Used Car Market Analysis

How much is my car worth? Which cars are good investments?

More shoppers today are likely to cite reliability (41% vs. 35% in 2022), finding a vehicle that fits their budget (40% vs. 33% in 2022), and expected costs (26% vs. 21% in 2022) as the most important factors in selecting a vehicle... with 89% saying they'd be willing to switch models and 69% open to switching brands.

— Car Guru Consumer Preferences Survey

Used car buyers want a vehicle that will last them as long as possible without spending money on costly repairs. Local demand for vehicles could vary a great deal: such as a higher or lower demand for luxury vehicles, or pickup trucks, or maybe a specific make or model. Manufacturers, additionally, can gain insights into which vehicles are more successful including the 'Where?' such as 'pickup trucks are in high demand across all regions' or 'Why?' such as 8 cylinder vehicles hold their value at high mileage more than 4 cylinder vehicles.

Data Wrangling

400k Used Vehicles Listings Craigslist (Feb 2021) - Kaggle

Categorical Data: manufacturer, model, cylinders, transmission, drive, title status, fuel type, size, type, condition, paint color, VIN, description, state, region
Numerical data: latitude, longitude, odometer, price

Data Problem 1: **User Entered Data**

- Incorrect information: ex: 8 cylinder car listed as 6 cylinders
- Unorganized: identical values entered slightly differently ex. Impala vs. Impala LT

Data Problem 2: **No Sale Price**

- Only Listed Price so there is more variance

Data Problem 3: **Duplicate Car Listings**

Other datasets could not address both problems. If a sale price was listed, the other columns were not robust enough to obtain insights into the vehicle.

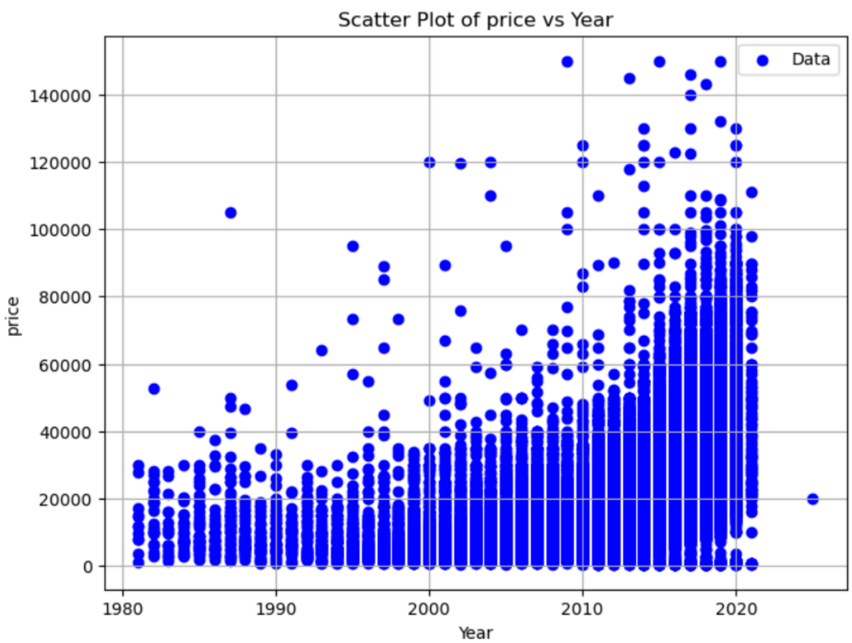
Solution: **VIN Decoder**

from NHTSA.gov

- **Removes Duplicates**, avoiding skewed predictions
- **Verifies and Organizes Features:**
    - Make
    - Model
    - Year
    - Cylinders
    - Engine Size - 3.0L Engine, 4.6L Engine, etc.
    - Fuel Type - Gasoline, Hybrid, Diesel
    - BodyClass - Sedan, Coupe, Convertible, Pickup, Van, Cargo Van, SUV, MPV
    - VehicleType - Truck, Car
    - Gross Vehicle Weight Rating (GVWR)

