Loans-Safety-Prediction

June 4, 2020

1 Loan Safety Prediction

In this example, we are going to build a model to predict whether a loan request is safe to be assigned using the data downloaded from the Lending Club Corporation. The company provided files containing complete loan data for all loans issued over a certain time window, including the current loan status (Current, Late, Fully Paid, etc.) and latest payment information. We are going to use a small subset of the available data which were previously preprocessed. At the moment, it seems that the data are not available anymore though.

1.1 Libraries

As the very first step, we load all the relevant libraries.

[1]:
```python
import numpy as np
import pandas as pd

# Statistical libraries
from scipy import stats

# Plotting libraries
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Preprocessing
from sklearn.preprocessing import StandardScaler

# Evaluation Procedures
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import StratifiedKFold

# Classification methods
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier

from sklearn.ensemble import VotingClassifier

# Evaluation Metrics
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import f1_score
```

Next we define some utility functions.

[2]:
```
def PrintConfusionMatrix(model, true_y, predicted_y, positive=1, negative=-1):
    cm = confusion_matrix(true_y,predicted_y)
    print("\t"+str(model.classes_[0])+"\t"+str(model.classes_[1]))
    print(str(model.classes_[0]) + "\t",cm[0][0],"\t",cm[0][1])
    print(str(model.classes_[1]) + "\t",cm[1][0],"\t",cm[1][1])

def PrintSignificance(stat, c):
    if (stat[1]<(1-c)):
        print("The difference is statistically significant (cf %3.2f p-value=%.
 ↪4f)"%(c,stat[1]))
    else:
        print("The difference is not statistically significant (cf %3.2f␣
 ↪p-value=%.4f)"%(c,stat[1]))
```

1.2 Data, Training, and Test Sets

We load the data, define the input data X and the target column y. Next, we set the random seed, define a training/test partition, and the crossvalidation procedure we will use to compare the models.

Note that in this notebook we don't perform any data exploration or preparation since we already performed it before.

[3]:
```
loans = pd.read_csv('LoansNumerical.csv')
target_variable = 'safe_loans'
input_variables = loans.columns[loans.columns!=target_variable]
```

```
X = loans[input_variables]
y = loans[target_variable]
```

[4]:
```
np.random.seed(1234)

X_train, X_test, y_train, y_test = \
    train_test_split(X, y,\
    test_size= 1/3.0, random_state =1234, shuffle=True)

crossvalidation = StratifiedKFold(n_splits=10, shuffle=True)
```

1.3 Baseline Performance (Majority Voting)

At first, let's check what is the class distribution. As we can see the dataset is quite imbalanced with 81.1% of loans that have been classified as safe with only 18/9% of the loans classified as risky. Thus, a very simple model classifying all the loans as safe would reach an 81.1% accuracy (an impressive result in many applications) however, it would be useless for the real goal of this analysis, that is, to create a model to identify risky loans.

[5]:
```
print("Class %2d  %.1f%%\nClass %2d  %.1f%%\n"%((y.value_counts()/y.shape[0]).
 ↪index[0],100*(y.value_counts()/y.shape[0]).values[0],(y.value_counts()/y.
 ↪shape[0]).index[1],100*(y.value_counts()/y.shape[0]).values[1]))
```

```
Class  1  81.1%
Class -1  18.9%
```

2 Model Evaluation

We now evaluate different models using some setup we investigated early. We will consider some basic methods (linear regression, naive bayes, and k-NN) as well as ensemble methods.

[6]:
```
n_estimators = 50

methods = {
    'Lasso':LogisticRegression(penalty="l1",C=100, random_state=1234,␣
 ↪max_iter=300, solver="liblinear"),
    'NaiveBayes':GaussianNB(),
    'k-NN(5)':KNeighborsClassifier(n_neighbors=5, algorithm='kd_tree'),
    'Decision Tree':DecisionTreeClassifier(max_depth=None),
    'Bagging(Tree)':
 ↪BaggingClassifier(DecisionTreeClassifier(max_depth=3),n_estimators=n_estimators),
    'Bagging(kNN)':BaggingClassifier(KNeighborsClassifier(n_neighbors=10,␣
 ↪algorithm='kd_tree'),n_estimators=n_estimators),
    'Random Forest':
 ↪RandomForestClassifier(n_estimators=n_estimators,max_depth=3,oob_score=True),
```

```
    'Extremely Randomized Trees':
↪ExtraTreesClassifier(n_estimators=n_estimators,max_depth=3),
    'Ada Boost':
↪AdaBoostClassifier(DecisionTreeClassifier(max_depth=3),n_estimators=n_estimators)
}
```

