CS613 FINAL PROJECT

Connor Secen, Richard Strouss, Tristan Marshall



PROBLEM STATEMENT

- COMPARE THE RESULTS OF MULTIPLE METHODS ON PREDICTING THE DISCRETIZED CRIME RATE
 OF VARIOUS LOCALITIES GIVEN A RELEVANT FEATURE SET
- TO INCREASE PRACTICAL APPLICABILITY, DIMENSIONALITY WILL BE REDUCED WHILE MAINTAINING ACCEPTABLE VALIDATION SCORES



PRIOR WORK

- Ingilevich, V. & Ivanov, S. (2018). Crime Rate Prediction in the Urban Environment Using Social Factors. Procedia Computer Science, 136, 472-478. https://doi.org/10.1016/j.procs.2018.08.261
 - COMPARED RESULTS FROM LINEAR REGRESSION, LOGISTIC REGRESSION, AND GRADIENT BOOSTED DECISION TREES
 - FOUND GRADIENT BOOSTING TO BE THE MOST APPROPRIATE TECHNIQUE OF THE THREE
- ALVES, L. G. A., RIBIERO, H. V., & RODRIGUES, F. A. (2018). CRIME PREDICTION THROUGH URBAN METRICS AND STATISTICAL LEARNING. PHYSICA A, 55, 435-443. https://doi.org/10.1016/j.physa.2018.03.084
 - Used a random forest model
 - Out performed previous linear models
- KSHATRI, S. S., SINGH, D., NARAIN, B., BHATIA, S., QUASIM, M. T., & SINHA, G. R. (2021). AN EMPIRICAL ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR CRIME PREDICTION USING STACKED GENERALIZATION: AN ENSEMBLE APPROACH. IEEE ACCESS. ADVANCED ONLINE PUBLICATION. https://doi.org/10.1109/ACCESS.2021.3075140
 - Compared J48 decision tree algorithm, random forests, sequential minimal optimization (SVM), bagging, and naïve bayes classifiers
 - Best results from stacking the models
 - Random forest was nearly as good as the stacked model on all validation metrics



PRIOR WORK

- Zhu, J., S. Rosset, H. Zou, and T. Hastie. 2009. Multi-Class AdaBoost. Statistics and its Interface2 (3):349–360.
 - MULTI-CLASS ADABOOST EXTENSION
 - FIXES PROBLEM WITH HIGH MULTI-CLASS ERROR
- GENERAL LESSONS
 - FEATURES ARE IMPORTANT
 - Subject similarity does not guarantee learning performance similarity



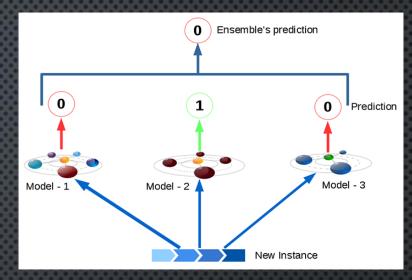
DATASET

- COMMUNITIES AND CRIMES DATASET FROM THE UC IRVINE MACHINE LEARNING REPOSITORY
 - HTTP://ARCHIVE.ICS.UCI.EDU/ML/DATASETS/COMMUNITIES+AND+CRIME
- Combines socio-economic data from 1990 US Census, law enforcement data from 1990 US LEMAS (Law Enforcement Management and Administrative Statistics) survey, and crime data from 1995 FBI UCR (Uniform Crime Reporting)
- Dataset contains 1994 instances and 128 Attributes
 - MIX OF CATEGORICAL AND CONTINUOUS FEATURES
- 102 ATTRIBUTE WITH REMOVAL OF MISSING DATA INCLUDING
- Converted the target value to categorical by binning the data into 11 different groups separated by .1



