

Case study of Decision Tree Classification and Random Forest Classification

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Abstract

Every day hundreds and thousands of messages are being sent all over the world. Some of them are important messages while the rest is marketing or even scam messages. In our phones or emails, our messages are classified for us. In this case study we will learn two methods on how these classifications are made and most important we will be able to study different classification methods and find out their accuracy for a given dataset. In this report, we will be classifying email messages as spam or ham using Decision Tree Classification and Random Forest Classification and studying their classification accuracies.

1 Introduction

For the case study we were given a dataset containing 57 attributes that encode the total number a word or character occurs, and a total of 4601 instances. The dataset classifies email messages as spam or ham. In the given dataset we had to apply the Random Forest Classification and Decision Tree Classification and report the following findings:

- Compare the accuracies of the Random Forest classifier as a function of the number of base learners (e.g., 10, 50, 100, 500, 1000, and 5000) and the number of features to consider at each split (e.g., auto or sqrt)
- Compare the results of all the classifiers (with the best possible parameter setting for each classifier). Use classification accuracy (number of instances correctly classified/total number of instances presented for classification), per class classification accuracy, and confusion matrix to compare the classifiers.

2 Understanding the data

2.1 Getting started with the data

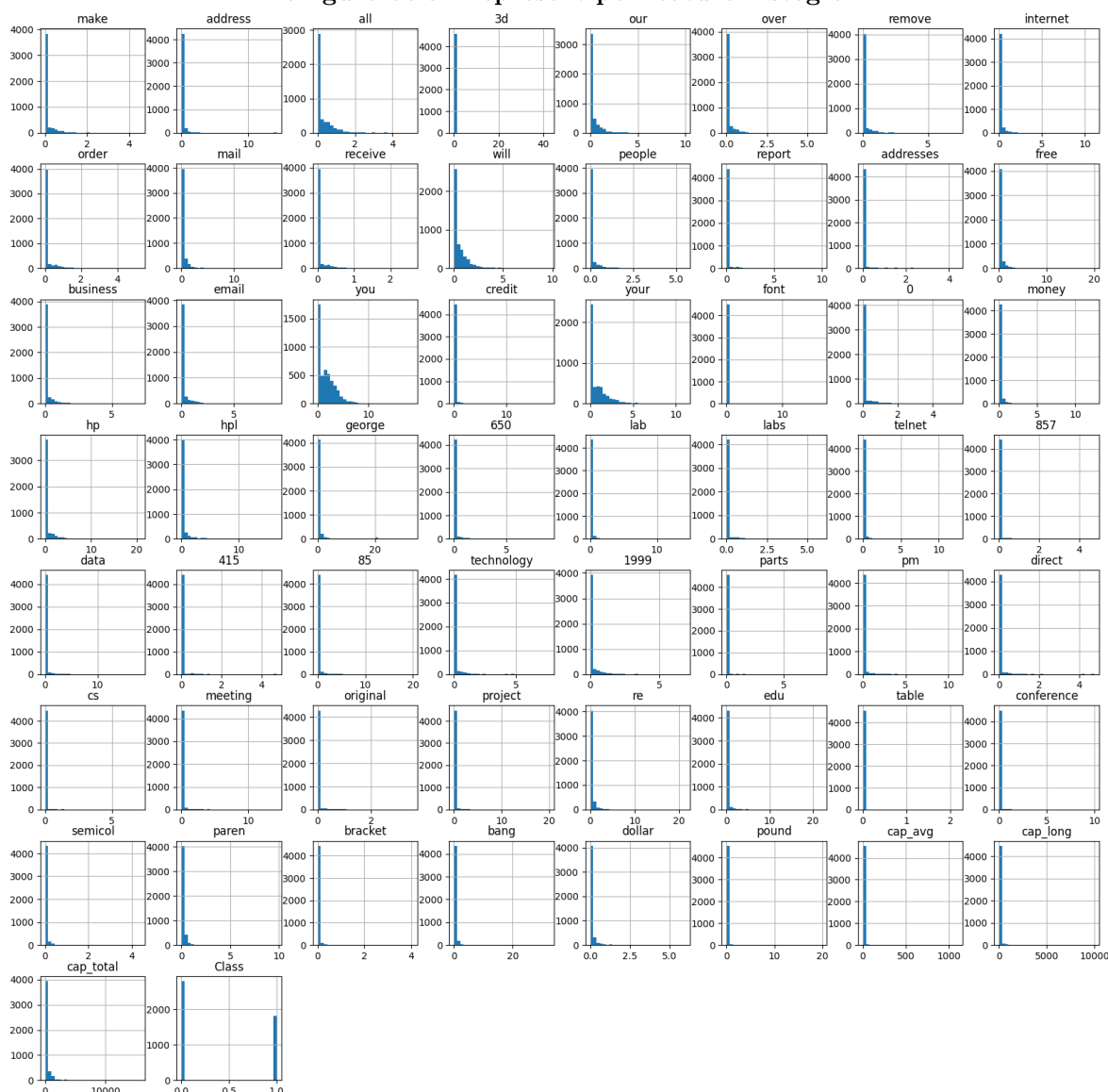
Before implementing the classification methods is a good practice to understand the data you are working with, and make the necessary changes to get the best output. Some of the changes may include cleaning it, checking for missing data, replacing some values, naming the features. All of the preparations of the data depend on the dataset that we were given.

Important elements from the dataset:

- The Dataset consists of 57 features 4601 samples.
- The data consists of 55 float type, 2 int type, and 1 object type.
- The object type named "Class" takes to values, either ham or spam.
- There are no missing values in the dataset.

2.2 Visualizing the dataset

The figure below represent per feature histogram



I have assigned 1 to 'spam' and 0 to ham in the dataset, because it makes it easier for me to work with having them as integers. The replacement is seen in the following code:

```
[5] spam_dataset_dataframe['Class']=spam_dataset_dataframe['Class'].apply(lambda x: 1 if x=='spam' else 0)
spam_dataset_dataframe.head()
```

Here we can see the changes that happened to "Class" column in the dataset.

	make	address	all	3d	our	over	remove	internet	order	mail	...	semicol	paren	bracket	bang	dollar	pound	cap_avg	cap_long	cap_total	Class
0	0.00	0.00	0.29	0.0	0.00	0.00	0.00	0.00	0.00	0.00	...	0.000	0.178	0.0	0.044	0.000	0.00	1.666	10	180	0
1	0.46	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	...	0.000	0.125	0.0	0.000	0.000	0.00	1.510	10	74	0
2	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	...	0.000	0.000	0.0	0.000	0.000	0.00	1.718	11	55	0
3	0.33	0.44	0.37	0.0	0.14	0.11	0.00	0.07	0.97	1.16	...	0.006	0.159	0.0	0.069	0.221	0.11	3.426	72	819	1
4	0.00	2.08	0.00	0.0	3.12	0.00	1.04	0.00	0.00	0.00	...	0.000	0.000	0.0	0.263	0.000	0.00	1.428	4	20	1

5 rows x 58 columns

2.3 Splitting the dataset

The dataset was split for training and testing, the respective variables were the following: **spam_training_set**, **spam_test_set**. The training set contains 1000 instances and the testing set

contains 3501 instances. The following figures show the implementation of the split method.

```
[8] #Create a training and test set
    spam_training_set, spam_test_set = train_test_split(spam_dataset_dataframe, test_size = 3601
    , random_state = 42)
    spam_dataset_dataframe.keys()

spam_training_data, spam_training_target = spam_training_set[["make", "address", "all", "3d", "our", "over", "remove", "internet", "order", "mail", "receive", "will",
spam_test_data, spam_test_target = spam_test_set[["make", "address", "all", "3d", "our", "over", "remove", "internet", "order", "mail", "receive", "will", "people", "i",
spam_training_data.head()
```

2.4 Optimizing the parameters for the Random Forest

A random forest has a multitude of parameters that can be changed and adopted to give the best output. For this assignment we are going to concentrate only on two of them, as required from the assignment.