[7]:
```
xval_results = {}
roc_results = {}
feature_importance_model = {}

method = []
accuracy_mean = []
accuracy_std = []
precision = []
recall = []
f1 = []
auc = []

for method_name in methods:


    clf = methods[method_name];

    # evaluate the model using crossvalidation
    xval_score = cross_val_score(clf,X,y,cv=crossvalidation)

    # store the raw results of crossvalidation that we might want to use for␣
↪t-test/mann-whitney comparison
    xval_results[method_name] = xval_score

    # compute the basic statistics
    accuracy_mean.append(np.average(xval_score))
    accuracy_std.append(np.std(xval_score))

    clf.fit(X_train,y_train)

    # if the mode can return an evaluation of feature importance we store it to␣
↪analyze it later
    if hasattr(clf, 'feature_importances_'):
            feature_importance_model[method_name] = (clf,clf.
↪feature_importances_)

    # compute the prediction which, for probabilistic classifiers, is using a␣
↪threshold of 0.5
    yp = clf.predict(X_test)
```

```
    # ask for the probability values
    yprob = clf.predict_proba(X_test)

    # computes the data needed to draw the ROC curve
    fpr_nb, tpr_nb, thresholds = roc_curve(y_true=y_test, y_score = yprob[:,1],␣
↪pos_label=1)

    # computes the AUC
    roc_auc = roc_auc_score(y_true=y_test, y_score = yprob[:,1])
    auc.append(roc_auc)

    # store the information to plot the ROC curves afterwards
    roc_results[method_name] = (fpr_nb, tpr_nb, thresholds, roc_auc)

    precision.append(precision_score(y_test,yp))
    recall.append(recall_score(y_test,yp))
    f1.append(f1_score(y_test, yp))

    print("%40s"%method_name)
    print("========================================")
    print("\t  Accuracy (CV) %.3f %.3f"%(np.average(xval_score),np.
↪std(xval_score)))
    print("\tAccuracy (Test) %.3f"%precision_score(y_test, yp))
    print("\t      Precision %.3f"%precision_score(y_test, yp))
    print("\t      Recall    %.3f"%recall_score(y_test, yp))
    print("\t      F1        %.3f"%f1_score(y_test, yp))
    print("\n")

    method.append(method_name)
```

```
                                   Lasso
========================================
          Accuracy (CV) 0.813 0.001
        Accuracy (Test) 0.821
              Precision 0.821
              Recall    0.981
              F1        0.894


                              NaiveBayes
========================================
          Accuracy (CV) 0.773 0.003
        Accuracy (Test) 0.840
              Precision 0.840
              Recall    0.891
              F1        0.865
```

```
                               k-NN(5)
========================================
          Accuracy (CV) 0.784 0.002
        Accuracy (Test) 0.816
              Precision 0.816
              Recall    0.944
              F1        0.875


                         Decision Tree
========================================
          Accuracy (CV) 0.733 0.003
        Accuracy (Test) 0.841
              Precision 0.841
              Recall    0.827
              F1        0.834


                         Bagging(Tree)
========================================
          Accuracy (CV) 0.815 0.000
        Accuracy (Test) 0.818
              Precision 0.818
              Recall    0.989
              F1        0.895


                          Bagging(kNN)
========================================
          Accuracy (CV) 0.804 0.001
        Accuracy (Test) 0.814
              Precision 0.814
              Recall    0.980
              F1        0.889


                         Random Forest
========================================
          Accuracy (CV) 0.811 0.000
        Accuracy (Test) 0.810
              Precision 0.810
              Recall    1.000
              F1        0.895


              Extremely Randomized Trees
========================================
```

