "Number exemple: \n- training set: {}\n- test set: {}".format(y_train.shape[0],y_test.sha
         print "Number of features: p={}".format(X_train.shape[1])
```

```
Number exemple:
- training set: 1324
- test set: 653
Number of features: p=3
```

```
In [23]: balancing = y_train.groupby(by=[u'label'], as_index=True)\
         .agg({u'label' : 'count'})\
         .rename(columns={u'label' : 'N'})\
         .sort_values("N",ascending = False)
         balancing
```

Out[23]:

label	N
0	1095
1	229

```
In [24]: from sklearn.linear_model import LogisticRegression
         clf = LogisticRegression(class_weight='balanced')
         clf.fit(X_train,y_train)
         y_pred = clf.predict(X_test)
```

```
//anaconda/lib/python2.7/site-packages/sklearn/utils/validation.py:515: DataConversionWarning: A column-
  y = column_or_1d(y, warn=True)
```

```
In [25]: clf.score(X_test,y_test)
```

```
Out[25]: 0.74119448698315471
```

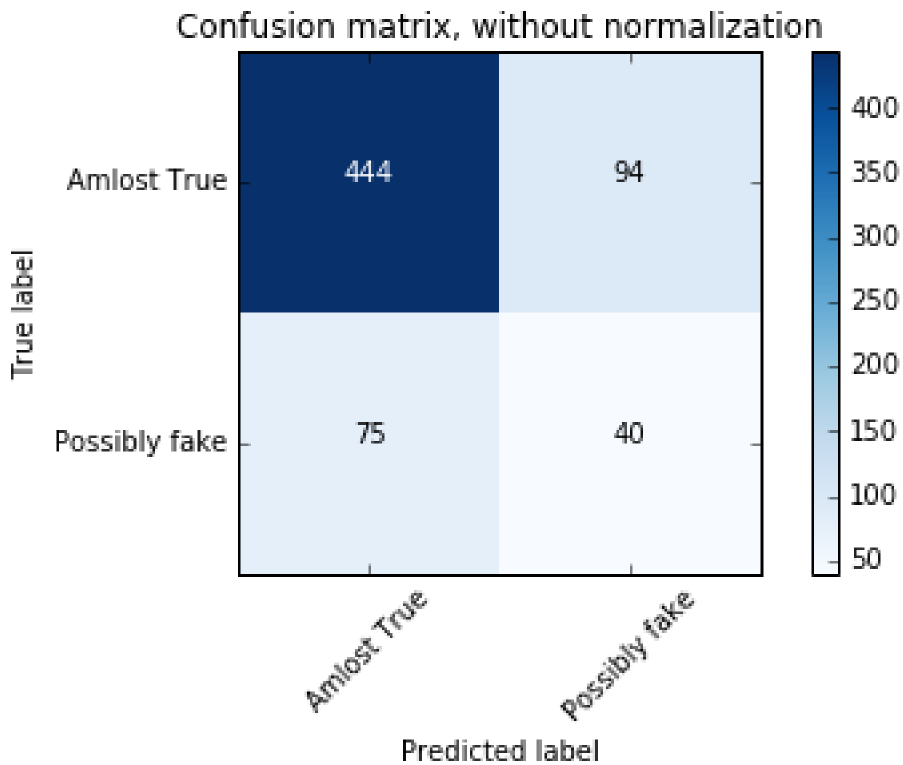
```
In [26]: from sklearn.metrics import confusion_matrix
```

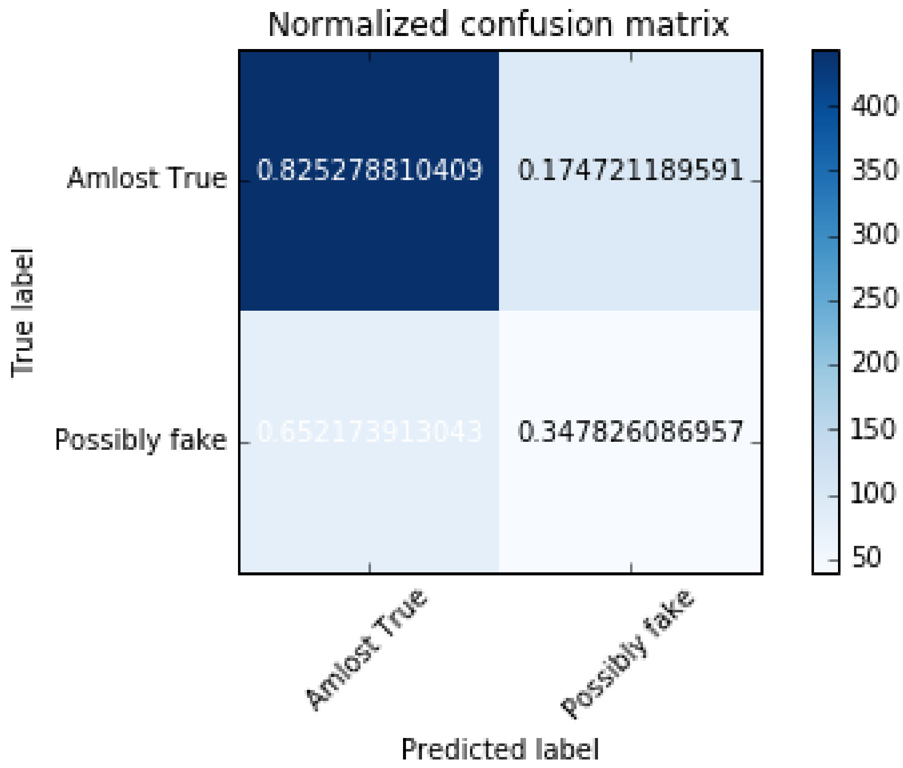
In [27]:
```
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [28]:
```
# Compute confusion matrix
y_pred = clf.predict(X_test)
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
class_names = ['Amlost True','Possibly fake']
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[444  94]
 [ 75  40]]
```