- The first parameter is `n_estimators` which denotes the number of trees in the forest. For this purpose we will be considering the following list `n_estimators = [10, 50, 100, 500, 1000, 5000]`. We are going to be iterating through all of the elements of the list `n_estimators` compare the accuracies and find the optimal value for `n_estimators`.
- The second parameter that is going to be considered is `max_features`, that represents the number of features to consider when looking for the best split. There are three possible choices here, `max_features = ["sqrt", "log2", None]`. We are going to be iterating through each of them, comparing the accuracies and finding the highest accuracy.
 - "sqrt" represents the square root of n-features.
 - "log2" represents the logarithm with base 2 of n-features.
 - None means that all features are considered.
- There is a third parameter that is considered for the Random Forest classifier, and that is `random_state`. Random state is used to reproduce the same result across different run. In both of the classifiers I have assigned `random_state = 101`.

The following code shows the implementation of the optimization of parameters

```
n_estimators = [10, 50, 100, 500, 1000, 5000]
max_features = ["sqrt", "log2", None]
highest_accuracy = 0
a = 0
b = ""

for x in max_features:
    for n in n_estimators:
        clf1 = RandomForestClassifier(n_estimators = n, max_features = x, random_state = 101)
        clf1.fit(spam_training_data, spam_training_target)
        spam_test_target_predict = clf1.predict(spam_test_data)
        print("For n_estimators = ", n, " and max_features = ", x, " the accuracy score is: ", accuracy_score(spam_test_target, spam_test_target_predict))

        if accuracy_score(spam_test_target, spam_test_target_predict) > highest_accuracy:
            highest_accuracy = accuracy_score(spam_test_target, spam_test_target_predict)
            a = n
            b = x

print("The random forest with the highest accuracy ", highest_accuracy, " has the following parameters: n_estimators = ", a, " and max_features = ", b)
```

As

we wrote above the parameter optimization is considering only two of the parameters that Random Forest has. For the first feature `n_estimators` we had 6 elements, and for the second feature `max_features` there are 3 elements. Hence to find to best accuracy we have to compare all the possible combinations, in this case we get 18 accuracy values. We need to compare those and get the highest accuracy.

```
For no_estimators = 10 , and max_fetures = sqrt the accuracy score is: 0.918911413496251
For no_estimators = 50 , and max_fetures = sqrt the accuracy score is: 0.9266870313801722
For no_estimators = 100 , and max_fetures = sqrt the accuracy score is: 0.9311302415995557
For no_estimators = 500 , and max_fetures = sqrt the accuracy score is: 0.9316856428769786
For no_estimators = 1000 , and max_fetures = sqrt the accuracy score is: 0.9341849486253818
For no_estimators = 5000 , and max_fetures = sqrt the accuracy score is: 0.9355734518189391
For no_estimators = 10 , and max_fetures = log2 the accuracy score is: 0.928353235212441
For no_estimators = 50 , and max_fetures = log2 the accuracy score is: 0.9369619550124966
For no_estimators = 100 , and max_fetures = log2 the accuracy score is: 0.9411274645931685
For no_estimators = 500 , and max_fetures = log2 the accuracy score is: 0.9364065537350736
For no_estimators = 1000 , and max_fetures = log2 the accuracy score is: 0.9358511524576506
For no_estimators = 5000 , and max_fetures = log2 the accuracy score is: 0.9352957511802277
For no_estimators = 10 , and max_fetures = None the accuracy score is: 0.9164121077478479
For no_estimators = 50 , and max_fetures = None the accuracy score is: 0.9236323243543461
For no_estimators = 100 , and max_fetures = None the accuracy score is: 0.9239100249930575
For no_estimators = 500 , and max_fetures = None the accuracy score is: 0.9233546237156346
For no_estimators = 1000 , and max_fetures = None the accuracy score is: 0.9236323243543461
For no_estimators = 5000 , and max_fetures = None the accuracy score is: 0.9233546237156346
```

After the program is run we see the following parameters produce the highest accuracy:

- `random_state = 101` (Is constant)
- `n_estimators = 100`
- `max_features = log2`

And the accuracy we get is = 0.9411274645931685

```
The random forest with the highest accuracy 0.9411274645931685 has the following parameters: n_estimators = 100 and max_features = log2
```

3 Optimizing the parameters for the Decision Tree

The second part of the assignment asks to compare the Decision Tree Classifier with the Random Forest Classifier. Before doing the comparison we need to find the optimal parameters to get the highest accuracy from the Decision Tree Classifier. Same as the random forest, the decision tree has a multitude of parameters that can be changed and adopted to give the best output. For this assignment we are going to concentrate on four of them.

- The first parameter is `criterion` which measures the quality of a split. For this purpose we will be considering the following `criterion_DT = ["gini", "entropy"]`. We are going to be iterating through all of the elements of the list `criterion_DT` compare the accuracies and find the optimal value for `criterion`.
- The second parameter that is going to be considered is `max_features`, that represents he number of features to consider when looking for the best split. There are three possible choices here, `max_features = ["sqrt", "log2", None]`. We are going to be iterating thorough each of them, comparing the accuracies and finding the highest accuracy.
 - "sqrt" represents the square root of n-features.
 - "log2" represents the logarithm with base 2 of n-features.
 - None means that all features are considered.
- The third parameter that is considered is `splitter` which denotes the strategy used to choose the split at each node. The list has two elements as following `splitter= ["best", "random"]`.
- the fourth parameter that is considered is `max_depth` that is the maximum depth of the tree. For this case we are going to be looking at the following list `max_depth = [2,4,6,8,10,12]`.

- There is a fifth parameter that is considered for the Decision Tree classifier, and that is `random_state`. Random state is used to reproduce the same result across different run. In both of the classifiers I have assigned `random_state = 101`.

The following code shows the implementation of the optimization of parameters

```
criterion_DT = ["gini", "entropy"]
splitter_DT = ["best", "random"]
max_features_DT = ["sqrt", "log2", None]
max_depth_DT = [2,4,6,8,10,12]
highest_accuracy_DT = 0
f = ""
g = ""
h = ""
y = ""
for y in max_depth_DT:
    for x in max_features_DT:
        for n in criterion_DT:
