Feature Selection Methods on Car Crash Data in 49 States

Zakk Loveall W Connor Kasarda

Presentation Organization

- 1. Introduction
- 2. Research
- 3. Methodology/Experiment
- 4. Results
- 5. Conclusion & Future Work

Introduction



Problem Statement

- Change in project direction...
 - Original Approach
 - Feature selection and prediction of car crash severity between nations
 - Tried to reconcile/combine features from multiple datasets between countries
 - This proved to be infeasible give time allotted
 - Even if there were similar features, had different scalings
 - Found dataset that contained car accidents between states
 - Sobhan Moosavi. (2022). US Accidents (2016 2021) [Data set]. Kaggle. https://doi.org/10.34740/KAGGLE/DSV/3286750
- What's the best way to predict the severity of car crashes between states?
 - Factors to consider...
 - Feature Selection Techniques
 - Variance
 - Accuracy
 - Computation Time

Research

Current Research

- https://www.iihs.org/topics/fatality-statistics/detail/state-by-state
 - Fatal crash totals; deaths by road user; crash types; DUI; restraint use; rural versus urban
- R. E. AlMamlook, K. M. Kwayu, M. R. Alkasisbeh and A. A. Frefer, "Comparison of Machine Learning Algorithms for Predicting Traffic Accident Severity," 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), Amman, Jordan, 2019, pp. 272-276, doi: 10.1109/JEEIT.2019.8717393.
 - Select factors and model for classifying severity (w/ respect to country, not state-wise)
- Zhang S, Khattak A, Matara CM, Hussain A, Farooq A (2022) Hybrid feature selection-based machine learning Classification system for the prediction of injury severity in single and multiple-vehicle accidents. PLoS ONE 17(2): e0262941. https://doi.org/10.1371/journal.pone.0262941
 - Use of feature selection, but no use of subsetting the dataset

Novel Approach

- Separate feature selection on subsets of dataset
 - Each dataset subset contains data from one state only
 - Predicated on the fact that there may be difference between states in the U.S.
- Try different strategies for said feature selection
 - Already existing feature selection methods
 - Variance Thresholding
 - Machine Learning Algorithm Components

Methodology/ Experiment

Sampling Method

- Stratified data based on states
- Randomly sampled 5000 points if larger than 5000
- Normalized the data
- Encoded it to account for strings
- Split into test and training data

Feature Selection Methods

- Selected top 10 features from each method...
 - Feature Selection Based:
 - 1. Recursive Feature Elimination
 - 2. <u>Sequential Feature Selection</u>
 - 3. Variance Threshold
 - ML Algorithm Based:
 - **4.** Random Forest
 - 5. Neural Network
- Cross validated on MLPClassifier
 - o 3 Folds
 - Mean Scores Over Folds

What we Measured

- Ran each state through feature selection and calculated total mean
 - Accuracy score was utilized
- Calculated variance between selected features for each state
 - How different were the features between each state?
- Calculated time it took to run each selection method
 - o Includes features selection, cross validations, variance calculations for each method
- In the python code, we tried to parallelize wherever possible
 - Typically involves setting 'n_jobs' to -1

Results



Sequential Selection

- Iteratively selects a feature subset and evaluates performance using a metric
- Adds or removes features from the subset until criteria is met
- Goal is to find the smallest (10) subset that has the best performance
 - Score: 80% Accurate
 - Time Elapsed: **854 Seconds**
 - Variance: o.75 Variation

Recursive Selection

- Works similarly to sequential
- Works backwards when adding/removing features
- Recursively finds subsets
 - Score: **79% Accurate**
 - Time Elapsed: 325 Seconds
 - Variance: 1.02 Variation

Variance Threshold

- Used threshold of o.o1
 - If variance < 0.01, feature is not considered
 - o Else, feature is kept
- Works by removing features with low variance
 - Score: **76% Accurate**
 - Time Elapsed: 147 Seconds
 - Variance: 1.93 Variation
 - This value may need some review...

Random Forest Selection

- Used random forest algorithm to measure importance of each feature
 - Gini Importance
 - Splitting based on features
- Importance scores are assigned to each feature based on performance
- Features with least importance are removed
 - Score: **76% Accurate**
 - Time Elapsed: 254 Seconds
 - Variation: **0.93 Variation**

Neural Network Selection

- Uses neural network algorithm to select features
 - Use of permutation importance
 - Reshuffling values in each column
 - Re-evaluate model with shuffled feature
- Similar to random forest in the sense that it assigns importance
 - Score: **76% Accurate**
 - Time Elapsed: 226 Seconds
 - Variation: **0.79**

Comparison

- Best time(s):
 - Variance Threshold (147 seconds)
 - Neural Network (226 seconds)
 - Random Forest (254 seconds)
- Most Variation:
 - Recursive Selection (1.02)
 - o Random Forest (0.93)
 - Neural Network (0.79)
- Most Accurate:
 - Sequential Selection (80%)
 - Recursive Selection (79%)
 - Neural Network, Random Forest, Variance Threshold (76%)

Conclusion & Future Work

Conclusion

- Recommend Random Forest Selection for this specific problem
 - High Variability (0.93)
 - High Accuracy (76%)
 - Low Comp. Time (254 seconds)
 - Good tradeoff between computation time and accuracy, while not losing a lot of information

• Issues:

- Intense dataset (a lot of samples)
- Hard to find good predictors
- Hard to find a direction

Future Work

- Neural Network and Random Forest faster, still lack a little in accuracy
 - Perhaps ML algorithms could be improved or simplified
 - Make it more accurate and keep speed of algorithm?
- Make predictions with varied ML algorithms
- Improve feature selection accuracy
 - Maybe investigate why certain features selected

References

- https://scikit-learn.org/stable/modules/classes.html
- https://www.kaggle.com/datasets/sobhanmoosavi/us-accidents
- https://www.iihs.org/topics/fatality-statistics/detail/state-by-state
- https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0262941