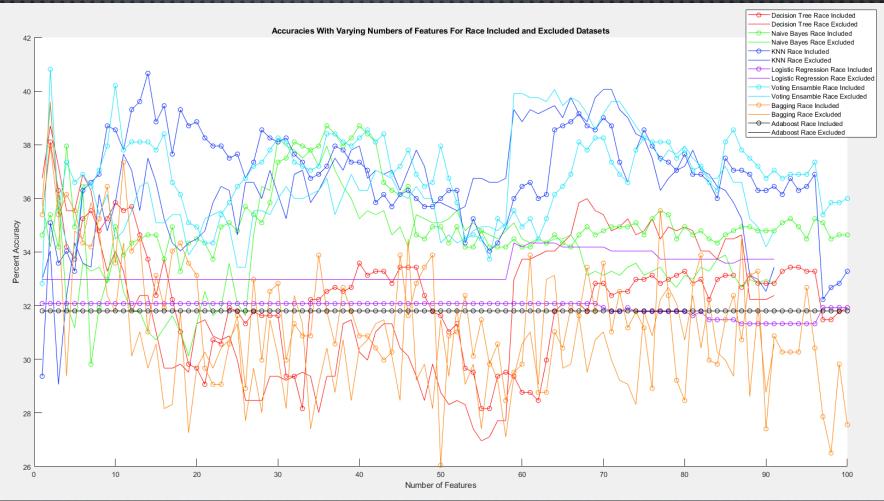
APPROACH

- FOUND THE CORRELATION BETWEEN EACH FEATURE AND THE TARGET VALUE
 - SPLIT THE DATASET INTO ONE, ONE CONTAINING AND ONE NOT CONTAINING RACE DATA
 - SORTED THE FEATURE FROM MOST CORRELATED TO LEAST AND PROGRESSIVELY ADDED THE FEATURES TO THE DATASET CURRENTLY BEING SORTED.
- COMPARE SIMPLE CLASSIFICATION METHODS
 - LOGISTIC REGRESSION VS DECISION TREE
- Compare more complex Ensemble methods
 - VOTING
 - Logistic regression
 - ID3 DECISION TREE
 - KNN
 - Naïve bayes
 - BAGGING
 - BOOSTING
 - BETA VALUE FOR WEIGHT UPDATE CALCULATE AS FOLLOWS: BETA = LOG(1-ERROR/ERROR)+LOG(K-1) WHERE K IS THE CLASS
- DETERMINE WHICH METHOD WORKS BEST FOR THE GIVEN DATA BY COMPARING THE ACCURACY





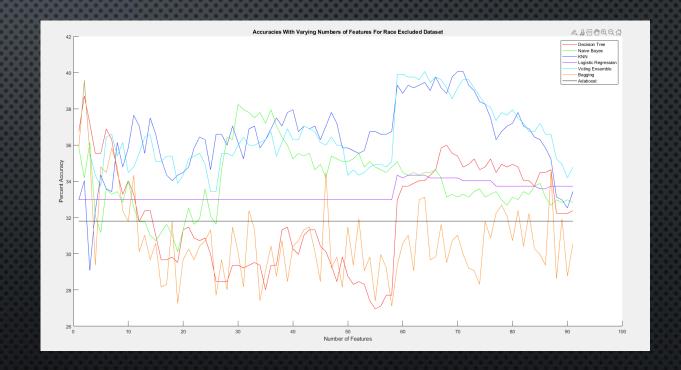
RESULTS





OBSERVATIONS AND DISCUSSION

- MAXIMUM ACCURACY 40.06%
- BEST CLASSIFIERS VOTING ENSEMBLE AND KNN
- RACE DATA DID NOT ADD SIGNIFICANTLY TO ACCURACY AND IN MANY CASES DECREASED ACCURACY
- LOGISTIC REGRESSION AND ADABOOST HAD CONSISTENT ACCURACIES, BUT ADHERED TO SPECIFIC CLASSES





OBSERVATIONS AND DISCUSSION

- LOW ACCURACY POTENTIALLY A RESULT OF THE DATA ITSELF.
- DATASET INCLUDES:
 - CENSUS DATA WHICH HAS A 10% MARGIN OF ERROR
 - CATEGORIES THAT SHOULD NOT HOLD NON-ZERO DATA BUT DO
 - POTENTIALLY SUBJECTIVE CATEGORIES



FUTURE WORK/EXTENSIONS

- ATTEMPT TO USE MORE COMPLEX CLASSIFIERS
 - ARTIFICIAL NEURAL NETWORKS
- Change the learning task to be a regression style task.
 - THE TARGET IN THE DATASET IS CONTINUOUS LENDING ITSELF TO REGRESSION.
- COLLECT MORE DATA
 - More examples to reduce overfitting
 - DIFFERENT FEATURES TO AVOID BIAS
 - REDUCE THE NUMBER OF FEATURES BY COLLECTING FEATURES THAT ARE BETTER PREDICTORS



THANK YOU!