            for z in splitter_DT:
                clf = DecisionTreeClassifier(criterion = n, max_features = x, splitter= z, max_depth = y, random_state = 101)
                clf.fit(spam_training_data, spam_training_target)
                spam_test_target_predict = clf.predict(spam_test_data)
                print("For criterion_DT = ", n, ", and max_features_DT = ", x, " and splitter_DT = ", z, "max_depth_DT = ", y, " the accuracy score is: ", accuracy_score(spam_test_target, spam_test_target_predict))

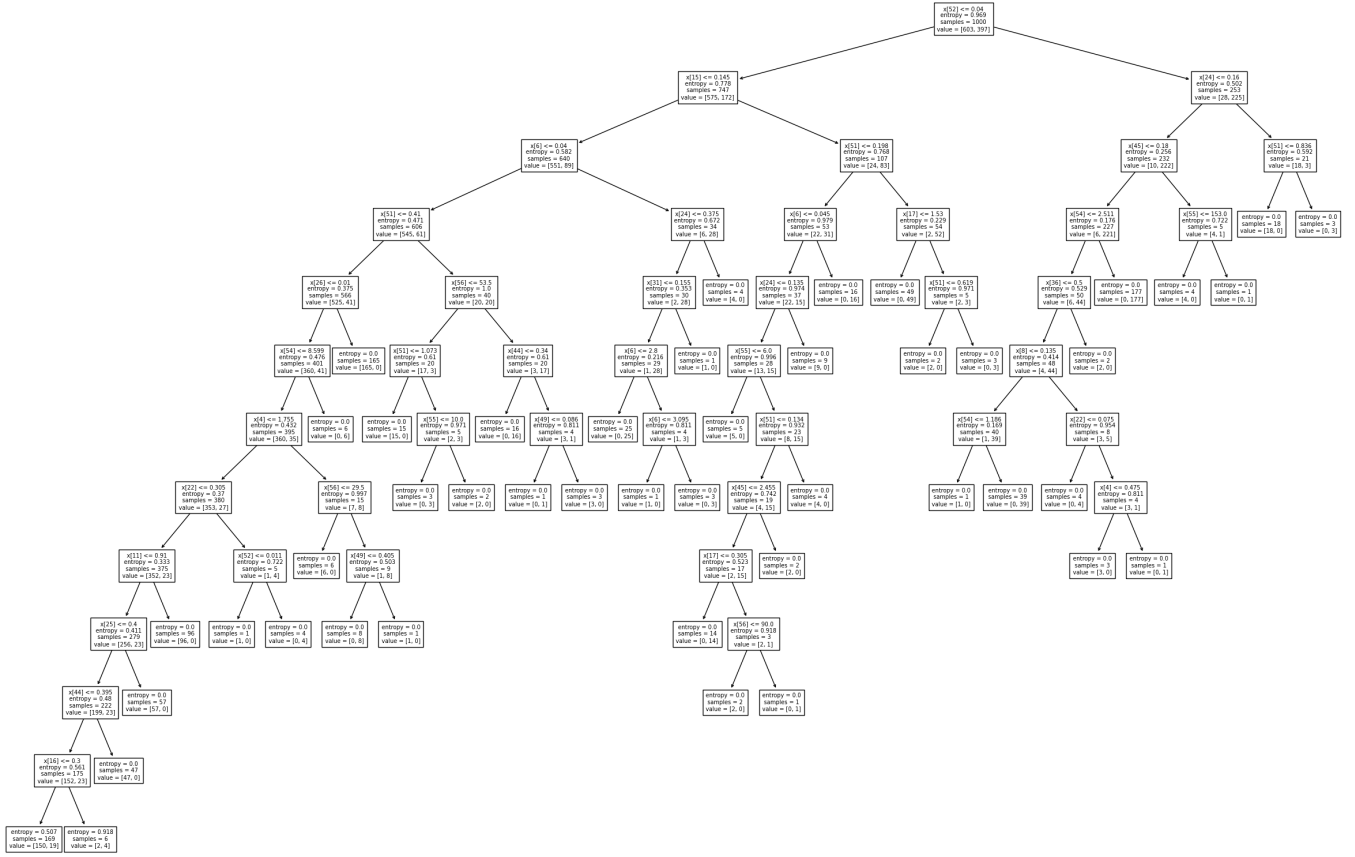
                if accuracy_score(spam_test_target, spam_test_target_predict) > highest_accuracy_DT:
                    highest_accuracy_DT = accuracy_score(spam_test_target, spam_test_target_predict)
                    f = n
                    g = x
                    h = z
                    w = y

print("The decision tree with the highest accuracy ", highest_accuracy_DT, " has the following parameters: criterion_DT = ", f, "max_depth_DT = ", y, " max_features_DT = ", g)
```

As

we wrote above the parameter optimization is considering four of the parameters that Decision Tree has. For the first parameter criterion we had 2 elements, and for the second feature max_features there are 3 elements, for the third parameter we had 6 values and for the fourth parameter we had 2 values. Hence to find to best accuracy we have to compare all the possible combinations, in this case we get 72 accuracy values. We need to compare those and get the highest accuracy.

”Visualizing the decision tree”



4 Comparing Decision Tree Classifier and Random Forest Classifier

We have previously decided the best parameters to be used for both of the classifiers to get the highest accuracy. Now it is time to compare the results we get from these two classifiers.

Outputting 20 predicted values for Decision Tree

```
Prediction for 20 observation: [0 0 1 0 1 1 1 0 1 1 0 0 0 0 1 1 0 1 1 1]
Actual values for 20 observation: [0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 1 1 0 1 0 1]
```

Outputting 20 predicted values for Random Forest

```
Prediction for 20 observation: [0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 1 1 0 1 0 1]
Actual values for 20 observation: [0 0 1 0 0 1 1 0 1 1 0 0 0 0 0 1 1 0 1 0 1]
```

The Decision Tree Classifier Outputs the following: Here we need to remember that 0 represents "ham", and 1 represents "spam".

```

[[2091  94]
 [ 118 1298]]
precision    recall  f1-score   support

   0       0.92     0.91     0.92     2185
   1       0.87     0.88     0.88     1416

 accuracy          0.90     3601
 macro avg       0.90     0.90     0.90     3601
weighted avg       0.90     0.90     0.90     3601

0.9016939738961399

```

"ham precision"	0.92
"spam precision"	0.87
Accuracy	0.9016939738961399

The Random Forest Classifier Outputs the following: Here we need to remember that 0 represents "ham", and 1 represents "spam".

```

[[2091  94]
 [ 118 1298]]
precision    recall  f1-score   support

   0       0.95     0.96     0.95     2185
   1       0.93     0.92     0.92     1416

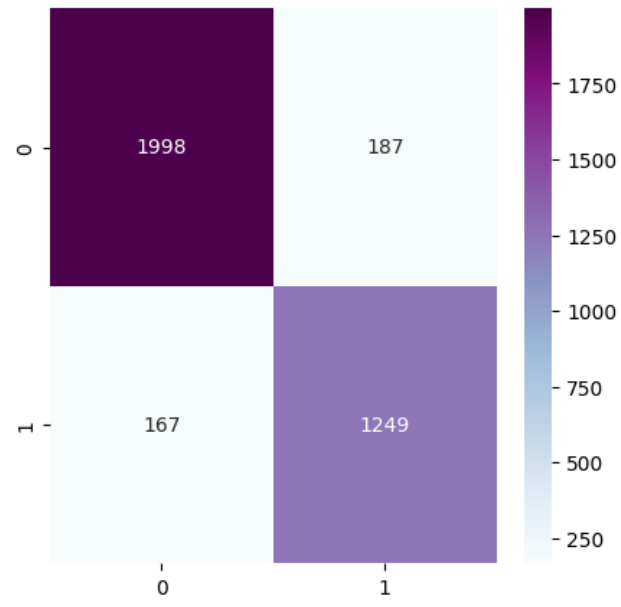
 accuracy          0.94     3601
 macro avg       0.94     0.94     0.94     3601
weighted avg       0.94     0.94     0.94     3601

0.9411274645931685

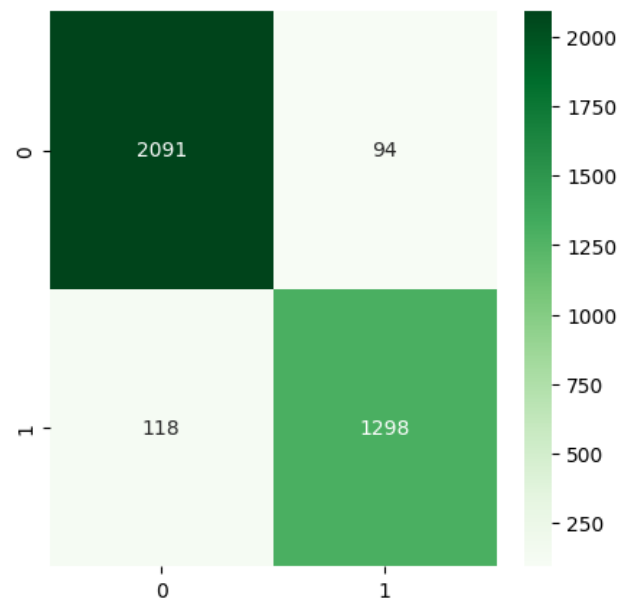
```

"ham precision"	0.95
"spam precision"	0.93
Accuracy	0.9411274645931685

Confusion Matrix for Decision Tree Classifier



Confusion Matrix for Random Forest Classifier



Conclusion

From the above observation we can reach to the conclusion that:

- Random Forest Classifier has a higher accuracy than Decision Tree.
- Random Forest Classifier has a higher precision than Decision Tree.
- From the Confusion Matrix we can clearly notice that:
 - False Positive of Random Forest $<$ False Positive of Decision Tree
 - False Negative of Random Forest $<$ False Negative of Decision Tree