Deception Detection using Random Forest-based Ensemble Learning

Kun Bu[1,*] **and Kandethody Ramachandran**[1]

[1]University of South Florida, Department of Mathematics & Statistics, Tampa, FL 33620-5700, USA
[*]kunbu@usf.edu

ABSTRACT

The purpose of this work is to detect people lying using different ensemble machine learning algorithms to conclude a better classification model through comparison. Random Forest (RF) did an efficient work while dealing with both classification and regression problems; In this paper, we proposed a Random Forest-based ensemble learning, which is the combination of RF with SVM, GLM, KNNs, and GBM to improve the model performance. The data set that we used to fit into the machine learning models is Miami University Deception Detection Database (MU3D). MU3D is a free resource containing 320 videos of Black and White targets, female and male, telling truths and lies. We fit the MU3D video level data set into Random Forest-based ensemble learning models, which includes RF+SVM.Linear, RF+SVM.Poly, RF+GLM, RF+KNNs, RF+GBM(Stochastic Gradient Boosting) and RF+WSRF(Weighted Subspace Random Forest). As a comprehensive comparison of the model performance, we conclude our new combination of algorithms performs better than the traditional machine learning models. Our contribution in this work provides a robust classification method which improves the predicted performance while avoiding model over-fitting.

Introduction

Traditional lie detection machine is a polygraph, which can provide people with an averaging accuracy between 58% to 90%. With 90% accuracy, it seems to do a very good job on detecting lying, however, with 58% accuracy, we can hardly have much confidence to say this person is lying. In other words, the polygraph test is easy to pass for those well-trained people (ie. company spies or country spies). Even ordinary people who search for the word “polygraph” online, the next searching suggestion would be “How to Pass a Polygraph Test?” Since the polygraph operating principle is to detect lies by looking for signs of an examinee’s physiological changes. Once the examinee lies, it puts a blip on the polygraph machine that serves as a signature of that examinee’s lies. Besides, polygraph test is a time-based test that only captures the examinee’s body reaction in each specific question, which means the examinees themselves know that they’re being tested whether they are lying. Therefore, polygraphs are not useful for those underground and secret cases. Therefore, artificial intelligence (AI) approaches come to scientist’s minds. Why don’t we just detect lying by applying machine learning algorithms to see if the accuracy of deception detection would be improved.

The Miami University Deception Detection Database (MU3D) is a free resource containing 320 videos of Black and White targets, female and male, telling truths and lies. Eighty (20 Black female, 20 Black male, 20 White female, and 20 White male) targets were recorded speaking honestly and dishonestly about their social relationships. Each target generated four different videos (i.e., positive truth, negative truth, positive lie, negative lie), yielding 320 videos fully crossing target race, target gender, statement valence, and statement veracity. The stimuli and an information codebook can be accessed free of charge for academic research purposes from http://hdl.handle.net/2374.MIA/6067. In the previous studies of MU3D, scholars conducted research using standardized stimuli that can aid in building comprehensive theories of interpersonal sensitivity, enhance replication among labs, facilitate the use of signal detection analyses, and promote consideration of race, gender, and their interactive effects in deception detection research.

Ensemble learning, sometimes referred to as a multi-classifier system, builds and combines multiple classifiers to complete the learning task. Generally speaking, there are two choices for getting multiple classifiers. The first is supposed that all individual classifiers are of the same type, or homogenous. For example, both decision tree individual classifiers, or both neural network individual classifiers (i.e. Bagging and boosting, for example, Random Forest). The second is supposed that all individual classifiers are not homogeneous, or heterogeneous. For example, in this paper, we have a classification problem of deception detection, we use support vector machine (SVM) individual learner, logistic regression (LR) individual learner and k-Nearest Neighbors (KNNs) individual learner to learn the training set, and then determine the final strong classifier by some combination strategy. This integration is called Stacking. In the experimental section, we applied both Bagging, boosting and stacking, and selected a better ensemble model to classify people lying.

Results

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References

1. Hao, Z., AghaKouchak, A., Nakhjiri, N. & Farahmand, A. Global integrated drought monitoring and prediction system (GIDMaPS) data sets. *figshare* http://dx.doi.org/10.6084/m9.figshare.853801 (2014).

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