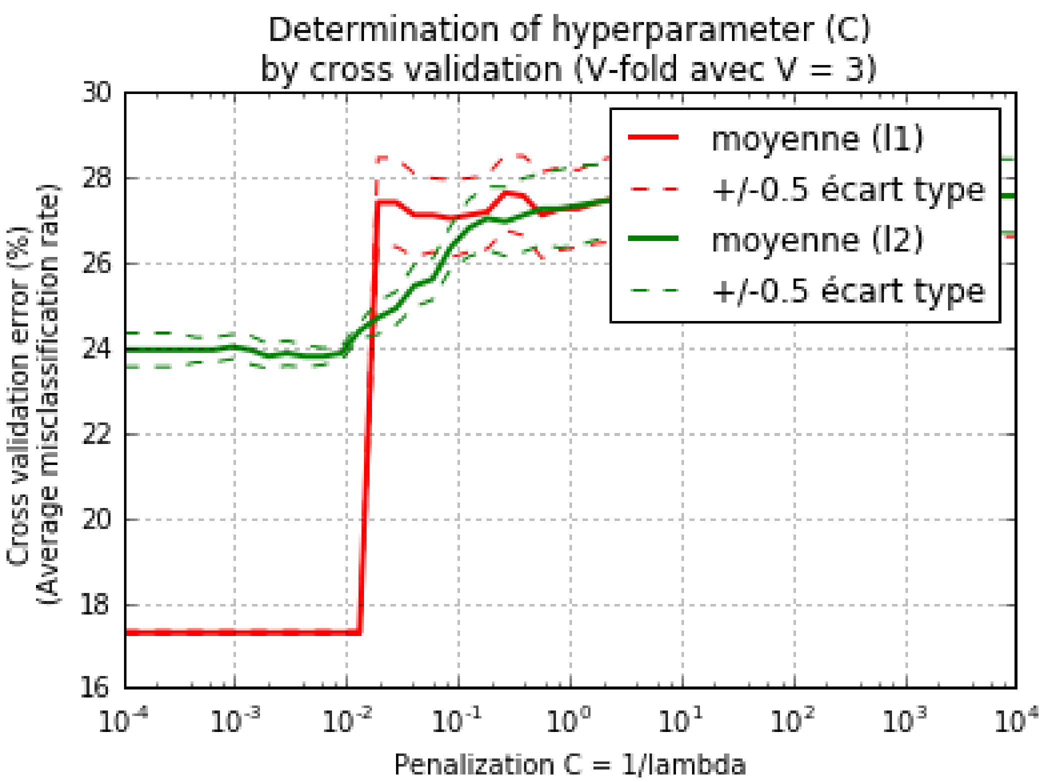
```
Normalized confusion matrix
[[ 0.83  0.17]
 [ 0.65  0.35]]
```






```
In [29]: nb_value = 50 # Number of values to be tested for hyperparameters
         mean_score_l1 = np.zeros(nb_value)
         mean_score_l2 = np.zeros(nb_value)
         C_log = np.logspace(-4,4,nb_value)
         cv = 3 # V-fold, numbers of fold

         mean_score_l1 = np.empty(nb_value)
         std_scores_l1 = np.empty(nb_value)

         mean_score_l2 = np.empty(nb_value)
         std_scores_l2 = np.empty(nb_value)

         np.random.seed(seed=42)

         startTime = time.time()

         for i, C in enumerate(C_log):
             clf = LogisticRegression(C=C, penalty='l1', tol=0.01, random_state=42, class_weight='balan
             mean_score_l1[i] = 100*np.mean(1-cross_val_score(clf, X_train, y_train.loc[:,'label'], cv=c
                                                               scoring='accuracy'))
             std_scores_l1[i] = 100*np.std(1-cross_val_score(clf, X_train, y_train.loc[:,'label'], cv=cv
                                                              scoring='accuracy'))


         for i, C in enumerate(C_log):
             clf = LogisticRegression(C=C, penalty='l2', tol=0.01, random_state=42, class_weight='balan
```

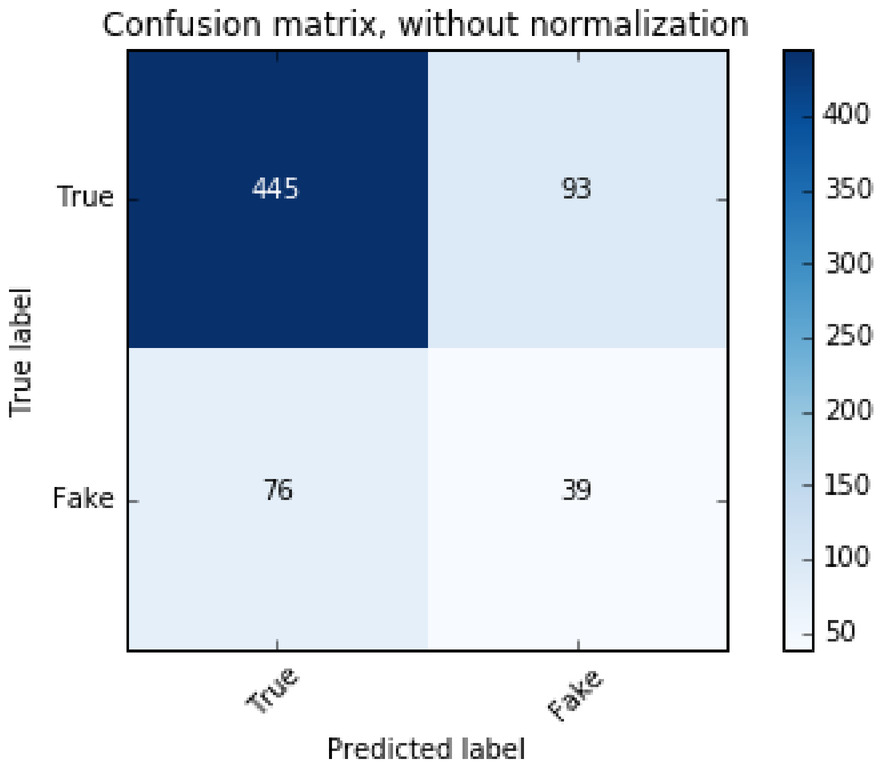
```
    mean_score_l2[i] = 100*np.mean(1-cross_val_score(clf, X_train, y_train.loc[:,'label'], cv=c
                                                          scoring='accuracy'))
    std_scores_l2[i] = 100*np.std(1-cross_val_score(clf, X_train, y_train.loc[:,'label'], cv=cv
                                                        scoring='accuracy'))



plt.figure()
plt.semilogx(C_log,mean_score_l1[:],'r',linewidth=2,label='moyenne (l1)')
plt.semilogx(C_log,mean_score_l1[:]-0.5*std_scores_l1[:], 'r--', label=u'+/-0.5 écart type')
plt.semilogx(C_log,mean_score_l1[:]+0.5*std_scores_l1[:],'r--')

plt.semilogx(C_log,mean_score_l2[:],'g',linewidth=2,label='moyenne (l2)')
plt.semilogx(C_log,mean_score_l2[:]-0.5*std_scores_l2[:], 'g--', label=u'+/-0.5 écart type')
plt.semilogx(C_log,mean_score_l2[:]+0.5*std_scores_l2[:],'g--')

plt.xlabel(u"Penalization C = 1/lambda")
plt.ylabel(u"Cross validation error (%)\n(Average misclassification rate)")
plt.title(u"Determination of hyperparameter (C)\nby cross validation \
(V-fold avec V = %s)" % (cv))
plt.legend(bbox_to_anchor=(1, 1))
plt.grid()
plt.show()
print("Determination of optimal hyperparameters in %0.1f s" % (time.time() - startTime))
print("l1 penalty, optimal value : C = %0.4f" % (C_log[np.argmin(mean_score_l1)]))
print("l2 penalty, optimal value : C = %0.4f" % (C_log[np.argmin(mean_score_l2)]))
```

