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In [7]: | #!/usr/bin/env python3
         # -*- coding: utf-8 -*-
         Created on Tue Dec 3 21:50:54 2019
         @author: jorgeagr
         import numpy as np
         import pandas as pd
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.model_selection import KFold
         from sklearn.metrics import confusion matrix
         import matplotlib as mpl
         import matplotlib.pyplot as plt
         import matplotlib.ticker as mtick
         width = 10
         height = 10
         mpl.rcParams['figure.figsize'] = (width, height)
         mpl.rcParams['font.size'] = 18
         mpl.rcParams['figure.titlesize'] = 'small'
         mpl.rcParams['legend.fontsize'] = 'small'
         mpl.rcParams['xtick.major.size'] = 12
         mpl.rcParams['xtick.minor.size'] = 8
         mpl.rcParams['xtick.labelsize'] = 18
         mpl.rcParams['ytick.major.size'] = 12
mpl.rcParams['ytick.minor.size'] = 8
mpl.rcParams['ytick.labelsize'] = 18
In [8]: # load training set
         data_train = pd.read_csv('../data/election_data_train.csv')
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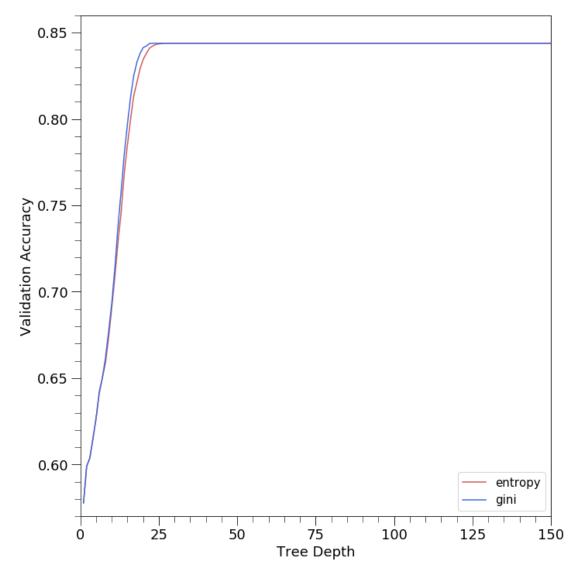
```
In [8]: # load training set
    data_train = pd.read_csv('../data/election_data_train.csv')

# split into features and labels
    x_train = data_train.values[:, :-1]
    y_train = data_train.values[:,-1]

# Split the training data in 10 folds to perform cross validation
    # and see performance as a function of number of trees
    folds = 10
    kfold = KFold(n_splits=folds, shuffle=True, random_state=0)
    max_trees = np.arange(150) + 1
```

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In [9]: # find optimal model
         fig, ax = plt.subplots()
         criterion list = ['entropy', 'gini']
         colors = ['indianred', 'royalblue']
         highest acc = 0
         for c, criterion in enumerate(criterion list):
             num tree accval = np.zeros((len(max trees), 2))
             num tree tpr = np.zeros((len(max trees), 2))
             num_tree_tnr = np.zeros((len(max_trees), 2))
             for t in max_trees:
                  val_acc = np.zeros(folds)
                  val tpr = np.zeros(folds)
                  val tnr = np.zeros(folds)
                  for i, inds in enumerate(kfold.split(x_train)):
                      train_ind = inds[0]
                      val_ind = inds[1]
                      tree = DecisionTreeClassifier(criterion=criterion, max depth=t, rando
         m_state=0)
                      tree.fit(x train, y train)
                      val acc[i] = tree.score(x train[val ind], y train[val ind])
                      # Confusion Matrix considers the case vote = 1 as positive,
                      # so considers voting for Rep
                      tn, fp, fn, tp = confusion_matrix(y_train[val_ind], tree.predict(x_tr
         ain[val_ind])).ravel()
                      val_tpr[i] = tp / (tp + fn)
                      val tnr[i] = tn / (tn + fp)
                      if val acc[i] > highest acc:
                           # save the best tree (highest acc)
                          best_tree = tree
                          highest_acc = val_acc[i]
                  num_tree_accval[t-1,0] = val_acc.mean()
                  num_tree_accval[t-1,1] = val_acc.std()
                  num_tree_tpr[t-1,0] = val tpr.mean()
                  num tree tpr[t-1,1] = val tpr.std()
                  num tree tnr[t-1,0] = val tnr.mean()
                  num_tree_tnr[t-1,1] = val_tnr.std()
             acc_meanval = num_tree_accval[:,0]
             acc_stdval = num_tree_accval[:,1]
             ax.plot(max_trees, acc_meanval, color=colors[c], label=criterion, zorder=1)
         ax.xaxis.set_major_locator(mtick.MultipleLocator(25))
ax.xaxis.set_minor_locator(mtick.MultipleLocator(5))
ax.yaxis.set_major_locator(mtick.MultipleLocator(0.05))
ax.yaxis.set_minor_locator(mtick.MultipleLocator(0.01))
         ax.set_xlim(0, 150)
         ax.set_ylim(0.57, 0.86)
         ax.set xlabel('Tree Depth')
         ax.set_ylabel('Validation Accuracy')
         ax.legend(loc='lower right')
         fig.tight_layout(pad=0.5)
         #fig.savefig('../prob2.eps', dpi=500)
         print('Optimal performance with {} criterion, {} trees with {:.2f} +/- {:.2f}% ac
         c, {:.2f} +/- {:.2f}% tpr, {:.2f} +/- {:.2f}% tnr'.format(best_tree.criterion,
                    best tree.max depth,
                    num_tree_accval[best_tree.max_depth-1][0]*100, num_tree_accval[best_tre
         e.max_depth-1][1]*100,
                    num_tree_tpr[best_tree.max_depth-1][0]*100, num_tree_tpr[best_tree.max_
         depth-1][1]*100,
                    num_tree_tnr[best_tree.max_depth-1][0]*100, num_tree_tnr[best_tree.max_
         depth-1][1]*100))
```

Optimal performance with entropy criterion, 24 trees with 84.38 +/- 1.30% acc, 80. 48 +/- 1.14% tpr, 87.95 +/- 2.09% tnr



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In [10]: # load testing set to predict election results
         data_test = pd.read_csv('../data/election_data_test.csv')
         x_test = data_test.values[:,:-1]
         # need to take into account vote weight due to (racial) turnout
         w test = data test.values[:,-1]
         # decided to predict using the different training set folds,
         # this way we can obtain an uncertainty in the election results
         total_votes = w_test.sum()
         dem_results = np.zeros(folds)
         rep_results = np.zeros(folds)
         for i, inds in enumerate(kfold.split(x train)):
                 train ind = inds[0]
                 tree = DecisionTreeClassifier(criterion='entropy', max_depth=best_tree.ma
         x_depth, random_state=0)
                 tree.fit(x_train[train_ind], y_train[train_ind])
                 y_pred = tree.predict(x_test)
                 dem_results[i] = w_test[y_pred==0].sum() / total_votes
                 rep_results[i] = w_test[y_pred==1].sum() / total_votes
         print('Dem votes: {:.2f} +/- {:.2f}'.format(dem_results.mean()*100, dem_results.s
         td()*100))
         print('Rep votes: {:.2f} +/- {:.2f}'.format(rep_results.mean()*100, rep_results.s
         td()*100))
         Dem votes: 58.78 +/- 3.14
         Rep votes: 41.22 +/- 3.14
```

In []: