In [110]:
```
'''
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'''
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression, ElasticNetCV, Elast
icNet
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier, BaggingClassifier,
GradientBoostingClassifier
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV

from sklearn.metrics import accuracy_score, roc_curve, roc_auc_score, au
c

#from sklearn.inspection import plot_partial_dependence
```

Conceptual: Cost functions for classification trees

1. (15 points) Consider the Gini index, classification error, and cross-entropy in simple classification settings with two classes. Of these three possible cost functions, which would be best to use when growing a decision tree? Which would be best to use when pruning a decision tree? Why?

Because classification error is simply the fraction of misclassified training observations it is not sensitive enough for tree growing. The other two impurity measures, the Gini index and cross-entropy are considered to be best because they control for variance across the classes which helps to optimize splitting for growth. For pruning, classifcation error is considered to be an appropriate measure because it prioritizes accuracy.

Application: Predicting attitudes towards racist college professors

Estimate the models

2. (35 points; 5 points/model) Estimate the following models, predicting colrac using the training set (the training .csv) with 10-fold CV:

```
- Logistic regression
- Naive Bayes
- Elastic net regression
- Decision tree (CART)
- Bagging
- Random forest
- Boosting
```

Tune the relevant hyperparameters for each model as necessary. Only use the tuned model with the best performance for the remaining exercises. Be sure to leave sufficient time for hyperparameter tuning. Grid searches can be computationally taxing and take quite a while, especially for tree-aggregation methods.

In [86]:
```
#load data
train = pd.read_csv("./data/gss_train.csv")
test = pd.read_csv("./data/gss_test.csv")
```

In [42]:
```
#inspect
train.head()
#don't have to check for nulls because of preprocessinh
```

Out[42]:

	age	attend	authoritarianism	black	born	childs	colath	colrac	colcom	colmil	...	partyid_
0	21	0	4	0	0	0	1	1	0	1	...	
1	42	0	4	0	0	2	0	1	1	0	...	
2	70	1	1	1	0	3	0	1	1	0	...	
3	35	3	2	0	0	2	0	1	0	1	...	
4	24	3	6	0	1	3	1	1	0	0	...	

5 rows × 56 columns

In [16]:
```
# dropping colrac column and set predictors
X_train = train.drop(['colrac'], axis=1)
X_test = test.drop(['colrac'], axis=1)

#setting prediction output to colrac
y_train, y_test = train['colrac'], test['colrac']
```

Logistic regression

In [85]:
```
log_reg = LogisticRegression()

log_score = cross_val_score(log_reg, X_train,
                            y_train, scoring = 'roc_auc', cv = 10)
log_roc = np.mean(log_score)


log_accu = cross_val_score(naive_bayes, X_train,
                           y_train, scoring = 'accuracy', cv = 10)
log_err = np.mean(log_accu)

print("AUC/ROC", log_roc)
print("Error", log_err)
```

```
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/line
ar_model/logistic.py:432: FutureWarning: Default solver will be changed
to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/line
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  FutureWarning)
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  FutureWarning)
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/line
ar_model/logistic.py:432: FutureWarning: Default solver will be changed
to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)

AUC/ROC 0.8703107556427476
Error 0.7344474902240962
```

Naive Bayes

In [99]:
```
naive_bayes = GaussianNB()

#AUC
nb_score = cross_val_score(naive_bayes, X_train,
                           y_train, scoring = 'roc_auc', cv = 10)
nb_roc = np.mean(nb_score)

#
nb_accu = cross_val_score(naive_bayes, X_train,
                          y_train, scoring = 'accuracy', cv = 10)
nb_err = np.mean(nb_accu)

print("AUC/ROC", nb_roc)
print("Accuracy", nb_err)
```

```
AUC/ROC 0.8080500250922787
Accuracy 0.7344474902240962
```

Elasticnet Regression

In [87]:
```
#Elastic net regression

elas = ElasticNetCV(cv=10)
elas.fit(X_train, y_train)

# have to tune alpha and l1
print( elas.alpha_, elas.l1_ratio)
```

```
0.0038452641680228584 0.5
```