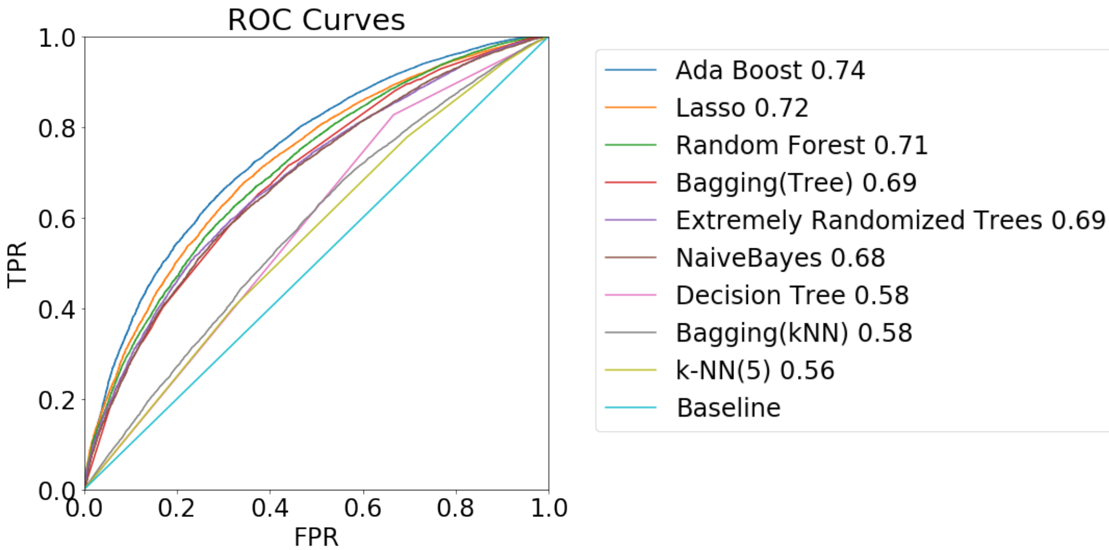
```
          Accuracy (CV) 0.811 0.000
        Accuracy (Test) 0.810
              Precision 0.810
              Recall    1.000
              F1        0.895


                               Ada Boost
========================================
          Accuracy (CV) 0.820 0.002
        Accuracy (Test) 0.833
              Precision 0.833
              Recall    0.968
              F1        0.896
```

2.1 Receiver Operating Characteristic (ROC) Curves

We can compare the classifiers using the area under the curve values and the corresponding ROC curves. This measure provides an overall evaluation of the model. But at the end we are interested in evaluating one specific performance (accuracy, precision, recall, etc.)

[8]:

```python
# we sort the AUC values so to have a better legend
sorted_roc_results = sorted(roc_results.items(), key=lambda x: x[1][3],␣
↪reverse=True)

plt.figure(1, figsize=(8, 8));
font = {'family':'sans', 'size':24};
plt.rc('font', **font);
plt.xlabel('FPR');
plt.ylabel('TPR');
for result in sorted_roc_results:
    plt.plot(result[1][0], result[1][1],label=result[0]+' %.2f'%result[1][3])


# plt.plot(fpr,thresholds,label='Thresholds')
plt.plot([0.0,1.0],[0.0,1.0],label='Baseline')
plt.yticks(np.arange(0.0,1.01,.2))
plt.title('ROC Curves')
plt.ylim([0.0,1.0])
plt.xlim([0.0,1.0])
plt.legend(bbox_to_anchor=(2.25, 1.0))

plt.show();
```

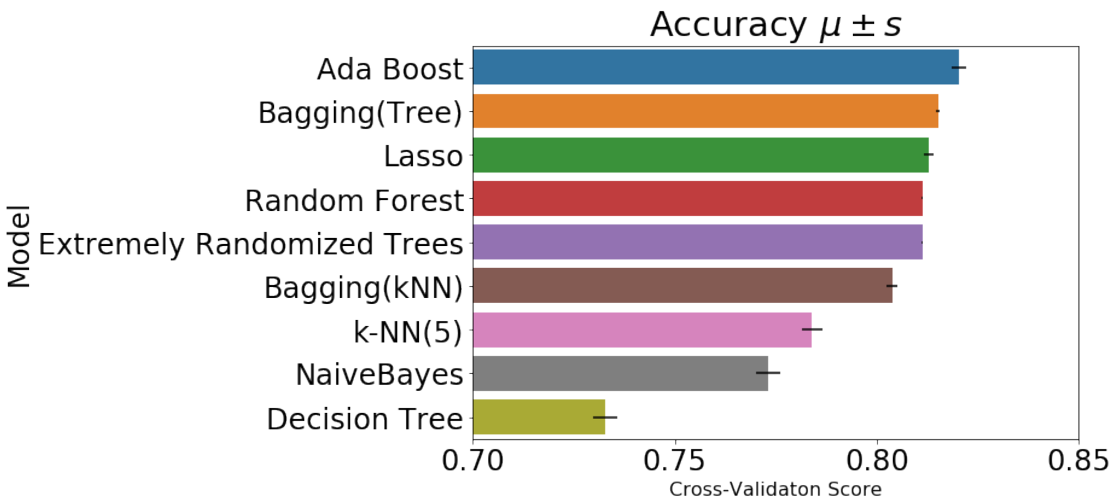


2.2 Comparing Classifier Performance using Statistical Tests

We can now compare the performance of the classifiers. First, we plot all the performance scores and then we focus on the most interesting ones (that is, the best performing ones) and we check check whether the difference in performance is is statistically significant.