Notebook: Batch VIN Decoding
Notebook: Data Wrangling

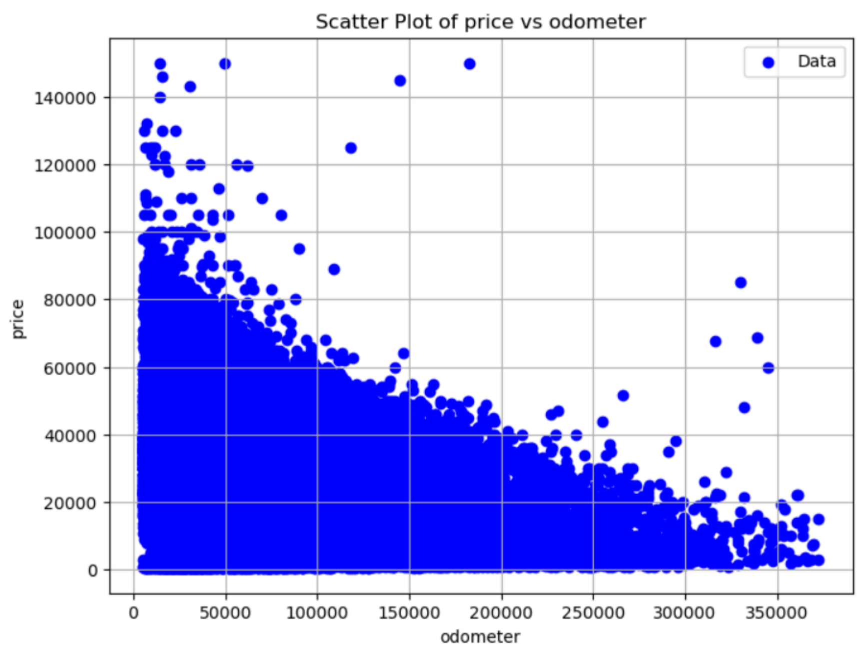
EDA



Mean Price: $19,000

Using 3 standard deviations to remove outliers was ineffective as it only removed prices above $76,000. Price outliers were difficult to spot because refurbished vehicles had high miles but were listed at high price.

Larger vehicles held their value despite being older and higher miles so there was not a consistent ratio of price to odometer or year.



Problem

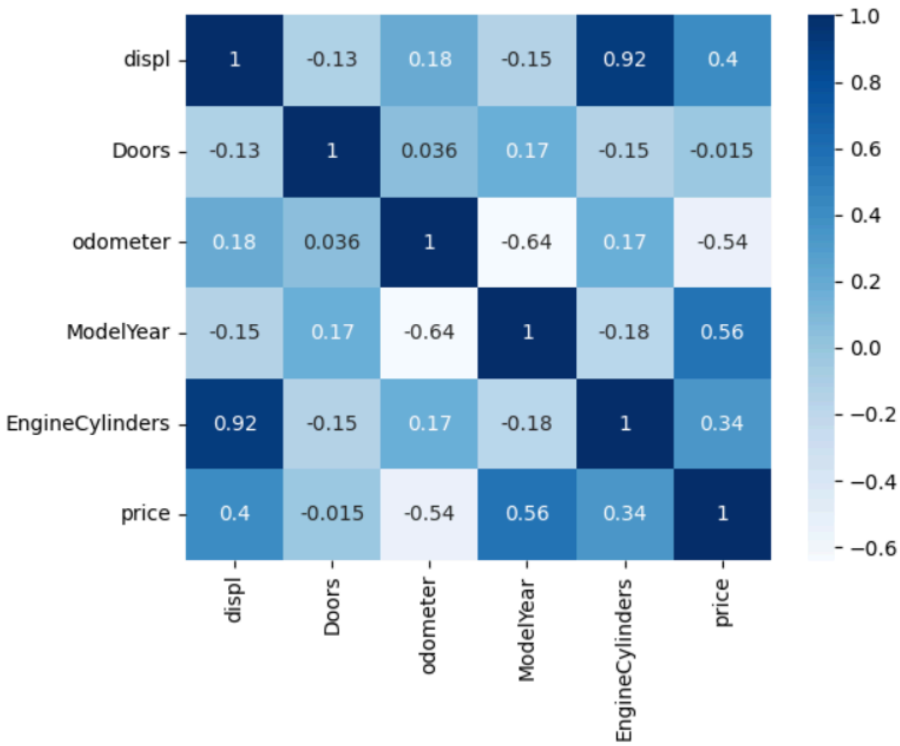
New Vehicles with Low Miles and Low Price

Many 2019-2020 Vehicles are priced between $0 and $20,000.

Cars with < 50,000 miles are priced < $20,000.

Way too many vehicles at all years and mileages are priced at near $0.

Odometer and Year are highly collinear. Older Vehicles tend to have more miles.



Scaled Correlation

(numerical features)

Model Year*:* 0.56

odometer*:* -0.54

Engine Size 'displ'*:* 0.4

Cylinders *:* 0.34

Doors*:* 0.015

Problem: Lack of Additional Vehicle Information

The same model of a vehicle may come in multiple configurations and levels that have a huge impact on price.

