prediction_random_forest

September 24, 2019

In [1]:
```
import pandas as pd

# some lines have too many fields (?), so skip bad lines
imgatt = pd.read_csv("CUB_200_2011/attributes/image_attribute_labels.txt",sep='\s+',
                     header=None, error_bad_lines=False,
                    warn_bad_lines=False, usecols=[0,1,2],
                     names=['imgid', 'attid', 'present'])

# description from dataset README:
#T he set of attribute labels as perceived by MTukers for each image is contained
#in the file attributes/image_attribute_labels.txt,
# with each line crresponding to one image/attribute/worker triplet:

# <image_id> <attribute_id> <is_present> <certainty_id> <time>

# where <image_id>, <attribute_id>, <certainty_id> coresspond to the IDs in images.txt
# attributes.txt, and attributes/certainties.txt
# respectively. <is_present> is 0 or i (1 denotes that the attribute is present).
# <time> denotes the time spent by the MTurker is seconds.
```

In [2]:
```
imgatt.head()
```

Out[2]:

	imgid	attid	present
0	1	1	0
1	1	2	0
2	1	3	0
3	1	4	0
4	1	5	1

In [3]:
```
imgatt.shape
```

Out[3]: (3677856, 3)

In [4]:
```
# Image ID number 1 dose not have attibutes 1,2,3, or 4, but it dose have attribute 5.
# The shpe will tell us how many rows and columns we have.
# It has 3.7 milion rows and three columns. This is not the actual formula that you wa
# You want attributes to be the columns, not rows.
# need to reorganize imgatt to have one row per imgid, and 312 columns(one column per
```

```python
# with 1/0 in each cell representing
# if that imgid has that attribute or not
imgatt2 = imgatt.pivot(index='imgid', columns='attid', values='present')
```

In [5]:
```python
imgatt2.head()
```

Out[5]:
```
attid  1    2    3    4    5    6    7    8    9    10   ...  303  304  305  \
imgid                                                  ...
1        0    0    0    0    1    0    0    0    0    0 ...    0    0    0
2        0    0    0    0    0    0    0    0    0    0 ...    0    0    0
3        0    0    0    0    1    0    0    0    0    0 ...    0    0    0
4        0    0    0    0    1    0    0    0    0    0 ...    0    0    0
5        0    0    0    0    1    0    0    0    0    0 ...    0    0    1

attid  306  307  308  309  310  311  312
imgid
1        0    0    1    0    0    0    0
2        0    0    0    0    0    0    0
3        0    0    1    0    0    1    0
4        1    0    0    1    0    0    0
5        0    0    0    0    0    0    0

[5 rows x 312 columns]
```

In [6]:
```python
# feed data into a random forest. In the previous example, we have 312 columns and 312
# which is ultimately
# about 12,000 images or 12,000 different examples of birds:
imgatt2.shape
```

Out[6]:
```
(11788, 312)
```

In [7]:
```python
# need to load the answers, such as whether it;s a bird and which spcies it is.
# Since it is an image class labels file, the separators
# are spaces. There is no header row and the two columns are imgid and label.
# We will be using set_index('imgid') to have the same result
# produced by imgatt2.head(), where the rows are idenfitied by the image ID

# load the image true classes
imglabels = pd.read_csv("CUB_200_2011/image_class_labels.txt", sep=' ', header=None, na
imglabels = imglabels.set_index('imgid')

# decription from dataset README:
# The ground truth class labels (bird species labels) for each image are contained
# in the file image_class_labels.txt,
# with each line corresponding to one image:
# <image_id> <class_id>
# where <image_id> and <class_id> correspond to the IDs in images.txt and classes.txt,
```

In [8]:
```python
imglabels.head()
```

```
Out[8]:        label
        imgid
        1          1
        2          1
        3          1
        4          1
        5          1
```

```
In [9]: imglabels.shape
```

```
Out[9]: (11788, 1)
```

```
In [10]: df=imgatt2.join(imglabels)
         df=df.sample(frac=1)
```

```
In [11]: df_att=df.iloc[:, :312]
         df_label=df.iloc[:, 312:]
```

```
In [12]: df_att.head()
```

```
Out[12]:        1    2    3    4    5    6    7    8    9    10   ...  303  304  305  \
         imgid                                                     ...
         9426   0    0    0    0    0    0    1    0    0    0    ...    0    1    0
         7056   0    0    0    0    0    0    0    1    0    0    ...    0    0    0
         6321   0    0    0    0    0    0    0    0    0    0    ...    0    0    1
         6359   0    0    0    0    0    0    1    0    0    0    ...    0    0    1
         11409  0    1    0    0    0    0    0    0    0    0    ...    0    0    0

                306  307  308  309  310  311  312
         imgid
         9426   0    0    0    0    0    0    0
         7056   0    0    0    0    1    0    0
         6321   0    0    0    0    0    0    1
         6359   0    0    0    0    0    0    1
         11409  0    0    1    0    0    1    0

         [5 rows x 312 columns]
```

```
In [62]: df_train_att = df_att[:8000]
         df_train_label = df_label[:8000]
         df_test_att = df_att[8000:]
         df_test_label = df_label[8000:]

         df_train_label = df_train_label['label']
         df_test_label = df_test_label['label']
```

```
In [64]: from sklearn.ensemble import RandomForestClassifier
         clf = RandomForestClassifier(max_features=50,random_state=0, n_estimators=100)
```

```
In [65]: clf.fit(df_train_att, df_train_label)
```

```
Out[65]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                        max_depth=None, max_features=50, max_leaf_nodes=None,
                        min_impurity_decrease=0.0, min_impurity_split=None,
                        min_samples_leaf=1, min_samples_split=2,
                        min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
                        oob_score=False, random_state=0, verbose=0, warm_start=False)
```

```
In [66]: print(clf.predict(df_train_att.head()))
```

```
[161 121 108 109 194]
```

```
In [67]: clf.score(df_test_att, df_test_label)
```

```
Out[67]: 0.4334741288278775
```

```
In [68]: from sklearn.metrics import confusion_matrix
         pred_labels = clf.predict(df_test_att)
         cm = confusion_matrix(df_test_label, pred_labels)
```

```
In [69]: cm
```

```
Out[69]: array([[ 6,  0,  1, ...,  0,  0,  0],
                [ 1, 13,  0, ...,  0,  0,  0],
                [ 3,  0,  4, ...,  0,  0,  0],
                ...,
                [ 0,  0,  1, ...,  4,  0,  0],
                [ 0,  0,  0, ...,  0, 11,  0],
                [ 0,  0,  0, ...,  0,  0, 14]], dtype=int64)
```

```
In [76]: import matplotlib.pyplot as plt
         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.
             """
             if normalize:
                 cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                 print("Normalized confusion matrix")
             else:
                 print('Confusion matrix, without normalization')
             print(cm)

             plt.imshow(cm, interpolation='nearest', cmap=cmap)
             plt.title(title)
```

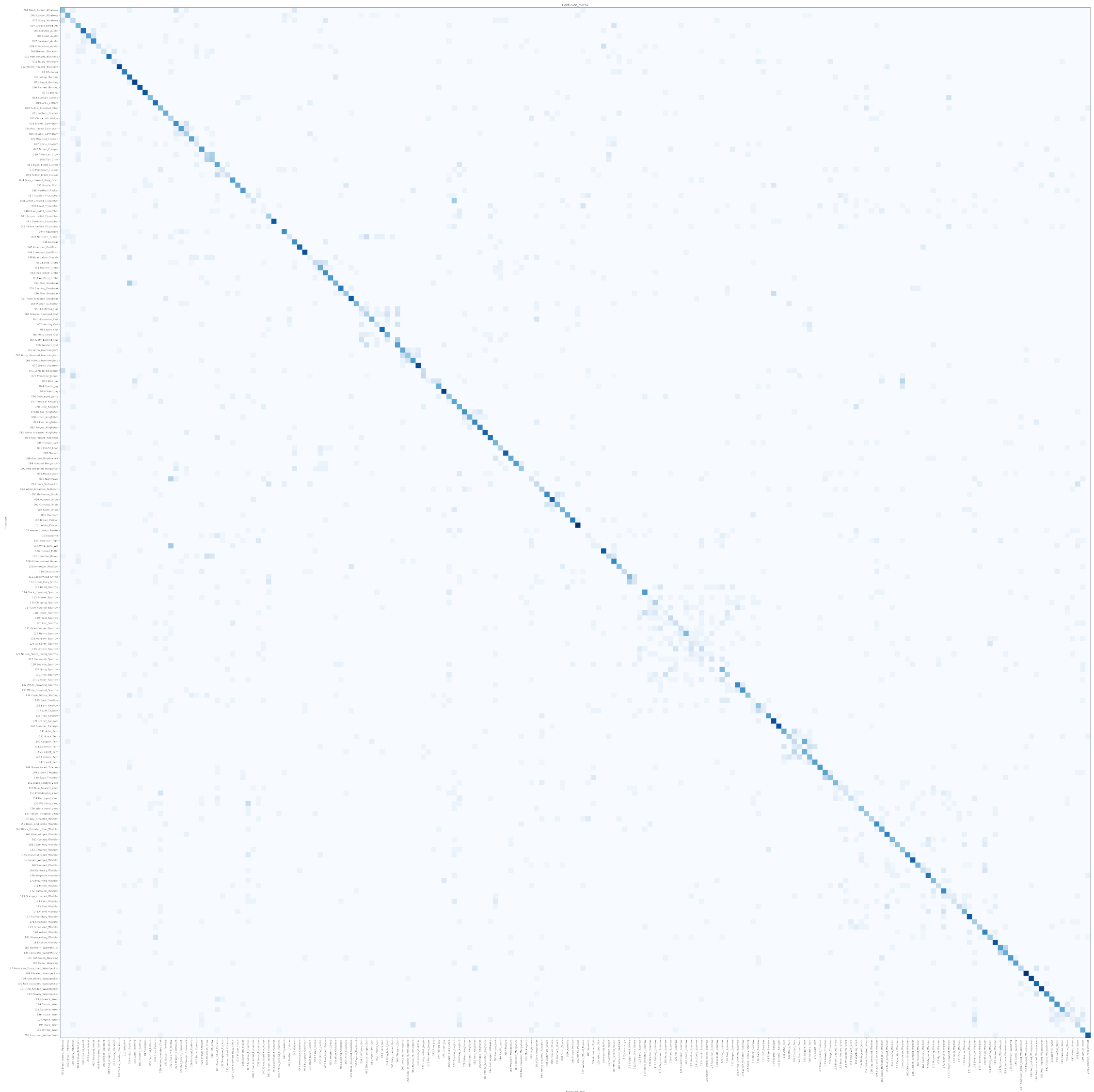
```
    tick_marks=np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=90)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max()/2
    plt.tight_layout()
    plt.ylabel("True label")
    plt.xlabel("Predicted label")
```

In [77]:
```
birds = pd.read_csv("CUB_200_2011/classes.txt",
                    sep='\s+', header=None, usecols=[1], names=['birdname'])
birds = birds['birdname']
birds
```

Out[77]:
```
0      001.Black_footed_Albatross
1            002.Laysan_Albatross
2             003.Sooty_Albatross
3           004.Groove_billed_Ani
4              005.Crested_Auklet
                  ...
195               196.House_Wren
196               197.Marsh_Wren
197                198.Rock_Wren
198              199.Winter_Wren
199      200.Common_Yellowthroat
Name: birdname, Length: 200, dtype: object
```

In [78]:
```
import numpy as np
np.set_printoptions(precision=2)
plt.figure(figsize=(60,60), dpi=300)
plot_confusion_matrix(cm, classes=birds, normalize=True)
plt.show()
```

```
Normalized confusion matrix
[[0.4  0.   0.07 ... 0.   0.   0.  ]
 [0.04 0.5  0.   ... 0.   0.   0.  ]
 [0.19 0.   0.25 ... 0.   0.   0.  ]
 ...
 [0.   0.   0.06 ... 0.25 0.   0.  ]
 [0.   0.   0.   ... 0.   0.5  0.  ]
 [0.   0.   0.   ... 0.   0.   0.82]]
```



```
In [79]: from sklearn import tree
         clftree = tree.DecisionTreeClassifier()
         clftree.fit(df_train_att, df_train_label)
         clftree.score(df_test_att, df_test_label)
```

```
Out[79]: 0.26689545934530096
```

```
In [84]: from sklearn import svm
         clfsvm = svm.SVC(gamma='auto')
         clfsvm.fit(df_train_att, df_train_label)
         clfsvm.score(df_test_att, df_test_label)
```

```
Out[84]: 0.29197465681098206
```

In [86]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(clf, df_train_att, df_train_label, cv=5)
print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std()*2))
```

```
Accuracy: 0.44 (+/- 0.01)
```

In [88]:
```
scorestree = cross_val_score(clftree, df_train_att, df_train_label, cv=5)
print("Accuracy: %0.2f (+/-%0.2f)" % (scorestree.mean(), scores.std()*2))
```

```
Accuracy: 0.25 (+/-0.01)
```

In [89]:
```
scoressvm = cross_val_score(clfsvm, df_train_att, df_train_label, cv=5)
print("Accuracy: %0.2f (+/-%0.2f)" % (scoressvm.mean(), scoressvm.std()*2))
```

```
Accuracy: 0.27 (+/-0.00)
```

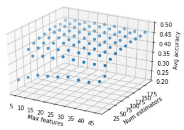
In [91]:
```
max_features_opts = range(5,50,5)
n_estimators_opts = range(10,200,20)
rf_params = np.empty((len(max_features_opts)*len(n_estimators_opts),4),float)
i=0
for max_features in max_features_opts:
    for n_estimators in n_estimators_opts:
        clf = RandomForestClassifier(max_features=max_features, n_estimators=n_estima
        scores = cross_val_score(clf, df_train_att, df_train_label, cv=5)
        rf_params[1,0] = max_features
        rf_params[i,1] = n_estimators
        rf_params[i,2] = scores.mean()
        rf_params[i,3] = scores.std()*2
        i+=1
        print("Max featues: %d, num estimators: %d, accuracy: %0.2f (+/- %0.2f)" % \
             (max_features, n_estimators, scores.mean(), scores.std()*2))
```

```
Max featues: 5, num estimators: 10, accuracy: 0.27 (+/- 0.02)
Max featues: 5, num estimators: 30, accuracy: 0.35 (+/- 0.02)
Max featues: 5, num estimators: 50, accuracy: 0.39 (+/- 0.01)
Max featues: 5, num estimators: 70, accuracy: 0.41 (+/- 0.01)
Max featues: 5, num estimators: 90, accuracy: 0.42 (+/- 0.01)
Max featues: 5, num estimators: 110, accuracy: 0.43 (+/- 0.01)
Max featues: 5, num estimators: 130, accuracy: 0.44 (+/- 0.01)
Max featues: 5, num estimators: 150, accuracy: 0.44 (+/- 0.01)
Max featues: 5, num estimators: 170, accuracy: 0.44 (+/- 0.02)
Max featues: 5, num estimators: 190, accuracy: 0.45 (+/- 0.01)
Max featues: 10, num estimators: 10, accuracy: 0.29 (+/- 0.03)
Max featues: 10, num estimators: 30, accuracy: 0.38 (+/- 0.02)
Max featues: 10, num estimators: 50, accuracy: 0.41 (+/- 0.01)
Max featues: 10, num estimators: 70, accuracy: 0.42 (+/- 0.01)
```

```
Max featues: 10, num estimators: 90, accuracy: 0.43 (+/- 0.01)
Max featues: 10, num estimators: 110, accuracy: 0.45 (+/- 0.02)
Max featues: 10, num estimators: 130, accuracy: 0.44 (+/- 0.01)
Max featues: 10, num estimators: 150, accuracy: 0.45 (+/- 0.01)
Max featues: 10, num estimators: 170, accuracy: 0.45 (+/- 0.01)
Max featues: 10, num estimators: 190, accuracy: 0.45 (+/- 0.01)
Max featues: 15, num estimators: 10, accuracy: 0.31 (+/- 0.02)
Max featues: 15, num estimators: 30, accuracy: 0.39 (+/- 0.02)
Max featues: 15, num estimators: 50, accuracy: 0.42 (+/- 0.00)
Max featues: 15, num estimators: 70, accuracy: 0.43 (+/- 0.02)
Max featues: 15, num estimators: 90, accuracy: 0.44 (+/- 0.01)
Max featues: 15, num estimators: 110, accuracy: 0.45 (+/- 0.01)
Max featues: 15, num estimators: 130, accuracy: 0.45 (+/- 0.02)
Max featues: 15, num estimators: 150, accuracy: 0.46 (+/- 0.01)
Max featues: 15, num estimators: 170, accuracy: 0.46 (+/- 0.01)
Max featues: 15, num estimators: 190, accuracy: 0.45 (+/- 0.02)
Max featues: 20, num estimators: 10, accuracy: 0.32 (+/- 0.02)
Max featues: 20, num estimators: 30, accuracy: 0.39 (+/- 0.02)
Max featues: 20, num estimators: 50, accuracy: 0.42 (+/- 0.01)
Max featues: 20, num estimators: 70, accuracy: 0.44 (+/- 0.01)
Max featues: 20, num estimators: 90, accuracy: 0.44 (+/- 0.01)
Max featues: 20, num estimators: 110, accuracy: 0.45 (+/- 0.01)
Max featues: 20, num estimators: 130, accuracy: 0.45 (+/- 0.02)
Max featues: 20, num estimators: 150, accuracy: 0.45 (+/- 0.02)
Max featues: 20, num estimators: 170, accuracy: 0.45 (+/- 0.01)
Max featues: 20, num estimators: 190, accuracy: 0.46 (+/- 0.01)
Max featues: 25, num estimators: 10, accuracy: 0.32 (+/- 0.01)
Max featues: 25, num estimators: 30, accuracy: 0.41 (+/- 0.01)
Max featues: 25, num estimators: 50, accuracy: 0.43 (+/- 0.02)
Max featues: 25, num estimators: 70, accuracy: 0.44 (+/- 0.02)
Max featues: 25, num estimators: 90, accuracy: 0.44 (+/- 0.01)
Max featues: 25, num estimators: 110, accuracy: 0.45 (+/- 0.01)
Max featues: 25, num estimators: 130, accuracy: 0.45 (+/- 0.01)
Max featues: 25, num estimators: 150, accuracy: 0.45 (+/- 0.01)
Max featues: 25, num estimators: 170, accuracy: 0.46 (+/- 0.01)
Max featues: 25, num estimators: 190, accuracy: 0.46 (+/- 0.00)
Max featues: 30, num estimators: 10, accuracy: 0.33 (+/- 0.01)
Max featues: 30, num estimators: 30, accuracy: 0.41 (+/- 0.01)
Max featues: 30, num estimators: 50, accuracy: 0.42 (+/- 0.01)
Max featues: 30, num estimators: 70, accuracy: 0.43 (+/- 0.01)
Max featues: 30, num estimators: 90, accuracy: 0.44 (+/- 0.02)
Max featues: 30, num estimators: 110, accuracy: 0.45 (+/- 0.01)
Max featues: 30, num estimators: 130, accuracy: 0.45 (+/- 0.00)
Max featues: 30, num estimators: 150, accuracy: 0.46 (+/- 0.01)
Max featues: 30, num estimators: 170, accuracy: 0.46 (+/- 0.01)
Max featues: 30, num estimators: 190, accuracy: 0.46 (+/- 0.01)
Max featues: 35, num estimators: 10, accuracy: 0.33 (+/- 0.02)
Max featues: 35, num estimators: 30, accuracy: 0.40 (+/- 0.01)
```