In [41]:
```
#using that alpha and l1 ratio
elas_best = ElasticNet(alpha = 0.0038452641680228584, l1_ratio=0.5)

# is MSE best?
elas_score = cross_val_score(elas_best, X_train, y_train,
                             scoring = 'neg_mean_squared_error', cv=10)
elas_mse = np.mean(elas_score)

#AUC/ROC
elas_score = cross_val_score(elas_best, X_train, y_train,
                             scoring = 'roc_auc', cv=10)
elas_roc = np.mean(elas_roc)

print("AUC/ROC", elas_roc)
print("MSE", -1*elas_mse)
```

```
AUC/ROC 0.8740225489138439
MSE 0.1471453221731916
```

Decison Tree (CART)

In [98]:
```
decision_tree = DecisionTreeClassifier()

#AUC/ROC
dt_score = cross_val_score(decision_tree, X_train, y_train,
                           scoring = 'roc_auc', cv=10)
dt_roc = np.mean(dt_score)

#Error
dt_accu = cross_val_score(decision_tree, X_train, y_train,
                          scoring = 'accuracy', cv=10)
dt_err = np.mean(dt_accu)

#roc a bye baby
print("AUC/ROC", dt_roc)
print("Accuracy", dt_err)
```

```
AUC/ROC 0.7217232298218214
Accuracy 0.7174588881444107
```

Bagging

In [47]:
```
#Bagging, but what is the base?
bagging = BaggingClassifier()

param_grid = {'n_estimators': [5, 10, 15, 20, 25, 30, 35, 40, 45, 50]}

#Gridsearch?
search = GridSearchCV(estimator = bagging, param_grid = param_grid,
                      cv = 10, n_jobs=-1, verbose = 2)
search.fit(X_train, y_train)
search.best_params_

#results = model_selection.cross_val_score(bagging, X_train, y_train, cv
= search)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent work
ers.
[Parallel(n_jobs=-1)]: Done  93 out of 100 | elapsed:    9.4s remainin
g:    0.7s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:   10.2s finished
```

Out[47]:
```
{'n_estimators': 30}
```

In [48]:
```
# taking those number of estimators
bagging_best = BaggingClassifier(n_estimators=30)
```

In [97]:
```
#AUC/ROC
bag_score = cross_val_score(bagging_best, X_train, y_train,
                            scoring = 'roc_auc', cv=10)
bag_roc = np.mean(bag_score)

#Error
bag_accu = cross_val_score(bagging_best, X_train, y_train,
                           scoring = 'accuracy', cv=10)
bag_err = np.mean(bag_accu)

#roc a bye baby
print("AUC/ROC", bag_roc)
print("Accuracy", bag_err)
```

```
AUC/ROC 0.8705380367452802
Accuracy 0.7818464643248919
```

Random Forest

In [55]:
```
random_forest = RandomForestClassifier()

param_grid = {'n_estimators': [5, 10, 15, 20, 25, 30, 35, 40, 45, 50],
              'max_features':[5, 10, 15, 20, 25, 30, 35, 40, 45, 50],
              'max_depth': [2, 4, 6, 8],
             }

#GridSearch
search_randf = GridSearchCV(estimator = random_forest, param_grid = para
m_grid,
                      cv = 10, n_jobs=-1, verbose = 2)
search_randf.fit(X_train, y_train)
search_randf.best_params_
```

```
Fitting 10 folds for each of 400 candidates, totalling 4000 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent work
ers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   10.7s
[Parallel(n_jobs=-1)]: Done 270 tasks      | elapsed:   17.7s
[Parallel(n_jobs=-1)]: Done 676 tasks      | elapsed:   32.3s
[Parallel(n_jobs=-1)]: Done 1242 tasks      | elapsed:   52.2s
[Parallel(n_jobs=-1)]: Done 1972 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 2862 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 3916 tasks      | elapsed:  3.2min
[Parallel(n_jobs=-1)]: Done 4000 out of 4000 | elapsed:  3.3min finishe
d
```

Out[55]:
```
{'max_depth': 8, 'max_features': 25, 'n_estimators': 35}
```

In [96]:
```
random_forest_best = RandomForestClassifier(max_depth= 8, max_features=
25, n_estimators=35)

#AUC/ROC
rf_score = cross_val_score(random_forest_best, X_train, y_train,
                           scoring = 'roc_auc', cv=10)
rf_roc = np.mean(rf_score)

#Error
rf_accu = cross_val_score(bagging_best, X_train, y_train,
                           scoring = 'accuracy', cv=10)
rf_err = np.mean(rf_accu)

#roc a bye baby
print("AUC/ROC", rf_roc)
print("Accuracy", rf_err)
```

```
AUC/ROC 0.8798170843241266
Accuracy 0.7750302007253109
```

