Stacked Generalization for Human Activity Recognition

Ambareesh Ravi

Center for Pattern Analysis and Machine Learning
Dept. of Electrical and Computer Engineering
University of Waterloo, Waterloo, CANADA
ambareesh.ravi@uwaterloo.ca

Abstract—This short paper aims to discuss the effectiveness and performance of classical machine learning approaches for Human Activity Recognition (HAR). It proposes two important models - Extra Trees and Stacked Classifier with the emphasis on the best practices, heuristics and measures that are required to maximize the performance of those models.

Index Terms—Stacked Classifiers, Human Activity Recognition (HAR)

I. INTRODUCTION

This work primarily focuses on the usage of lesser known, unconventional algorithms that can significantly enhance performance on complex data. Many classical machine learning algorithms suffer from the problem of overfitting. Sometimes the train data may not be a good representation of real time data but many times the model could be insufficient in terms of capacity to learn complex patterns in data. The ensemble methods proposed in this work, not only increase the accuracy of prediction but also the reliability of the performance on unseen data.

II. DATA SET AND FEATURE ENGINEERING

The data set taken for this study is UCIs HAR data set [1] which consists of human activity data recorded from a smartphone that spans across 6 classes. Each sample consists of 561 features from sensors in a smartphone that are processed and filtered. The data is split into two parts randomly - 70% for training and 30 Many of the features were found to be co-dependent and reducing the number of features could maximize the performance of the model by exposing it to the important features to learn. Feature (dimensionality) reduction was done using Principal Component Analysis (PCA), a simple and reliable algorithm. The number of components for PCA was selected as 200 for a Proportion of Variance of 99.75% to capture maximum information and the data was reduced.

III. MODEL SELECTION

For the task of classification, there is a palette of classical machine learning algorithms to chose from and the most important ones are reviewed and listed with mean accuracy in this section in Table I.

The models with the best individual performance were shortlisted for the next stage of the work. A review of important methods are given below:

A. Logistic Regression

Logistic Regression [5] is a statistical method that estimates the probability of occurrence of one more categorical variable with respect to others using a logistic function which is defined by the sigmoid function in equation 1.

\[ f(x) = \frac{1}{1 + e^{-x}} \] (1)

The logistic function directly calculates the probability of occurrence as the value of function ranges between 0 and 1. The logistic regression uses a hypothesis function to learn and calculate the probabilities whose parameters can be estimated using a loss function and an optimizer. The hypothesis, loss and optimizing functions can be chosen based on the data and problem setup.

B. Gradient Boosting

Gradient Boosting [6] is an ensemble technique that typically uses Decision Trees (usually regression trees). Boosting is the process of filtering out data samples that are learnt to focus more on the ones that are not. Gradient Boosting adds weak learners one by one in an additive nature and an optimizer is used to minimize the loss while adding trees using a loss function to check the correctness of the predictions of the subsequent trees. The contribution from each tree is weighted or shrunk using the optimizer while learning. Both loss and optimizer can be chosen based on the data and problem setup.
C. State Vector Machines

State Vector Machine [4] generally works to find a linear separation in data and in the absence of which it projects data to higher dimensional space to separate the data linearly. It works by maintaining and maximizing a margin of separation between the data which is supported by closest points of different classes called support vectors. Depending on the nature of the margin to allow some overlap of samples / misclassifications, SVM is categorized into soft and hard margin SVMs. SVM focuses mostly on differentiating the data points that are the very similar in nature in comparison to the other classifiers that pay attention to all of the points.

IV. REVIEW AND MODEL DESCRIPTION

Each of the models in the above list were found to perform well on the data. To improve the performance further, this project deals with two important ensemble methods Extra Trees Classifier and Stacked Generalization Classifier.

Ensemble methods use multiple weak learners or models to learn parts or whole of the data and combine the results from individual models to produce the final prediction to achieve the best possible performance. Ensemble methods are proven to have the following advantages [7][**1]:

1) Combining predictions from multiple models in ensembles works better since the predictions from the sub-models are at best weakly correlated as each model learns a subset of data and not the whole data.
2) Variance and/or Bias can be reduced.
3) Greedy or Local learning can be compensated for, with other algorithms to improve generalization.
4) A variety of different algorithms can be chosen and used in parallel for learning and prediction.

A. Extra Trees Classifier

Extra Trees Classifier or Extremely randomized classifier is a tree based ensemble method which uses Decision Trees as the primary components with top-down approach. It is similar to Random Forest in many aspects but the two key differences are that features to split on are chosen at random at all stages and there is no bootstrapping used while drawing samples. It is very useful while operating with a large number of varying continuous features since it reduces the burden of computing the best feature to split on by choosing at random. The bias/variance analysis has shown that Extra-Trees work by decreasing variance while at the same time increasing bias [2]. Some of the salient features of Extra Trees Classifier are given below[**2]:

1) Computationally efficient owing to the simplicity of node splitting procedure.
2) Without bootstrapping, we reduce the repetition of data in the learning process.
3) Works on both categorical and numerical variables with the ability to have multiple random splits at each node depending on the data and problem setup.
4) Even though randomization increases the variance of individual weak learners, it decreases the overall variance of the ensemble with respect to each sample. Also, the randomization can help the model generalize and avoid overfitting.

Though the nature of operations of Extra Trees Classifier is close to that of a Random Forest Classifier, there are significant performance differences between the two - Refer to the results section.