```
Max featues: 35, num estimators: 50, accuracy: 0.43 (+/- 0.01)
Max featues: 35, num estimators: 70, accuracy: 0.44 (+/- 0.01)
Max featues: 35, num estimators: 90, accuracy: 0.44 (+/- 0.01)
Max featues: 35, num estimators: 110, accuracy: 0.45 (+/- 0.01)
Max featues: 35, num estimators: 130, accuracy: 0.45 (+/- 0.02)
Max featues: 35, num estimators: 150, accuracy: 0.45 (+/- 0.01)
Max featues: 35, num estimators: 170, accuracy: 0.45 (+/- 0.02)
Max featues: 35, num estimators: 190, accuracy: 0.46 (+/- 0.01)
Max featues: 40, num estimators: 10, accuracy: 0.33 (+/- 0.02)
Max featues: 40, num estimators: 30, accuracy: 0.40 (+/- 0.01)
Max featues: 40, num estimators: 50, accuracy: 0.43 (+/- 0.02)
Max featues: 40, num estimators: 70, accuracy: 0.43 (+/- 0.02)
Max featues: 40, num estimators: 90, accuracy: 0.44 (+/- 0.01)
Max featues: 40, num estimators: 110, accuracy: 0.45 (+/- 0.01)
Max featues: 40, num estimators: 130, accuracy: 0.45 (+/- 0.00)
Max featues: 40, num estimators: 150, accuracy: 0.45 (+/- 0.01)
Max featues: 40, num estimators: 170, accuracy: 0.46 (+/- 0.01)
Max featues: 40, num estimators: 190, accuracy: 0.45 (+/- 0.01)
Max featues: 45, num estimators: 10, accuracy: 0.34 (+/- 0.02)
Max featues: 45, num estimators: 30, accuracy: 0.41 (+/- 0.02)
Max featues: 45, num estimators: 50, accuracy: 0.42 (+/- 0.02)
Max featues: 45, num estimators: 70, accuracy: 0.44 (+/- 0.02)
Max featues: 45, num estimators: 90, accuracy: 0.44 (+/- 0.01)
Max featues: 45, num estimators: 110, accuracy: 0.44 (+/- 0.01)
Max featues: 45, num estimators: 130, accuracy: 0.45 (+/- 0.01)
Max featues: 45, num estimators: 150, accuracy: 0.45 (+/- 0.02)
Max featues: 45, num estimators: 170, accuracy: 0.45 (+/- 0.02)
Max featues: 45, num estimators: 190, accuracy: 0.46 (+/- 0.01)
```

In [94]:
```
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from matplotlib import cm
fig = plt.figure()
fig.clf()
ax = fig.gca(projection='3d')
x = rf_params[:,0]
y = rf_params[:,1]
z = rf_params[:,2]
ax.scatter(x,y,z)
ax.set_zlim(0.2, 0.5)
ax.set_xlabel('Max features')
ax.set_ylabel('Num estimators')
ax.set_zlabel('Avg accuracy')
plt.show()
```



Avg accuracy
0.50
0.45
0.40
0.35
0.30
0.25
0.20
5 10 15 20 25 30 35 40 45
Max features
25 50 75 100 125 150 175
Num estimators


```
In [ ]:
```