[9]:
```
result_summary = pd.DataFrame({'Model':method,'Accuracy (Mean)':accuracy_mean,'Accuracy (Std)':accuracy_std,'Precision':precision,'Recall':recall,'F1':f1,'AUC':auc})
result_summary.to_csv('LoanSafety-Summary.csv')
```

[10]:
```
f, axe = plt.subplots(1,1, figsize=(9,6))

result_summary.sort_values(by=['Accuracy (Mean)'], ascending=False, inplace=True)

sns.barplot(x='Accuracy (Mean)', y='Model', data = result_summary, xerr=result_summary['Accuracy (Std)'], ax = axe)
axe.set_xlabel('Cross-Validaton Score', size=16)
axe.set_ylabel('Model')
axe.set_title("Accuracy $\mu\pm s$")
axe.set_xlim(0.7,0.85)
plt.show()
```



[11]:
```
df_crossvalidation = pd.DataFrame(xval_results)
```

[12]:
```
df_crossvalidation.drop(columns=['NaiveBayes','Decision␣
↪Tree','k-NN(5)'],inplace=True)
```

[13]:
```
confidence_level = 0.95

no_variables = len(df_crossvalidation.columns)

p_value = np.zeros((no_variables,no_variables))

for first,first_model in enumerate(df_crossvalidation.columns):

    p_value[first,first] = 1.0

    for second in range(first+1,(len(df_crossvalidation.columns))):

        second_model = df_crossvalidation.columns[second]

        paired_test = stats.ttest_rel(df_crossvalidation[first_model],␣
↪df_crossvalidation[second_model])

        p_value[first,second] = paired_test[1]
        p_value[second,first] = paired_test[1]

        if (paired_test[1]<(1-confidence_level)):
            print("%15s vs %15s => Difference is statistically significant (cf␣
↪%3.2f p-value=%.
↪4f)"%(first_model,second_model,confidence_level*100,paired_test[1]))
```

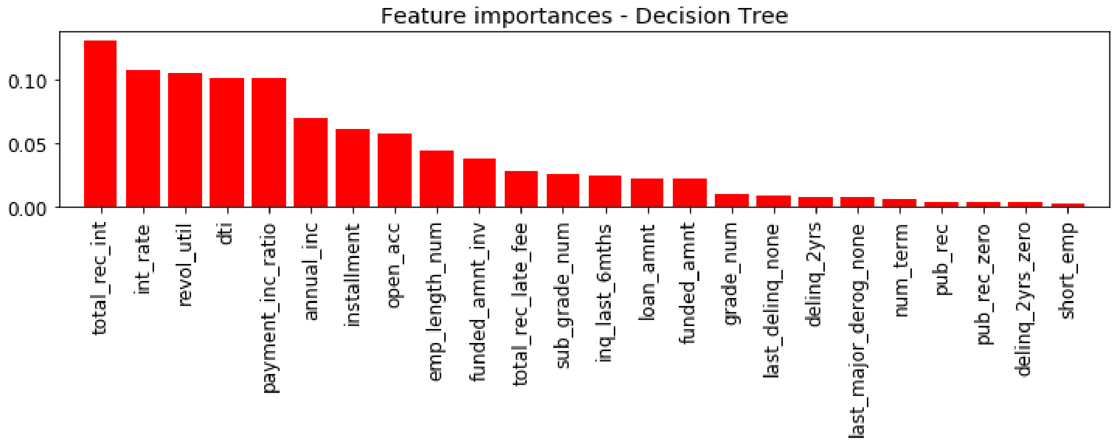
```
          Lasso vs   Bagging(Tree) => Difference is statistically significant
(cf 95.00 p-value=0.0003)
          Lasso vs    Bagging(kNN) => Difference is statistically significant
(cf 95.00 p-value=0.0000)
          Lasso vs   Random Forest => Difference is statistically significant
(cf 95.00 p-value=0.0019)
          Lasso vs Extremely Randomized Trees => Difference is statistically
significant (cf 95.00 p-value=0.0013)
          Lasso vs       Ada Boost => Difference is statistically significant
(cf 95.00 p-value=0.0000)
  Bagging(Tree) vs    Bagging(kNN) => Difference is statistically significant
(cf 95.00 p-value=0.0000)
  Bagging(Tree) vs   Random Forest => Difference is statistically significant
(cf 95.00 p-value=0.0000)
  Bagging(Tree) vs Extremely Randomized Trees => Difference is statistically
significant (cf 95.00 p-value=0.0000)
  Bagging(Tree) vs       Ada Boost => Difference is statistically significant
(cf 95.00 p-value=0.0000)
   Bagging(kNN) vs   Random Forest => Difference is statistically significant
(cf 95.00 p-value=0.0000)
   Bagging(kNN) vs Extremely Randomized Trees => Difference is statistically
significant (cf 95.00 p-value=0.0000)
   Bagging(kNN) vs       Ada Boost => Difference is statistically significant
(cf 95.00 p-value=0.0000)
  Random Forest vs       Ada Boost => Difference is statistically significant
(cf 95.00 p-value=0.0000)
Extremely Randomized Trees vs       Ada Boost => Difference is statistically
significant (cf 95.00 p-value=0.0000)
```