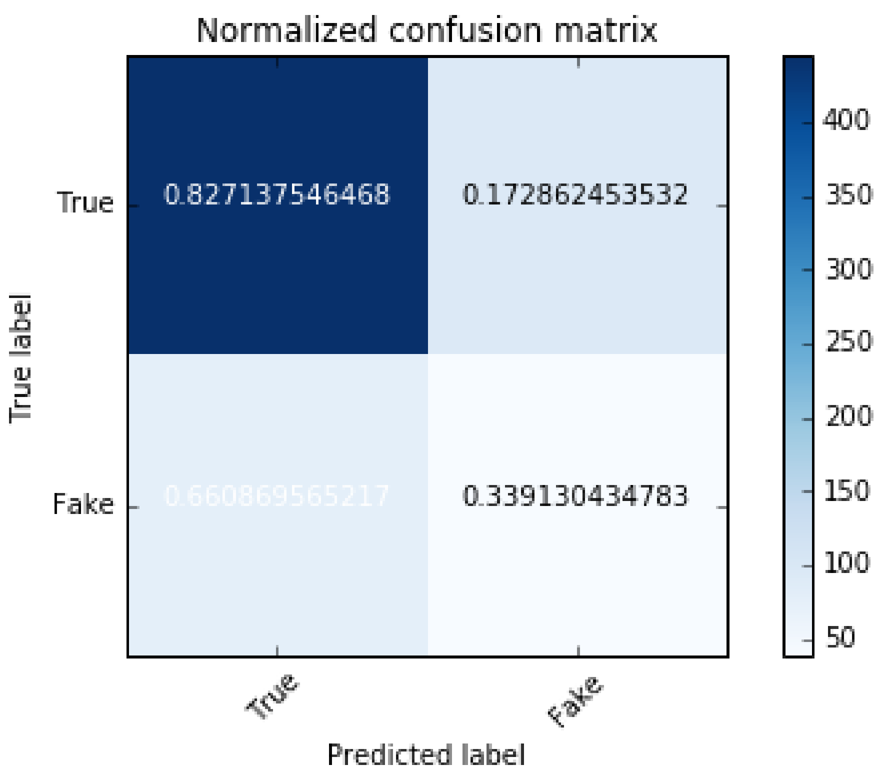


```
Determination of optimal hyperparameters in 9.5 s
l1 penalty, optimal value : C = 0.0001
l2 penalty, optimal value : C = 0.0063
```

In [30]:
```python
C = 10 #C_log[np.argmin(mean_score_l1)]
clf = LogisticRegression(C=C, penalty='l1', tol=0.01, random_state=42, class_weight='balanced')
clf.fit(X_train,y_train)

# Compute confusion matrix
y_pred = clf.predict(X_test)
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
class_names = ['True','Fake']
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
```