In [59]:
```
X_train.shape
```

Out[59]:
```
(1476, 55)
```

Gradient Boosting

In [78]:
```
gradient = GradientBoostingClassifier()

param_grid = { 'max_features': [10,20,30,40,50],
              'learning_rate': [.2,.4,.6,.8,1],
              'n_estimators': [10,20,30,40,50]
             }


gradient_search = GridSearchCV(estimator =gradient, param_grid = param_g
rid,
                              cv = 10, n_jobs = -1, verbose = 2)

#fit the model
gradient_search.fit(X_train,y_train)

gradient_search.best_params_
```

```
Fitting 10 folds for each of 125 candidates, totalling 1250 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent work
ers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:    9.6s
[Parallel(n_jobs=-1)]: Done 245 tasks      | elapsed:   18.3s
[Parallel(n_jobs=-1)]: Done 651 tasks      | elapsed:   36.7s
[Parallel(n_jobs=-1)]: Done 1217 tasks      | elapsed:   55.1s
[Parallel(n_jobs=-1)]: Done 1243 out of 1250 | elapsed:   56.5s remaini
ng:    0.3s
[Parallel(n_jobs=-1)]: Done 1250 out of 1250 | elapsed:   56.8s finishe
d
```

Out[78]:
```
{'learning_rate': 0.2, 'max_features': 30, 'n_estimators': 40}
```

In [80]:
```
gradient_best = GradientBoostingClassifier(learning_rate = 0.2,
                                           max_features = 30,
                                          n_estimators = 40)
```

In [100]:
```
#AUC/ROC
gradient_score = cross_val_score(gradient_best, X_train, y_train,scoring
= 'roc_auc')
gradient_roc = np.mean(gradient_score)

#Error
gradient_accu = cross_val_score(gradient_best, X_train, y_train,scoring
= 'accuracy')
gradient_err = np.mean(gradient_accu)

#roc a bye baby
print("AUC/ROC", gradient_roc)
print("Accuracy", gradient_err)
```

```
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/mode
l_selection/_split.py:1978: FutureWarning: The default value of cv will
change from 3 to 5 in version 0.22. Specify it explicitly to silence th
is warning.
  warnings.warn(CV_WARNING, FutureWarning)
/Users/reginacatipon/anaconda3/lib/python3.7/site-packages/sklearn/mode
l_selection/_split.py:1978: FutureWarning: The default value of cv will
change from 3 to 5 in version 0.22. Specify it explicitly to silence th
is warning.
  warnings.warn(CV_WARNING, FutureWarning)

AUC/ROC 0.8689044470809119
Accuracy 0.7845701510414426
```

Evaluate the models

3. (20 points) Compare and present each model's (training) performance based on

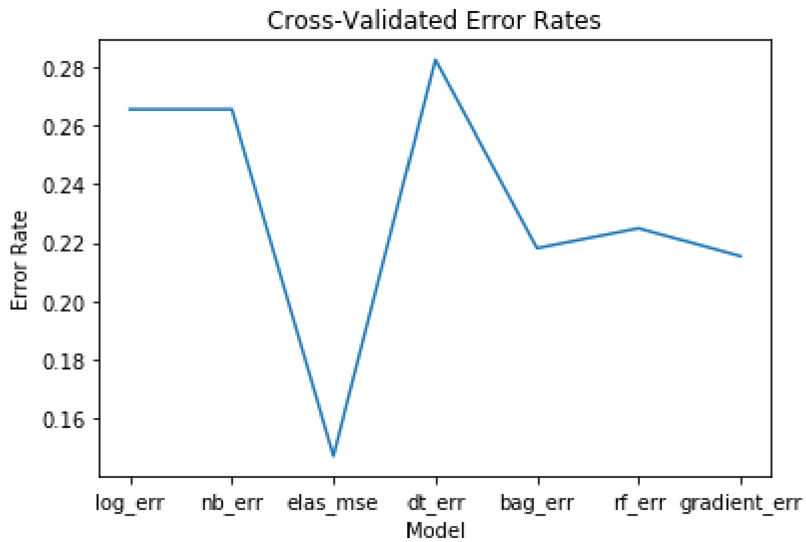
```
- Cross-validated error rate
- ROC/AUC
```

In [155]:
```
model_names = ['log_err', 'nb_err', 'elas_mse', 'dt_err',
               'bag_err', 'rf_err', 'gradient_err']
```