2012 Dodge Challenger

Trim	MSRP
SXT 2dr Coupe (3.6L 6cyl)	\$ 25,195
R/T 2dr Coupe (5.7L 8cyl)	\$ 29,995
SRT8 2dr Coupe (6.4L 8cyl)	\$ 44,125

Series and Trim columns were **~50% null.** Many new features, such as 'ABS' (anti-lock braking), were **75%** null.

```
AdaptiveCruiseControl
{'Optional': 4146, 'Standard': 3567, 'Not Available': 39}
nulls: 0.9143359154851757
```

```
ABS
{'Standard': 22507, 'Optional': 18}
nulls: 0.7510857193374073
```

Imputations

Rows: 93,031
Nulls Values for each Column:

1) **'Doors': 15,505**
   - Most were found to be BodyClass 'pickup'. The number of doors was found to always be 2 for regular cabs, and 4 for extended or mega cabs. Rest: imputed as 4 doors, which is the mode.
2) **DriveType (ex. RWD, FWD, 4WD): 26,070**
   - 5,000 were imputed using the value from craigslist 'drive column, 15,000 from the missing row's BodyClass & EngineCylinders 'DriveType' mode. Remaining 6,000 did not have EngineCylinders values and were imputed using as specific of information I could find: engine size, make, model, year, trim/series: mode.
3) **EngineCylinders: 8,493**
   - Mode was imputed, according to the vehicle's Make, Model, Year, and Engine Size.
4) **FuelTypePrimary: 3,149**
   - Referenced Engine Size for Pickup Trucks to find Diesel trucks. Mode Imputation: Gasoline
5) **GVWR: 924**
   - Mode Imputation: 6,000lb or Less
6) **'DisplacementCC': 828**
   - **Dropped**
7) **BodyCabType: 37,529**
   - Not Pickup trucks, Encoded as 'Not Applicable'
8) **EngineHP: 42,709**
   - Mean Imputation / Left as 'null' for LGBM, XGBoost, CatBoost
9) **EngineConfiguration: 42,709**
   - Mode Imputation based on Make/Model Combination's Mode Value

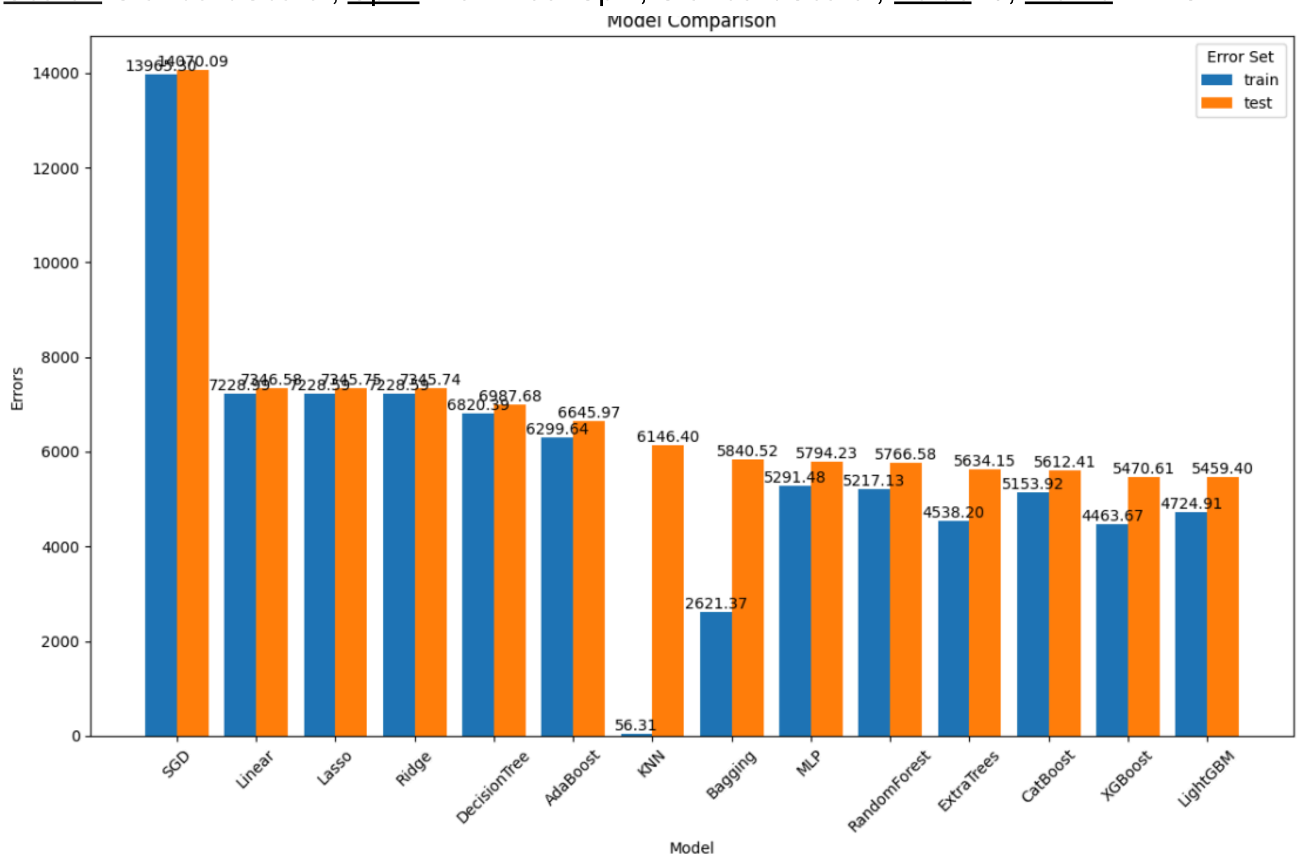
A big challenge for this project has been finding and implementing clean datasets that can increase the feature set for making better predictions. It is a data engineering problem to implement automated cleaning algorithms for the VIN Decoder output as well as the creation of clean datasets that can be referenced to input correct information.