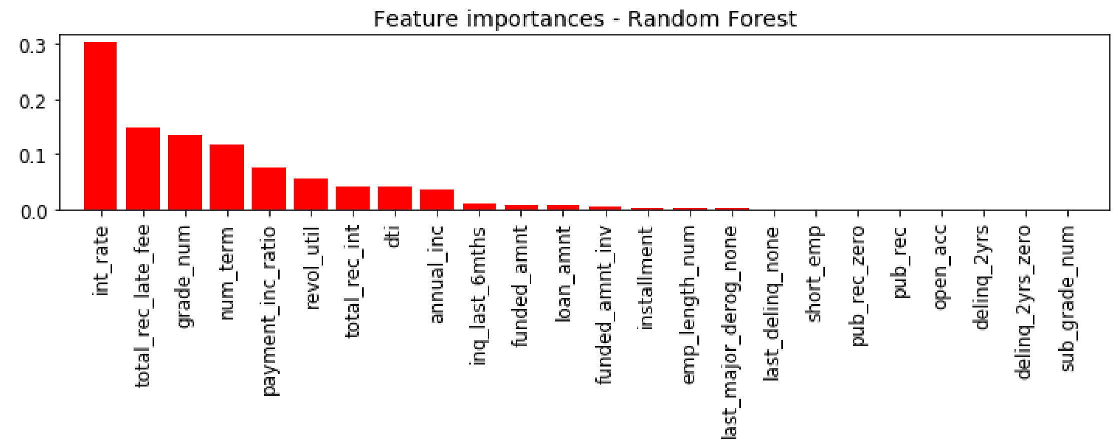
2.3 Variable Importance

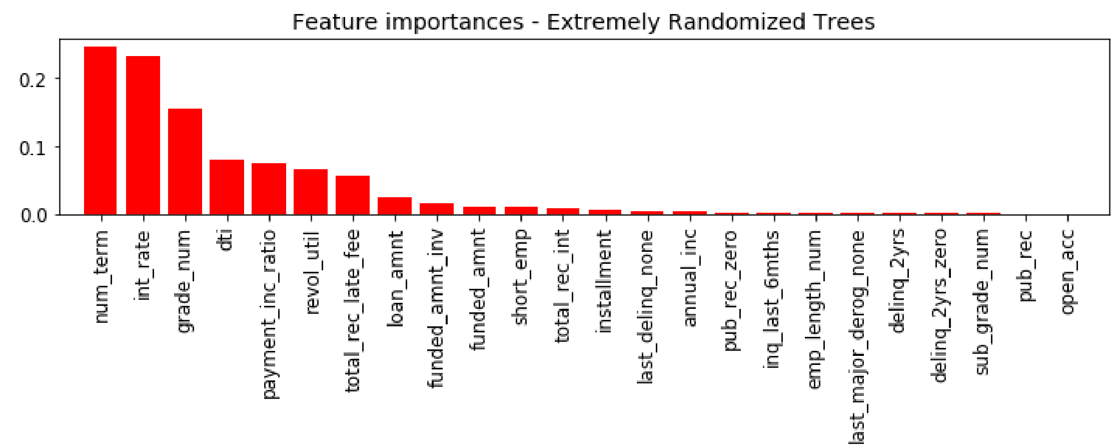
Ensembles generate models that are difficult to analyze but provide interesting ways to score the variable used by all the models in the ensembles. First, we fit each ensemble,