In [154]:
```
#CV-error rate
err_rates = [(1 - log_err), (1 -nb_err), (-1*elas_mse),
             (1 -dt_err), (1 -bag_err), (1 -rf_err), (1 -gradient_err)]
```

In [153]:
```
#Graph
plt.plot(model_names,err_rates)
plt.xlabel('Model')
plt.ylabel('Error Rate')
plt.title('Cross-Validated Error Rates')
```

Out[153]: `Text(0.5, 1.0, 'Cross-Validated Error Rates')`

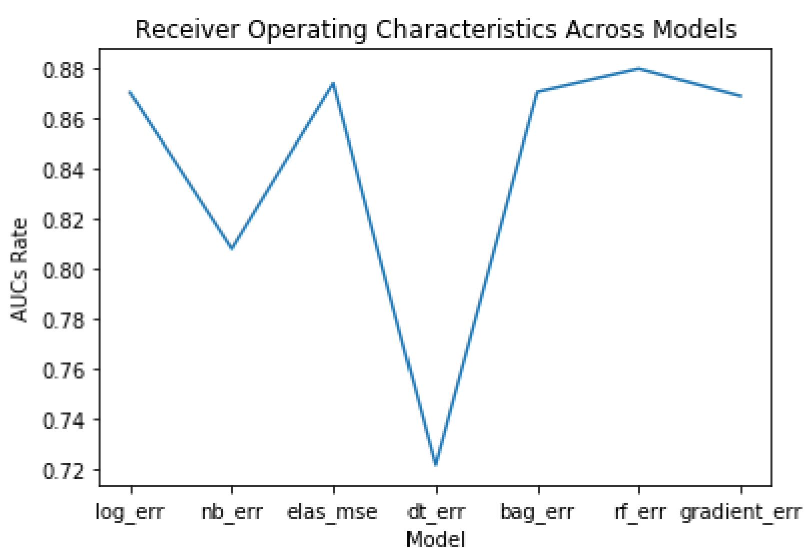


The lowest error rate was the Elasticnet classifier, the highest was the bagging classifier.

In [158]:
```
AUCs = [log_roc, nb_roc, elas_roc, dt_roc, bag_roc, rf_roc, gradient_roc
]
```

In [161]:
```
#Graph AUC/ROC comparison
plt.plot(model_names,AUCs)
plt.xlabel('Model')
plt.ylabel('AUCs Rate')
plt.title('Receiver Operating Characteristics Across Models')
```

Out[161]: `Text(0.5, 1.0, 'Receiver Operating Characteristics Across Models')`



From the graph, it looks like Random Forest performed had the higest AUC.

4.(15 points) Which is the best model? Defend your choice.

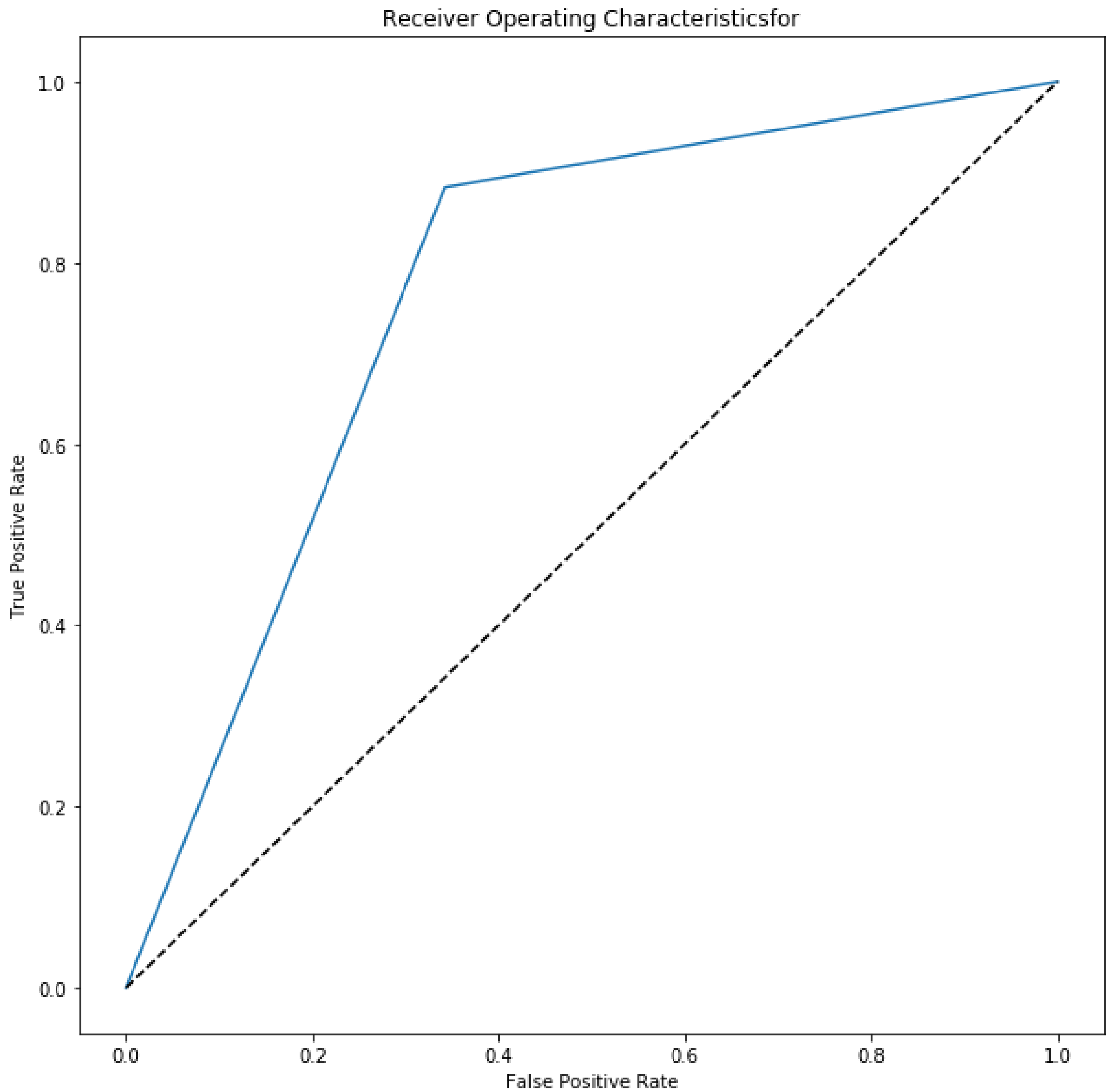
In [160]:
```
def plot_ROC(model):
    aucVals = []
    #Get the ROC curve
    model.fit(X_train,y_train)
    fpr, tpr, thresholds = roc_curve(y_test, model.predict(X_test))
    auc = metrics.auc(fpr, tpr)
    aucVals.append(auc)

    #setup axis for plotting
    fig, ax = plt.subplots(figsize = (10,10))
    #Plot the class's line
    ax.plot(fpr, tpr, auc)

    #display
    ax.set_title('Receiver Operating Characteristics')
    plt.plot([0,1], [0,1], color = 'k', linestyle='--')
    ax.set_xlabel('False Positive Rate')
    ax.set_ylabel('True Positive Rate')
    plt.show()
    plt.close()
    #return aucVals
```

In [149]:
```
#Graph ROC/AUC
print('')
print('Random Forest')
plot_ROC(random_forest_best)
```

```
Random Forest
```



The model that did the best was the Random Forest classifier. It scored an AUC/ROC rate of 0.879. While simpler models like Logistic Regression actually scored pretty close with 0.870, Random Forest also had one of the highest accuracy scores, second only to the Gradient Boosting in clssification error rate.

In [ ]:

Evaluate the best model

5. (15 points) Evaluate the final, best model's (selected in 4) performance on the test set (the test .csv) by calculating and presenting the classification error rate and AUC. Compared to the fit evaluated on the training set in questions 3-4, does the "best" model generalize well? Why or why not? How do you know?

In [91]:
```
random_forest_best.fit(X_train, y_train)
pred = random_forest_best.predict(X_test)
```

In [95]:
```
#Accuracy
accuracy = accuracy_score(y_test, pred)
print(accuracy)
```

```
0.7971602434077079
```

In [93]:
```
#ROC/AUC
roc = roc_auc_score(y_test, pred)
print(roc)
```

```
0.788356504468719
```

I think the model does an average job at generalizing. For example, the Naive Bayes classification, which is sometimes used as a baseline, had a ROC/AUC of 0.81 and an accuracy of 0.73. The ROC/AUC from the predicted y using the tuned Random Forest classification model was a little lower than the Naive Bayes rate at 0.79, and an accuracy score was a little higher than . It, of course, did not outperform the training results, but its accuracy was close to, if not sometimes better, than the training set fits.

In [ ]:
```

```