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Kicked Car Predictions

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# 0. Introduction

When you go to an auto dealership with the intent to buy a used car, you want a good selection to choose from and you want to be able to trust the condition of the car that you buy. Auto dealerships purchase many of their used cars through auto auctions with the same goals that you have: they want to buy as many cars as they can in the best condition possible. The problem that these dealerships often face is the risk of buying used cars that have serious issues, preventing them from being sold to customers. These bad purchases are called “kicks”, and they can be hard to spot for a variety of reasons. Many kicked cars are purchased due to tampered odometers or mechanical issues that could not be predicted ahead of time. For these reasons, car dealerships can benefit greatly from the predictive powers of machine learning. If there is a way to determine if a car would be kicked ahead of time, car dealerships can not only save themselves money, but also provide their customers with the best inventory selection possible.

The following paper is split up into 3 main sections describing our approach to solve this problem: Early Interpretation, Data Parsing, and Machine Learning Algorithms. First we identified possible trends by simply graphing data. Next, we came up with strategies for dealing with missing data and data presented in a text format. Finally, we applied various machine learning algorithms to the parsed data set in an attempt to predict which cars would have the highest risk of being kicked.

# 1. Early Interpretation

We obtained our data set from the Kaggle.com challenge “Don’t Get Kicked” hosted by Carvana. Our first step was to graph the data we had to gain some initial insight into which features would be the most important. The features we were provided along with their descriptions are shown in Table 1.1.

|  |  |
| --- | --- |
| **Feature** | **Short Description** |
| RefID | Unique vehicle identifier |
| IsBadBuy | Was the car kicked? |
| PurchDate | Auction Purchase date |
| Auction | Auction provider |
| VehYear | Vehicle year |
| VehicleAge | Years elapsed VehYear |
| Make | Vehicle Manufacturer |
| Model | Vehicle Model |
| Trim | Vehicle Trim Level |
| SubModel | Vehicle Submodel |
| Color | Vehicle Color |
| Transmission | Vehicle transmission type |
| WheelType | Indicates type of wheel |
| VehOdo | Vehicle Odometer reading |
| Nationality | Manufacturer’s country |
| Size | (Compact, SUV, etc.) |

|  |  |
| --- | --- |
| PrimeUnit | Car has higher demand? |
| AcquisitionType | (Auction buy, Trade in, etc.) |
| AucGuart | Guarantee provided by Auction |
| ByrNo | Unique identifier for buyer |
| VnZip | Zipcode of car purchase |
| VnSt | State of car purchase |
| VehBCost | Acquisition cost to buyer |
| IsOnlineSale | Was this an online purchase? |
| WarrantyCost | Warranty price |

|  |  |
| --- | --- |
| **Feature** | **Short Description** |
| RefID | Unique vehicle identifier |
| IsBadBuy | 1 if vehicle was kicked and 0 otherwise |
| PurchDate | Data vehicle was purchased at auction |
| Auction | Auction provider |
| VehYear | Manufacturer’s year of the vehicle |
| VehicleAge | Years elapsed since manufactured |
| Make | Vehicle Manufacturer |
| Model | Vehicle Model |
| Trim | Vehicle Trim Level |
| SubModel | Vehicle Submodel |
| Color | Vehicle Color |
| Transmission | Vehicle transmission type |
| WheelType | Indicates type of wheel |
| VehOdo | Vehicle Odometer reading |
| Nationality | Manufacturer’s country |
| Size | Size of the vehicle (Compact, SUV, etc.) |
| TopThreeAmericanName | Is manufacturer one of top three? |
| MMRAcquisitionAuctionAveragePrice\* | Average condition value at auction time |
| MMRAcquisitionAuctionCleanPrice\* | Great condition value at auction time |
| MMRAcquisitionRetailAveragePrice\* | Average condition retail value at auction time |
| MMRAcquisitionRetailCleanPrice\* | Great condition retail value at auction time |
| MMRCurrentAuctionAveragePrice\* | Average condition value currently |
| MMRCurrentAuctionCleanPrice\* | Great condition value currently |
| MMRCurrentRetailAveragePrice\* | Average condition retail value currently |
| MMRCurrentRetailCleanPrice\* | Great condition retail value currently |
| PrimeUnit | Identifies if car has higher demand |
| AcquisitionType | Identifies Auction buy, Trade in, etc. |
| AucGuart | Level of guarantee provided by Auction |
| ByrNo | Unique identifier for buyer |
| VnZip | Zipcode where car was purchased |
| VnSt | State where car was purchased |
| VehBCost | Acquisition cost paid for the vehicle by buyer |
| IsOnlineSale | Was this an online purchase? |
| WarrantyCost | Warranty price (36 month and 36k millage) |