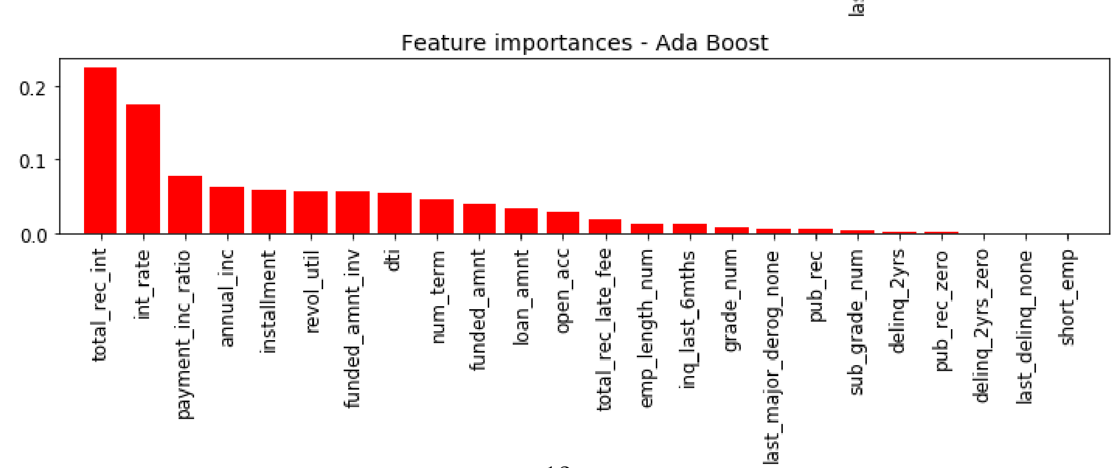
[14]:
```python
plot_idx = 1

plt.
 ↪subplots(len(feature_importance_model),1,figsize=(10,4*len(feature_importance_model)))
font = {'family' : 'sans', 'size'   : 12}
plt.rc('font', **font)


for model_name in feature_importance_model:
    model = feature_importance_model[model_name][0]

    # importance of features
    importances = model.feature_importances_
```

```python
    # indeces of the variables
    indices = np.argsort(importances)[::-1]

    plt.subplot(len(feature_importance_model),1,plot_idx)

    #
    plt.title("Feature importances - "+model_name)
    plt.xticks(range(X.shape[1]),X.columns[indices],rotation='vertical')


    plt.xlim([-1, X.shape[1]])

#     if hasattr(model, 'estimators_'):
#         std = np.std([tree.feature_importances_ for tree in model.
 ↪estimators_], axis=0)
#         plt.bar(range(X.shape[1]), importances[indices], color="r",␣
 ↪yerr=std[indices], align="center")# plt.xticks(range(X.shape[1]), indices)
#     else:
    plt.bar(range(X.shape[1]), importances[indices], color="r")


    plot_idx = plot_idx + 1

plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=1.0)

plt.show()
```


Feature importances - Decision Tree
0.10
0.05
0.00
total_rec_int
int_rate
revol_util
dti
payment_inc_ratio
annual_inc
installment
open_acc
emp_length_num
funded_amnt_inv
total_rec_late_fee
sub_grade_num
inq_last_6mths
loan_amnt
funded_amnt
grade_num
last_delinq_none
delinq_2yrs
last_major_derog_none
num_term
pub_rec
pub_rec_zero
delinq_2yrs_zero
short_emp


Feature importances - Random Forest
0.3
0.2
0.1
0.0
int_rate
total_rec_late_fee
grade_num
num_term
payment_inc_ratio
revol_util
total_rec_int
dti
annual_inc
inq_last_6mths
funded_amnt
loan_amnt
funded_amnt_inv
installment
emp_length_num
last_major_derog_none
last_delinq_none
short_emp
pub_rec_zero
pub_rec
open_acc
delinq_2yrs
delinq_2yrs_zero
sub_grade_num


Feature importances - Extremely Randomized Trees
0.2
0.1
0.0
num_term
int_rate
grade_num
dti
payment_inc_ratio
revol_util
total_rec_late_fee
loan_amnt
funded_amnt_inv
funded_amnt
short_emp
total_rec_int
installment
last_delinq_none
annual_inc
pub_rec_zero
inq_last_6mths
emp_length_num
last_major_derog_none
delinq_2yrs
delinq_2yrs_zero
sub_grade_num
pub_rec
open_acc


Feature importances - Ada Boost
0.2
0.1
0.0
total_rec_int
int_rate
payment_inc_ratio
annual_inc
installment
revol_util
funded_amnt_inv
dti
num_term
funded_amnt
loan_amnt
open_acc
total_rec_late_fee
emp_length_num
inq_last_6mths
grade_num
last_major_derog_none
pub_rec
sub_grade_num
delinq_2yrs
pub_rec_zero
delinq_2yrs_zero
last_delinq_none
short_emp

2.4 Voting Classifier

We can also build an heterogeneous ensemble classifier using a *VotingClassifier* available in Scikit-Learn that can be built either * by specifying a set of methods I selected or * by using all the methods we tested at once

Let's try to use all the methods we examined so far and let's see how this new ensemble performs. VotingClassifier requires a list of pairs (name,method) so we initially convert the dictionary we used to a list of pairs. Next we apply the same procedure used for the other approaches.