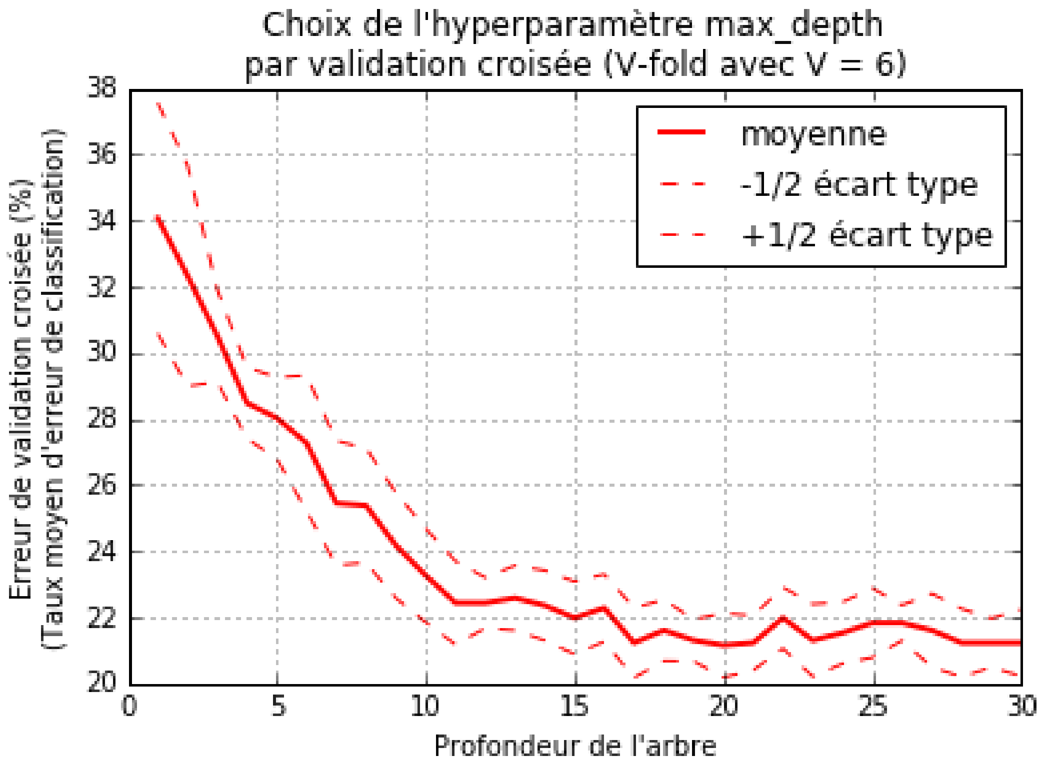
```
//anaconda/lib/python2.7/site-packages/sklearn/utils/validation.py:515: DataConversionWarning: A column-
  y = column_or_1d(y, warn=True)

Confusion matrix, without normalization
[[445  93]
 [ 76  39]]
Normalized confusion matrix
[[ 0.83  0.17]
 [ 0.66  0.34]]
```


Confusion matrix, without normalization
True label
True
Fake
445
93
76
39
True
Fake
Predicted label
400
350
300
250
200
150
100
50


Normalized confusion matrix
True label
True
Fake
0.827137546468
0.172862453532
0.660869565217
0.339130434783
True
Fake
Predicted label
400
350
300
250
200
150
100
50

In [ ]:

In [31]:
```
from sklearn.tree import DecisionTreeClassifier

# Plage étudiée de k=1 à k=n_neighbors_max
max_depth_max = 30
# V-fold, nombre de fold
cv = 6
mean_scores = np.empty(max_depth_max)
std_scores = np.empty(max_depth_max)
np.random.seed(seed=42)
startTime = time.time()
for max_depth in range(1,max_depth_max+1):
    clf = DecisionTreeClassifier(max_depth=max_depth,class_weight='balanced')
    mean_scores[max_depth-1] = 100*np.mean(1-cross_val_score(clf, X_train, y_train.loc[:,'label
                                                          scoring='accuracy'))
    std_scores[max_depth-1] = 100*np.std(1-cross_val_score(clf, X_train, y_train.loc[:,'label']
                                                        scoring='accuracy'))
plt.figure()
x=range(1,max_depth_max+1)
plt.plot(x,mean_scores[:],'r',linewidth=2,label='moyenne')
plt.plot(x,mean_scores[:]-0.5*std_scores[:], 'r--', label=u'-1/2 écart type')
plt.plot(x,mean_scores[:]+0.5*std_scores[:],'r--', label=u'+1/2 écart type')
plt.xlabel(u"Profondeur de l'arbre")
plt.ylabel(u"Erreur de validation croisée (%)\n(Taux moyen d'erreur de classification)")
plt.title(u"Choix de l'hyperparamètre max_depth\npar validation croisée \
(V-fold avec V = %s)" % (cv))
plt.legend(bbox_to_anchor=(1, 1))
plt.grid()
plt.show()

print("Détermination du paramètre optimal en %0.1f seconds " % (time.time() - startTime))
print("Profondeur optimale de l'arbre: max_depth = %i " % (np.argmin(mean_scores)+1))
```

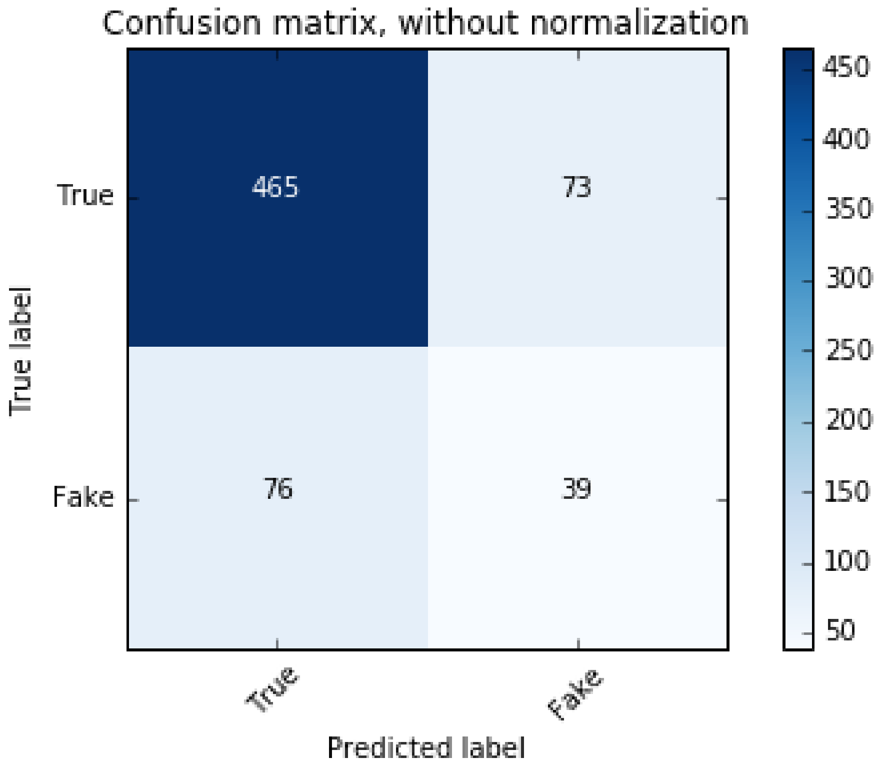


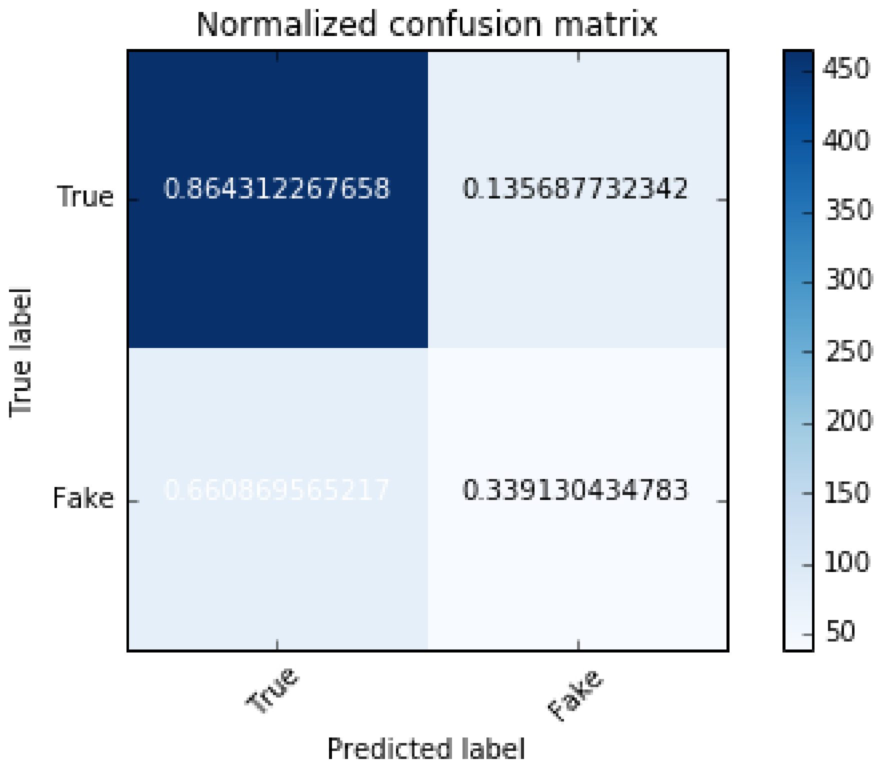

```
Détermination du paramètre optimal en 3.2 seconds
Profondeur optimale de l'arbre: max_depth = 20
```

In [ ]:
```
clf =  DecisionTreeClassifier(max_depth=20,class_weight='balanced')
clf.fit(X_train,y_train)

# Compute confusion matrix
y_pred = clf.predict(X_test)
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
class_names = ['True','Fake']
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[465  73]
```

```
 [ 76  39]]
Normalized confusion matrix
[[ 0.86  0.14]
 [ 0.66  0.34]]
```






```
In [ ]: from sklearn.svm import SVC
        from sklearn.cross_validation import StratifiedShuffleSplit
        from sklearn.grid_search import GridSearchCV

        startTime = time.time()
        C_range = np.logspace(0, 12, num=13, base=2)
        gamma_range = np.logspace(-8, 4, num=13, base=2)
        param_grid = dict(gamma=gamma_range, C=C_range)
        cv = StratifiedShuffleSplit(y_train, n_iter=5, test_size=0.2, random_state=42)
        grid = GridSearchCV(SVC(class_weight='balanced'), param_grid=param_grid, cv=cv)
        grid.fit(X_train, y_train.loc[:,'label'])
        print("Détermination des hyperparamètres optimaux en %0.1f s" % (time.time() - startTime))
        print("Les valeurs optimales sont  %s \nScore de validation croisée : %0.2f %%" \
              % (grid.best_params_, 100*grid.best_score_))

In [ ]: # Re apprentissage sur l'ensemble de jeux de validation avec C optimal
        clf = SVC(C=grid.best_params_['C'], gamma=grid.best_params_['gamma'],
                  kernel='rbf', random_state=42,class_weight='balanced').fit(X_train, y_train)
        clf.fit(X_train,y_train)
        accuracy = clf.score(X_test,y_test)
        print("Score de généralisation : %0.2f %%" % (100*accuracy))

        # Compute confusion matrix
        y_pred = clf.predict(X_test)
        cnf_matrix = confusion_matrix(y_test, y_pred)
        np.set_printoptions(precision=2)
```

```
# Plot non-normalized confusion matrix
class_names = ['True','Fake']
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
```

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.cross_validation import StratifiedShuffleSplit
from sklearn.grid_search import GridSearchCV

startTime = time.time()
max_depth_range = [1,2,5,10,15,20,25,30]
n_estimators_range = [1,5,10,20,50,100]
param_grid = dict(max_depth=max_depth_range, n_estimators=n_estimators_range)
cv = StratifiedShuffleSplit(y_train, n_iter=5, test_size=0.2, random_state=42)
grid = GridSearchCV(RandomForestClassifier(class_weight='balanced'), param_grid=param_grid, cv=
grid.fit(X_train, y_train.loc[:,'label'])
print("Détermination des hyperparamètres optimaux en %0.1f s" % (time.time() - startTime))
print("Les valeurs optimales sont  %s \nScore de validation croisée : %0.2f %%" \
      % (grid.best_params_, 100*grid.best_score_))
```

In [ ]:
```
# Re apprentissage sur l'ensemble de jeux de validation avec C optimal
clf = RandomForestClassifier(max_depth=grid.best_params_['max_depth'],
                             n_estimators=grid.best_params_['n_estimators'],
                             random_state=42,class_weight='balanced').fit(X_train, y_train)
clf.fit(X_train,y_train)
accuracy = clf.score(X_test,y_test)
print("Score de généralisation : %0.2f %%" % (100*accuracy))

# Compute confusion matrix
y_pred = clf.predict(X_test)
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
class_names = ['True','Fake']
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
```

In [ ]:

In [ ]:

In [ ]: