Implementation of Decision trees and Ensemble methods on People's Analytics project.

For week 10 journal entry, my team has decided to implement decision trees and ensemble methods to perform supervised machine learning binary classification task on People's Analytics project. The dataset for this project comes from Wharton's People Analytics Challenge 2018 case competition.

Data Source : https://wpa.wharton.upenn.edu/conference/2018-conference-competitions

The goal of the People Analytics project is to analyze real data from the fellow selection process at GHC(Global Health Corps) to recommend strategies to optimize their application review process.

GHC's mission is to mobilize a global community of emerging leaders who share a common belief: health is a human right. They are building this movement by recruiting young, cross-sector talent from around the world to join a one-year fellowship program and then stay engaged in our alumni community to pioneer a brighter future in global health. GHC competitively selects fellows with diverse skill sets to fill pre-identified talent gaps at high-impact health organizations in yearlong paid positions. Fellows are placed in cross-national pairs, with one national fellow from the placement country and one international fellow from a different country.

More information on Global Health Corps, could be found on: https://ghcorps.org/

Global Health Corps' selection process has five rounds of review; we are interested in analyzing Round 2 and Round 3 of the process.

Using this dataset:

- A binary classification task has been performed in this journal entry to predict GHC's Round 3 semifinalist Designation (whether an applicant qualifies as semifinalist or not).
- The importance of various features has been interpreted that effect Round3 reviewer's semifinalist designation decision.

Numpy,Pandas and Sklearn libraries have been used to perform data preprocessing and predictive modeling tasks. The performance of the predictive models have been measured using Area Under ROC Curve which evaluates the goodness of the classification model.

The data mining steps to prepare the data to be fed into the model, exploratory data analysis, various modeling techniques and parameter tuning - all of these constitute the experience of this project.

Data Preprocessing

Although the entire data mining operation for this work has been performed in a separate notebook, let's check if couple more cleaning up operation needs to be performed.

In [51]:
```
# Import the libraries
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [6]:
```
# Load the dataset
df = pd.read_csv('final.csv',sep='\t')
```

In [11]:
```
# Drop any missing values
df.dropna(how='any',axis=0,inplace=True)
```

Let's take a quick look at the dataset....

In [52]:
```
df.head()
```

Out[52]:

	American Indian	Asian	Black	Hispanic	Hawaiian	White	Other Race	Sex	Have you previously applied?	Round2 Reviews Plagirism Reviewer1
0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0
1	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	0
3	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0
4	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	0
5	0.0	0.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	0

5 rows × 110 columns

In [23]:

```
# check missing values
def check_nan(list_values):
    return sum(list_values.isnull())

#Using apply function to check missing values on every column of datafr
ame
print df.apply(check_nan)[0:50]
```

```
American Indian
   0
Asian
   0
Black
   0
Hispanic
   0
Hawaiian
   0
White
   0
Other Race
   0
```

```
Sex
   0
Have you previously applied?
   0
Round2 Reviews Plagirism Reviewer1
   0
Round2 Clear Purpose CF Reviewer1
   0
Round2 Commitment to Social Justice Reviewer1
   0
Round2 Innovation CF Reviewer1
   0
Round2 Commitment to learning2 Reviewer1
   0
Round2 Get Results Reviewer1
   0
Round2 Collaboration Reviewer1
   0
Round2 Inspire and Mobilize Reviewer1
   0
Round2 Experience Reviewer1
   0
Round2 Total Score Reviewer1
   0
Round2 Is this applicant moving on as a GHC Semi-Finalist Reviewer1
   0
Round2 GHC Semifinalist Reviewer1
   0
Round2 Is this applicant moving on as a GHC Alternate? Reviewer1
   0
Round2 GHC Alternate Reviewer1
   0
Round2 Plagirism Reviewer2
   0
Round2 Clear Purpose CF Reviewer2
   0
Round2 Commitment to Social Justice CF  Reviewer2
   0
Round2 Innovation CF Reviewer2
```