[15]:
```
estimators = [x for x in methods.items()]
```

[16]:
```
%%time
clf = VotingClassifier(estimators=estimators, voting='soft')

method_name = 'Voting'

# evaluate the model using crossvalidation
cross_val_score(clf,X,y,cv=crossvalidation)

# store the raw results of crossvalidation that we might want to use for t-test/
↪mann-whitney comparison
xval_results['Voting'] = xval_score

# compute the basic statistics
accuracy_mean.append(np.average(xval_score))
accuracy_std.append(np.std(xval_score))

clf.fit(X_train,y_train)

# compute the prediction which, for probabilistic classifiers, is using a␣
↪threshold of 0.5
yp = clf.predict(X_test)

# ask for the probability values
yprob = clf.predict_proba(X_test)

# computes the data needed to draw the ROC curve
fpr_nb, tpr_nb, thresholds = roc_curve(y_true=y_test, y_score = yprob[:,1],␣
↪pos_label=1)

# computes the AUC
roc_auc = roc_auc_score(y_true=y_test, y_score = yprob[:,1])
auc.append(roc_auc)
```

```
    # store the information to plot the ROC curves afterwards
    roc_results[method_name] = (fpr_nb, tpr_nb, thresholds, roc_auc)

    precision.append(precision_score(y_test,yp))
    recall.append(recall_score(y_test,yp))
    f1.append(f1_score(y_test, yp))

    print("%10s\tAccuracy  %.3f %.3f"%(method_name,np.average(xval_score),np.
 ↪std(xval_score)))
    print("          \tPrecision %.3f"%precision_score(y_test, yp))
    print("          \tRecall    %.3f"%recall_score(y_test, yp))
    print("          \tF1        %.3f"%f1_score(y_test, yp))

    method.append(method_name)
```

```
    Voting      Accuracy  0.820 0.002
                Precision 0.817
                Recall    0.993
                F1        0.897
CPU times: user 12min 14s, sys: 10.4 s, total: 12min 24s
Wall time: 18min 15s
```

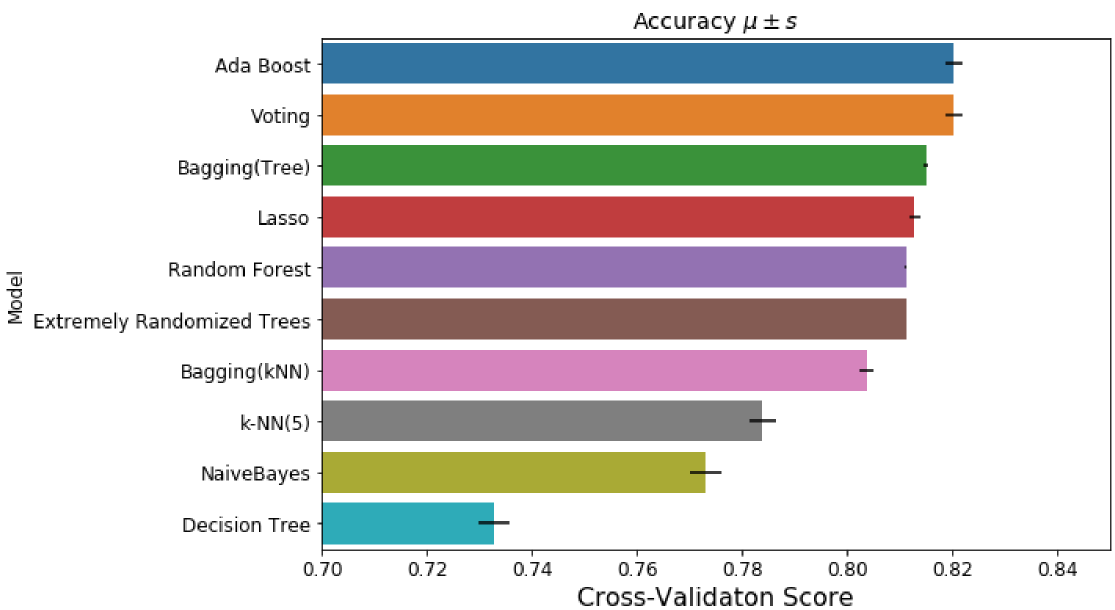
[17]:
```
result_summary_extra = pd.DataFrame({'Model':method,'Accuracy (Mean)':
 ↪accuracy_mean,'Accuracy (Std)':accuracy_std,'Precision':precision,'Recall':
 ↪recall,'F1':f1,'AUC':auc})
result_summary_extra.to_csv('LoanSafety-Summary-Extra.csv')
```