B. Stacked Generalization Classifier

The Stacked (Generalization) Classifier is another ensemble method that is used to combine the best properties of multiple models into a single best entity. In Stacked Classifier, the information learnt is passed from one level to another level to predict the final desired outcome [3]. Multiple classifiers are learned together and a final decision is made based on the output of all the classifiers in the stack by another classifier (Usually Logistic Regression) which is called the meta-learner.

Stacked Generalization by nature, works by reducing the bias of the individual models used in the stack [3], hence improves the generalization of the model and reduces the error rate significantly. It can also be thought of a replacement for cross validation where the best model on the validation data is chosen which might not be the overall best model [3]. But here, all the models are made to learn on parts of data and their overall performance is improved.[**3].

The parameters of individual models directly impact their performance on any given data. For example, number of neighbors (K) in KNN, number of trees, max depth in tree based methods, learning rate and optimizer in gradient based methods, regularization parameter (C) in SVM etc. and other factors like the first feature to split, number of tune-able weights in Logistic Regression etc. All these factors create strong bias towards the predictions of the model with respect to unseen data. All these are averted by using multiple classifier that perform well on the parts of data they learnt individually which is in the nature of stacked classifier.[**4]

Algorithm 1: Algorithm for Stacked Ensemble

1 Define T classifiers for the stack.
2 Learn T classifiers on data set D1.
3 Learn another level of classifier g from data set D2 using meta-data M defined by \( f_t(x_i), y_i \) where \( f_t(x_i) \) is the output of \( t^{th} \) classifier for \( t^{th} \) sample of data, \( \forall t \in T \).
4 Predict the output of new classifier g where \( y_i = g(f_t(x_i)) \) for \( t = 1..T \)

C. Best Practices

Theoretically, any number of levels can be added but it is wise to chose the number of levels depending on the performance of each level. Two levels are found to be sufficient to solve most of the problems [3]. In practice, domain knowledge
TABLE II

| Model               | Best Parameters               |
|---------------------|-------------------------------|
| Logistic Regression | OneVSRest, l1 norm            |
| Linear SVM          | C = 2.0                       |
| Gradient Boosting   | n estimators = 50, Learning rate = 0.2 |
| Extra Trees Classifier | n estimators = 100, max depth = 4 |

on the data will be helpful in configuring the model based on the nature of data and capacity of individual models. Careful choice of individual models and their respective configurations can significantly help in improving the performance over any other individual models.

Tuning the stacked classifier can prove to be difficult owing to the number of combinations with respect to the hyperparameters from all the individual models in the stack. So it is heuristic to tune and check the individual learners first and to proceed implementing the stack.

D. Methodology

So, after carefully considering the performance of the models tested previously and the stipulation to choose a novel, unconventional model, Stacked Classifier was chosen with the following individual models and best parameters based on individual performance based on 10 times 10 fold cross validation in Table II.

While fitting or training the data, the above four models in the stack learn from the data samples and output their respective predictions. These out-put predictions of those models which are called the meta-features will be learned by another classifier (usually and in this case, Logistic Regression) which is called the meta-learner. It is strongly advisable to split the data into two parts - one for training the first layer of the classifiers and other part to train the meta-learner. Justifications are marked with ** throughout the paper.

V. RESULTS

This section discusses the results and findings of the experiments conducted with Extra Trees and Stacked Classifiers.

A. Extra Trees VS Random Forest

Extra trees classifier performed better on the given data set with a training time which is a fraction of that of Random Forest details of which are given in the results section.

Performance differences between Random Forest and Extra Trees classifiers with 200 estimators on data after 10 times 10 fold cross validation on the data is shown in Table III.

The Multi-class Receiver Operator Characteristics (ROC) curve and Area Under ROC score, showing the classification performance of the stacked model on the test data are shown in figure 1.

The multi-class confusion matrix for the classes in the order walking, walking upstairs, walking downstairs, sitting, standing, laying of the stacked model on the test data is shown below:

\[
\begin{bmatrix}
489 & 5 & 2 & 0 & 0 & 0 \\
39 & 429 & 3 & 0 & 0 & 0 \\
6 & 12 & 402 & 0 & 0 & 0 \\
0 & 0 & 0 & 437 & 54 & 0 \\
0 & 0 & 0 & 9 & 523 & 0 \\
0 & 0 & 0 & 0 & 0 & 537 \\
\end{bmatrix}
\]

The complete classification report which denotes the class-wise performance of the stacked model is shown in the table.

In terms of computational performance, the stacked model took about 38 minutes to fit on a 6th Gen Core-i5 computer.

![Fig. 1. Multi-Class Performance](image-url)
with 12GB memory where as the other models took around 25 minutes. The prediction time of the model was 2.3 seconds. The model used 1.2GB of memory for fitting inclusive of 200MB for data.

Stacked classifier performs poor when compared to Linear SVM (by 0.06 bias due to low variance (Bias-Variance Trade Off). Also, Linear SVM finds a higher dimension to project the data to find a linear separation.

VI. FUTURE SCOPE

The following can be taken up as future works:
1) Finding an optimal way to tune the stack jointly is essential to get the best out of the models.
2) Study of the effect of number levels in the stack on a more complex data could help understand the potential of the algorithm.
3) Paralleling computations inside the stack to reduce the time could be a significant improvement.

VII. CONCLUSION

This study deals with two ensemble methods - Extremely Randomized Trees (ExtraTrees) Classifier and Stacked (Generalization) Classifiers for best performance in terms of speed and accuracy respectively with heuristics and best practices to employ them effectively. It also enunciates the effectiveness of the models with compelling results in comparison with the conventional ones that are used and how the stacking scheme improves generalization while learning to increase the accuracy of prediction on the given data.

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