```
   0
Round2 Commitment to learning2 Reviewer2
   0
Round2 Get Results Reviewer2
   0
Round2 Collaboration Reviewer2
   0
Round2 Inspire and Mobilize Reviewer2
   0
Round2 Experience Reviewer2
   0
Round2 Total Score Reviewer2
   0
Round2 Is this applicant moving on as a GHC Semi-Finalist Reviewer2
   0
Round2 GHC Semifinalist Reviewer2
   0
Round2 Is this applicant moving on as a GHC Alternate? Reviewer2
1478
Round2 GHC Alternate Reviewer2
   0
Citizen_ Other
   0
Citizen_ Rwanda
   0
Citizen_ Uganda
   0
Citizen_ United States
   0
Citizen_ Zambia
   0
Citizen_Malawi
   0
Citizen_Other
   0
Citizen_Rwanda
   0
Citizen_Uganda
   0
```

```
Citizen_United States
   0
Citizen_Zambia
   0
WorkedPublicHealth_Between_1_to_3_years
   0
WorkedPublicHealth_Never
   0
dtype: int64
```

In [21]:
```python
# check that all nulls are removed
df.isnull().sum().sum()
```

Out[21]: 1478

Looks like there 1478 missing values still left in "Round2 Is this applicant moving on as a GHC Alternate? Reviewer2" column. Let's go ahead and take care of that before performing the predictive modeling.

In [24]:
```python
# fill the missing values with 0
df['Round2 Is this applicant moving on as a GHC Alternate? Reviewer2'].
fillna(0,inplace=True)
```

In [53]:
```python
# Check if missing values are completely removed
df.isnull().sum().sum()
```

Out[53]: 0

No missing values.... Let's import the libraries for predictive modeling and perform the clasification task.

In [25]:
```python
# Import the libraries for machine learning
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
, ExtraTreesClassifier, GradientBoostingClassifier
from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.model_selection import StratifiedShuffleSplit, GridSearchC
V, train_test_split, KFold, cross_val_score
from sklearn.metrics import accuracy_score, roc_auc_score
from time import time
from sklearn.externals.six import StringIO
from IPython.display import Image
import pydotplus
from sklearn.tree import export_graphviz
```

In [26]:

```python
# Check out proportion of target values in the data set
1.0*df['SemifinalistDesignation'].value_counts()/df.shape[0]
```

Out[26]:

```
0.0    0.771093
1.0    0.228907
Name: SemifinalistDesignation, dtype: float64
```

Only 22.8% of the candidates are classified as semifinalists!!

In [27]:

```python
# perform train test split
X = df.drop('SemifinalistDesignation',axis=1)
y = df['SemifinalistDesignation']
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.20,str
atify=y)
```

In [56]:

```python
print "No. of features: ", X.shape[1]
```

```
No. of features:  109
```

Semifinalist Designation is the target variable and there are 109 feature columns.

In [57]:

```python
print "no. of rows for model training: ", X_train.shape[0]
print "no. of rows for model evaluation: ", X_test.shape[0]
```

```
no. of rows for model training:  4428
no. of rows for model evaluation:  1107
```

Predictive modeling

Let's start with decision tree classifier to get a quick glance on how the model looks like with just 10 features and max depth of 3.

In [29]:
```
# Decision tree Classifier
tree = DecisionTreeClassifier(max_depth=3, max_features=10)
kfold = KFold(n_splits=10, shuffle=True, random_state=1)
cross_val_scores = cross_val_score(tree, X_train, y_train, scoring='roc
_auc', cv=kfold)
print '10-fold Area Under ROC Curve:'
print [x for x in cross_val_scores]
print '\nMean of Cross Validated Area Under ROC Curve values:'
print np.mean(cross_val_scores)
print '\nStd of Cross Validated Area Under ROC Curve values:'
print np.std(cross_val_scores)
```

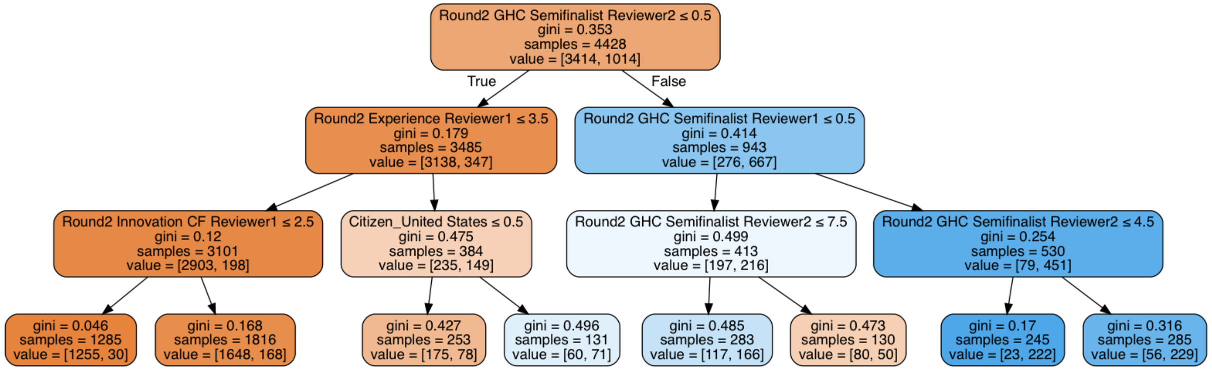
```
10-fold Area Under ROC Curve:
[0.7884324834749764, 0.8904839713663243, 0.8847823586912771, 0.72375036
97131026, 0.898956442831216, 0.8189050211736237, 0.8362078496406855, 0.
8612354892205637, 0.7023445463812437, 0.8087121212121211]

Mean of Cross Validated Area Under ROC Curve values:
0.8213810653705135

Std of Cross Validated Area Under ROC Curve values:
0.0644785010757141
```

A very naive version of the decision tree in this case looks like the following tree with mean 0.82 area under roc curve.

In [30]:
```
# visualize the decision tree
tree.fit(X_train, y_train)
dot_data = StringIO()
export_graphviz(tree, out_file=dot_data,
                    feature_names=X_train.columns,
                    filled=True, rounded=True,
                    special_characters=True)
```

```
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```

Out[30]:



Let's check out how ensemble methods like Random Forest behave in such setting....

In [31]:

```
# Random forest Classifier
rtree = RandomForestClassifier(max_depth=3, max_features=10)
kfold = KFold(n_splits=10, shuffle=True, random_state=1)
cross_val_scores = cross_val_score(rtree, X_train, y_train, scoring='ro
c_auc', cv=kfold)
print '10-fold Area Under ROC Curve:'
print [x for x in cross_val_scores]
print '\nMean of Cross Validated Area Under ROC Curve values:'
print np.mean(cross_val_scores)
print '\nStd of Cross Validated Area Under ROC Curve values:'
print np.std(cross_val_scores)
```

```
10-fold Area Under ROC Curve:
[0.9242524394082468, 0.942356572258533, 0.9249611868207693, 0.912348417
6279207, 0.9126134301270417, 0.9529038112522686, 0.9435185185185184, 0.
9183665008291872, 0.9261922472931646, 0.9057922979797979]

Mean of Cross Validated Area Under ROC Curve values:
0.9263305422115448

Std of Cross Validated Area Under ROC Curve values:
0.014606560067695997
```

Quite an improvement in the mean area under roc curve from 0.82(in case to Decision trees) to 0.92(in case of Random forests). Let's check out extra trees classifier as well.

In [32]:
```
# Extra trees classifier
extratree =ExtraTreesClassifier(max_depth=3, max_features=10)
kfold = KFold(n_splits=10, shuffle=True, random_state=1)
cross_val_scores = cross_val_score(extratree, X_train, y_train, scoring
='roc_auc', cv=kfold)
print '10-fold Area Under ROC Curve:'
print [x for x in cross_val_scores]
print '\nMean of Cross Validated Area Under ROC Curve values:'
print np.mean(cross_val_scores)
print '\nStd of Cross Validated Area Under ROC Curve values:'
print np.std(cross_val_scores)
```

```
10-fold Area Under ROC Curve:
[0.9205382436260623, 0.9319431476294222, 0.9281524926686215, 0.91916592
72404613, 0.9197217180883241, 0.8991681790683604, 0.940326147042565, 0.
9109867330016583, 0.9221974267845827, 0.8770359848484849]

Mean of Cross Validated Area Under ROC Curve values:
0.9169235999998543

Std of Cross Validated Area Under ROC Curve values:
0.017013564141922732
```

From the above results of 10 fold cross validation we can observe that extra trees classifier gives almost similar performance. Let's check out a boosting method like Adaboost classifier.....

In [33]:
```
# Adaboost Classifier
adatree = AdaBoostClassifier(n_estimators=50, learning_rate=1.0)
kfold = KFold(n_splits=10, shuffle=True, random_state=1)
cross_val_scores = cross_val_score(adatree, X_train, y_train, scoring=
'roc_auc', cv=kfold)
print '10-fold Area Under ROC Curve:'
print [x for x in cross_val_scores]
print '\nMean of Cross Validated Area Under ROC Curve values:'
```

```
print np.mean(cross_val_scores)
print '\nStd of Cross Validated Area Under ROC Curve values:'
print np.std(cross_val_scores)
```

```
10-fold Area Under ROC Curve:
[0.9402895813660685, 0.9416433239962652, 0.9410902190788338, 0.91650399
29015084, 0.9331669691470055, 0.9557168784029038, 0.9430071862907684,
0.9367606412382532, 0.9433699754800673, 0.9347537878787879]

Mean of Cross Validated Area Under ROC Curve values:
0.9386302555780462

Std of Cross Validated Area Under ROC Curve values:
0.009430800436988877
```

Well!! It is worth noticing the improvement in the area under roc curve values. Adaboost gives a mean value of 0.93. Let's go ahead and fit the different models with a range of parameters using grid search to figure out the best classifier that gives the highest area under roc curve.

In [34]:

```
# GridSearch to see if optimizing the parameters will improve the area
 under roc curve
classifiers = [('DecTreeClf', DecisionTreeClassifier(), {'max_depth': r
ange(2, 10, 2), 'max_features': [0.25, 0.5, 0.75, 1.0]}),
              ('RandomForestClf',RandomForestClassifier(),{'max_depth':
range(2,10,2),'n_estimators':range(10,80,10),'max_features':[0.25, 0.5,
 0.75, 1.0]}),
('ExtraTreeClf', ExtraTreesClassifier(),{'max_depth':range(2,10,2),'n_e
stimators':range(10,80,10),'max_features':[0.25, 0.5, 0.75, 1.0]}),
('AdaBoost', AdaBoostClassifier(),{'n_estimators':range(10,80,10), 'lea
rning_rate':[0.001,0.01,0.1,1]})]

names = []
params = []
results = []

for name, model, param in classifiers:
    kfold = KFold(n_splits=10, shuffle=True, random_state=1)
    clf_grid = GridSearchCV(model, param, cv=kfold, scoring='roc_auc')
```

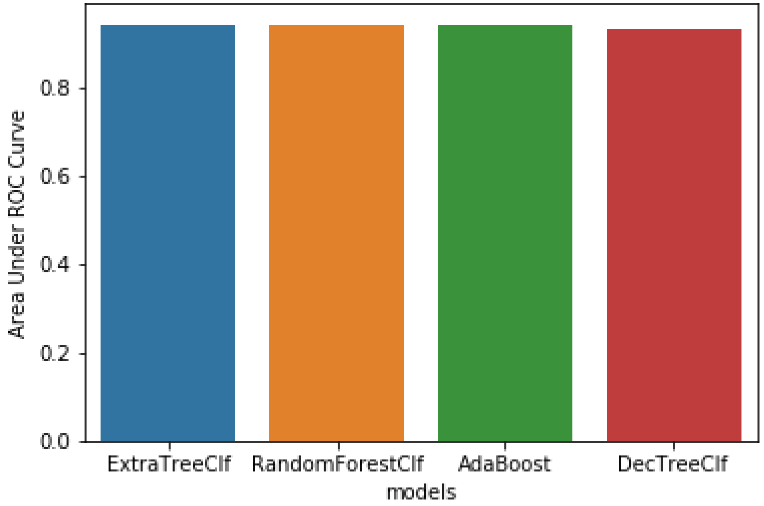
```
    clf_grid.fit(X_train, y_train)
    # just keep the results using the best parameters
    best_model = clf_grid.best_estimator_
    names.append(name)
    params.append(clf_grid.best_params_)
    results.append(clf_grid.best_score_)

result_df = pd.DataFrame({'models': names, 'results': results})
result_df.columns = ['models', 'Area Under ROC Curve']
result_df.sort_values(by='Area Under ROC Curve', ascending=False, inpla
ce=True)
print result_df
```

```
            models  Area Under ROC Curve
2     ExtraTreeClf              0.942963
1  RandomForestClf              0.942889
3         AdaBoost              0.940297
0       DecTreeClf              0.931330
```

In [38]:

```
# Visualize the performance of the above fitted models
sns.barplot(x='models',y='Area Under ROC Curve',data=result_df)
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1c1fc4d0>



From the above results it is clear that there is not much difference in the performance of various classifiers on this dataset. The highest area under roc curve was obtained with ExtratreesClassifier. Area under Roc curve provides the goodness of fit of the model. An area below 0.5 is a worthless model. A value of 0.5 is neutral. With increase in the area above 0.5, the goodness of the fit of the model increases....

In [42]:
```
# best parameters for the above models
params
```

Out[42]:
```
[{'max_depth': 4, 'max_features': 0.75},
 {'max_depth': 6, 'max_features': 0.5, 'n_estimators': 30},
 {'max_depth': 8, 'max_features': 0.25, 'n_estimators': 70},
 {'learning_rate': 0.1, 'n_estimators': 70}]
```

As it is clear that extratrees classifier gives the best results with max depth of 8, 25% of the features and with 70 trees in the ensemble. Let's see if we can optimize this model further....

In [46]:
```
# Hyper parameter tuning to optimize extra tree classifier model

# parameters
```

```
param =[{'max_depth':range(10,20,2),'n_estimators':range(80,200,10),'ma
x_features':[0.25, 0.5, 0.75, 1.0]}]
model = ExtraTreesClassifier()
kfold = KFold(n_splits=10, shuffle=True, random_state=1)
clf_grid = GridSearchCV(model, param, cv=kfold, scoring='roc_auc') #Gri
dsearchCV
# fit the model
clf_grid.fit(X_train,y_train)

# best model , best parameters, and best score
best_model = clf_grid.best_estimator_
best_parameters = clf_grid.best_params_
best_score = clf_grid.best_score_
```

In [48]:

```
print "The Best model :", best_model
print "The Best parameters for the model :", best_parameters
print "The Best mean Area Under ROC Curve score : ", best_score
```

```
The Best model : ExtraTreesClassifier(bootstrap=False, class_weight=Non
e, criterion='gini',
           max_depth=10, max_features=0.25, 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=170, n_jobs=1,
           oob_score=False, random_state=None, verbose=0, warm_start=Fa
lse)
The Best parameters for the model : {'max_features': 0.25, 'n_estimator
s': 170, 'max_depth': 10}
The Best mean Area Under ROC Curve score :  0.9429865850209619
```

From the above results, it becomes clear that the performance of the extra trees model is not improving further with are under roc curve value at 0.9429. Let's calculate the feature importance of the different variables used in the model.

In [49]:

```
#Collect the feature importances in a pandas dataframe
feature_importance = best_model.feature_importances_
attribs = X_train.columns
temp=pd.DataFrame(sorted(zip(feature_importance, attribs), reverse=True
```

```
))
temp.columns =['importance','feature']
```

In [50]:
```
temp
```

Out[50]:

	importance	feature
0	0.268235	Round2 Is this applicant moving on as a GHC Se...
1	0.209479	Round2 Is this applicant moving on as a GHC Se...
2	0.074992	Round2 GHC Semifinalist Reviewer2
3	0.066611	Round2 GHC Semifinalist Reviewer1
4	0.032620	Round2 Experience Reviewer1
5	0.029416	Round2 Experience Reviewer2
6	0.017108	Round2 Total Score Reviewer1
7	0.014138	Round2 Clear Purpose CF Reviewer2
8	0.014137	Round2 Total Score Reviewer2
9	0.013700	Round2 Innovation CF Reviewer2
10	0.011579	Round2 Is this applicant moving on as a GHC Al...
11	0.011089	Round2 Inspire and Mobilize Reviewer2
12	0.010054	Round2 Clear Purpose CF Reviewer1
13	0.009715	Round2 Is this applicant moving on as a GHC Al...
14	0.009450	Round2 Inspire and Mobilize Reviewer1
15	0.009014	Round2 Innovation CF Reviewer1
16	0.008906	Round2 Collaboration Reviewer1
17	0.008110	Round2 Commitment to learning2 Reviewer2

	importance	feature
18	0.008107	WorkedPublicHealth_Never
19	0.007982	Round2 Get Results Reviewer2
20	0.007792	Round2 Commitment to Social Justice CF Reviewer2
21	0.007595	Round2 Collaboration Reviewer2
22	0.006795	Round2 Commitment to Social Justice Reviewer1
23	0.006746	Round2 Get Results Reviewer1
24	0.006706	Round2 Commitment to learning2 Reviewer1
25	0.006302	Citizen_Zambia
26	0.006270	Sex
27	0.005984	StudiedPublicHealth_Atleast_1_Class
28	0.005790	StudiedPublicHealth_More_than_1_Class
29	0.005645	WorkedPublicHealth_Between_1_to_3_years
...	...	...
79	0.000032	firstLanguage_Vietnamese
80	0.000030	Citizen_ Zambia
81	0.000015	firstLanguage_EÊ‹egbe
82	0.000015	firstLanguage_Tigrigna
83	0.000015	firstLanguage_Bengali
84	0.000014	firstLanguage_Chinese
85	0.000014	firstLanguage_Russian
86	0.000013	firstLanguage_Korean
87	0.000008	firstLanguage_Tonga

	importance	feature
88	0.000007	firstLanguage_Portuguese
89	0.000000	firstLanguage_Sylheti
90	0.000000	firstLanguage_Swedish
91	0.000000	firstLanguage_Shona
92	0.000000	firstLanguage_Serbian language
93	0.000000	firstLanguage_Runyankore
94	0.000000	firstLanguage_Runyankole
95	0.000000	firstLanguage_Rukiga
96	0.000000	firstLanguage_Nepalese
97	0.000000	firstLanguage_Luo
98	0.000000	firstLanguage_Lithuanian
99	0.000000	firstLanguage_Kirundi
100	0.000000	firstLanguage_KINYARWANDA
101	0.000000	firstLanguage_Italian
102	0.000000	firstLanguage_Farsi
103	0.000000	firstLanguage_English and Gujarati
104	0.000000	firstLanguage_Dutch
105	0.000000	firstLanguage_Belarusian
106	0.000000	firstLanguage_Bangla
107	0.000000	firstLanguage_Amharic
108	0.000000	Citizen_ Rwanda

109 rows × 2 columns

From the above results it becomes clear that round 2 reviewers opinion about candidates profile really play a significant role in a candidate's selection as a semifinalist.

Discussion and Final Thoughts :

In this journal entry, we have performed a binary classification task using decision trees and ensemble methods. This is just a fraction of People's Analytics project. Our team is working further to perform better data exploration using interactive visualization techniques and other feature engineering techniques.

We also plan to implement other supervised classification techniques like Logistic Regression and Support Vector Machines to better understand the factors governing a candidates selection as a semifinalist.

Final work will be presented in the final version of semester project on People's Analytics.