[18]:
```
result_summary_extra
```

[18]:
```
                      Model  Accuracy (Mean)  Accuracy (Std)  Precision  \
0                     Lasso         0.812832        0.001073   0.820863
1                NaiveBayes         0.773056        0.002890   0.840115
2                  k-NN(5)         0.783908        0.002491   0.816393
3             Decision Tree         0.732733        0.003036   0.841176
4             Bagging(Tree)         0.815102        0.000484   0.817868
5              Bagging(kNN)         0.803727        0.001406   0.813719
6             Random Forest         0.811264        0.000152   0.810171
7  Extremely Randomized Trees         0.811190        0.000026   0.810171
8                 Ada Boost         0.820369        0.001767   0.833372
9                    Voting         0.820369        0.001767   0.817144

     Recall        F1       AUC
0  0.981253  0.893921  0.721683
1  0.891479  0.865035  0.682258
2  0.943547  0.875377  0.557943
3  0.826984  0.834019  0.580287
4  0.988752  0.895228  0.688886
```

```
5  0.979923  0.889121  0.578200
6  1.000000  0.895132  0.707711
7  1.000000  0.895132  0.687081
8  0.968463  0.895853  0.744297
9  0.993015  0.896536  0.696573
```

[19]:
```
f, axe = plt.subplots(1,1, figsize=(9,6))

result_summary_extra.sort_values(by=['Accuracy (Mean)'], ascending=False,␣
 ↪inplace=True)

sns.barplot(x='Accuracy (Mean)', y='Model', data = result_summary_extra,␣
 ↪xerr=result_summary_extra['Accuracy (Std)'], ax = axe)
axe.set_xlabel('Cross-Validaton Score', size=16)
axe.set_ylabel('Model')
axe.set_title("Accuracy $\mu\pm s$")
axe.set_xlim(0.7,0.85)
plt.show()
```



2.5 Stacking

Alternatively, we can build a stacking classifier by training a meta classifier to learn how to predict whether a loan is safe based on the prediction of other classifiers. Note that, with respect to the voting classifier, in this case we replace the hard/soft voting with another model. Further examples of stacking can be found at - http://rasbt.github.io/mlxtend/user_guide/classifier/StackingClassifier/ - https://medium.com/@rrfd/boosting-bagging-and-stacking-ensemble-methods-with-sklearn-and-mlens-a455c0c982de

We build a dataframe containing the prediction of each model we want to use. Next we train a meta learner on the dataset of predictions we generated. In this case, we use as a meta learner a logistic regression.

2.5.1 Building the Training Data

The training data are collected by fitting all the models we considered in the stack.

[20]:
```
stack_train = pd.DataFrame()
stack = {}

for method_name in methods:
    clf = methods[method_name]
    clf.fit(X_train,y_train)
    stack[method_name] = clf
    stack_train[method_name] = clf.predict(X_train)
```

2.5.2 Training the Meta Learner

Next, the output collected from the stacked models is used to train the meta learner.

[21]:
```
meta = LogisticRegression(penalty="l1",C=100, random_state=1234, max_iter=300,␣
 ↪solver="liblinear")
meta.fit(stack_train,y_train)
```

[21]:
```
LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=300,
                   multi_class='auto', n_jobs=None, penalty='l1',
                   random_state=1234, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

[22]:
```
stack_train.head()
```

[22]:
```
   Lasso  NaiveBayes  k-NN(5)  Decision Tree  Bagging(Tree)  Bagging(kNN)  \
0      1           1        1              1              1             1
1      1           1        1             -1              1             1
2      1           1        1              1              1             1
3      1           1        1              1              1             1
4      1           1        1              1              1             1

   Random Forest  Extremely Randomized Trees  Ada Boost
0              1                           1          1
1              1                           1          1
2              1                           1          1
3              1                           1          1
4              1                           1          1
```

2.5.3 Evaluation on the Test Set

To evaluate the performance on the test set we generate a data set containing the output of the fitted models on the test set. The resulting data set (contained in stack_test) is used as the input for the meta model.

[23]:
```
stack_test = pd.DataFrame()

for method_name in stack:
    stack_test[method_name] = methods[method_name].predict(X_test)

yp = meta.predict(stack_test)
```

[24]:
```
print("Accuracy %.3f"%(accuracy_score(y_test, yp)))
print("Precision %.3f"%precision_score(y_test, yp))
print("Recall %.3f"%recall_score(y_test, yp))
```

```
Accuracy 0.731
Precision 0.841
Recall 0.824
```

2.6 Final Remarks

We evaluated several classification approaches for predicting the safety of loans. We built a pipeline to evaluate each classifier using cross-validation and holdout. We collected several metrics of performance (accuracy, prediction, recall, f1, AUC). Note that some methods would not have required crossvalidation since they could have been used out-of-bag evaluation, yet we preferred to apply the same evaluation to all the methods to have a uniform comparison. In addition, we applied crossvalidation using accuracy as a metric but accuracy is not the most adequate metric since it does not distinguish between false positive and false negative errors. Depending on the problem we should have used another metric to improve our performance on a specific type of error. There are several other ways to extend the current analysis for example by including other methods or by performing an in-depth exploration analysis which might result in a different data set (e.g., we might apply normalization to the input variables)