Notebook: EDA

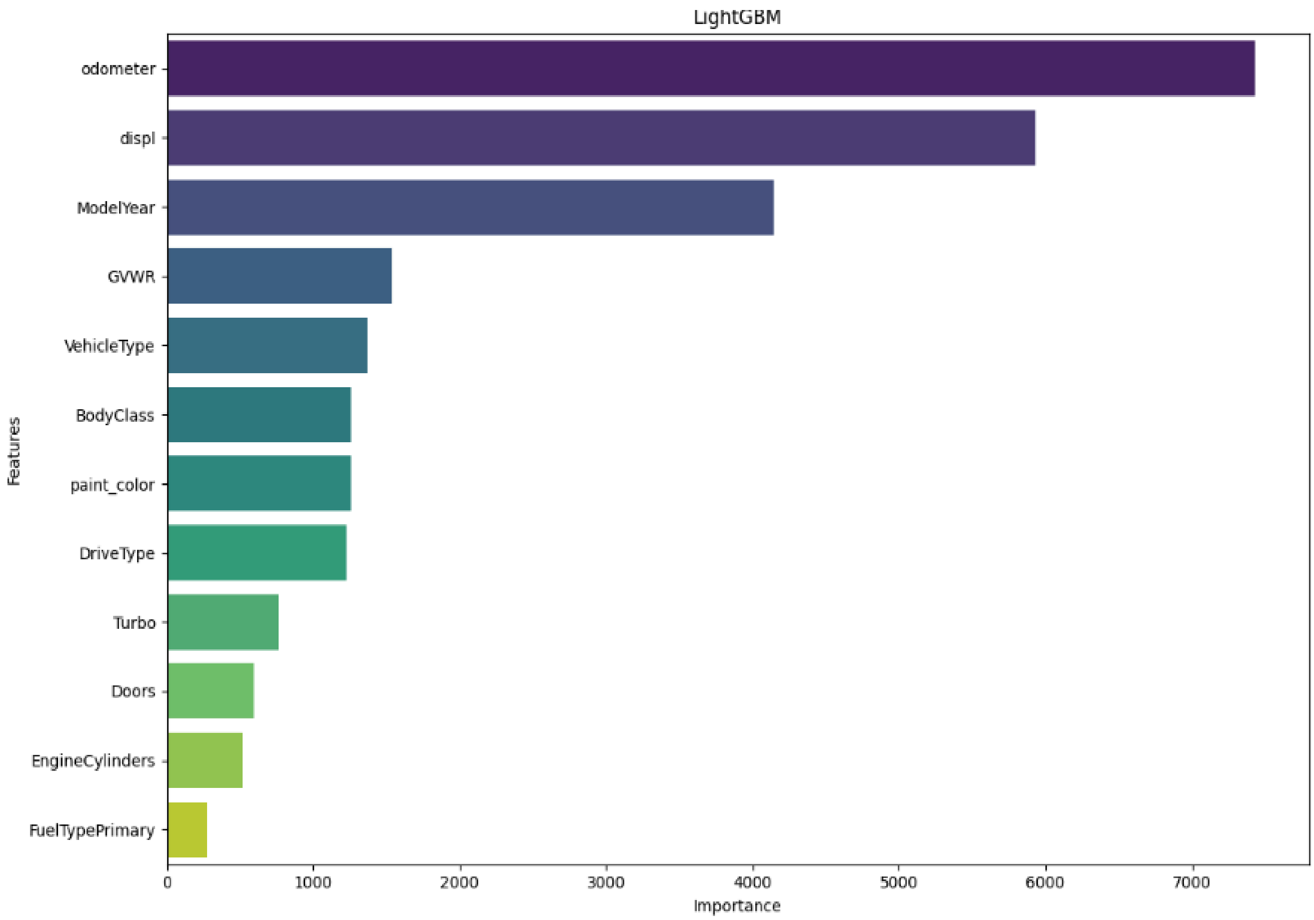
Modeling

Features Used:
Categories: 'Turbo', 'BodyClass', 'FuelTypePrimary', 'EngineCylinders', 'VehicleType', 'DriveType','GVWR', 'Doors', 'paint_color'
Numerical Data**:** 'odometer', 'ModelYear', 'displ'

Scaler: StandardScaler, Split: Train Test Split, StandardScaler, Folds: 3, Metric: RMSE



Test RMSE: $5459.40



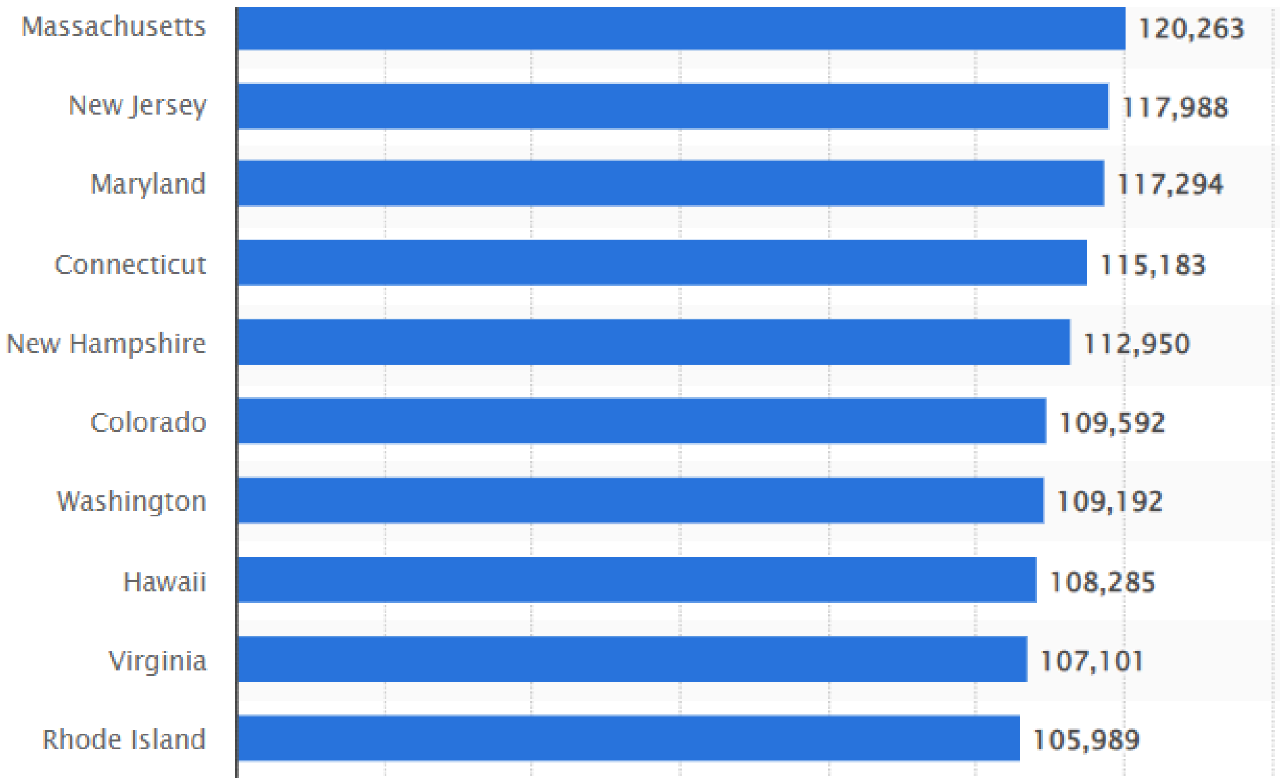
Odometer, displ (enginesize/displacement) and ModelYear proved to be the top Features throughout the entire Modeling process.

Local Economic Factors

How important is the specific Make/Model of the vehicle as opposed to competing Makes and Models that share the same BodyClass, Engine Size, EngineCylinders, and other features?

Does the specific state/region affect the local market for vehicles?

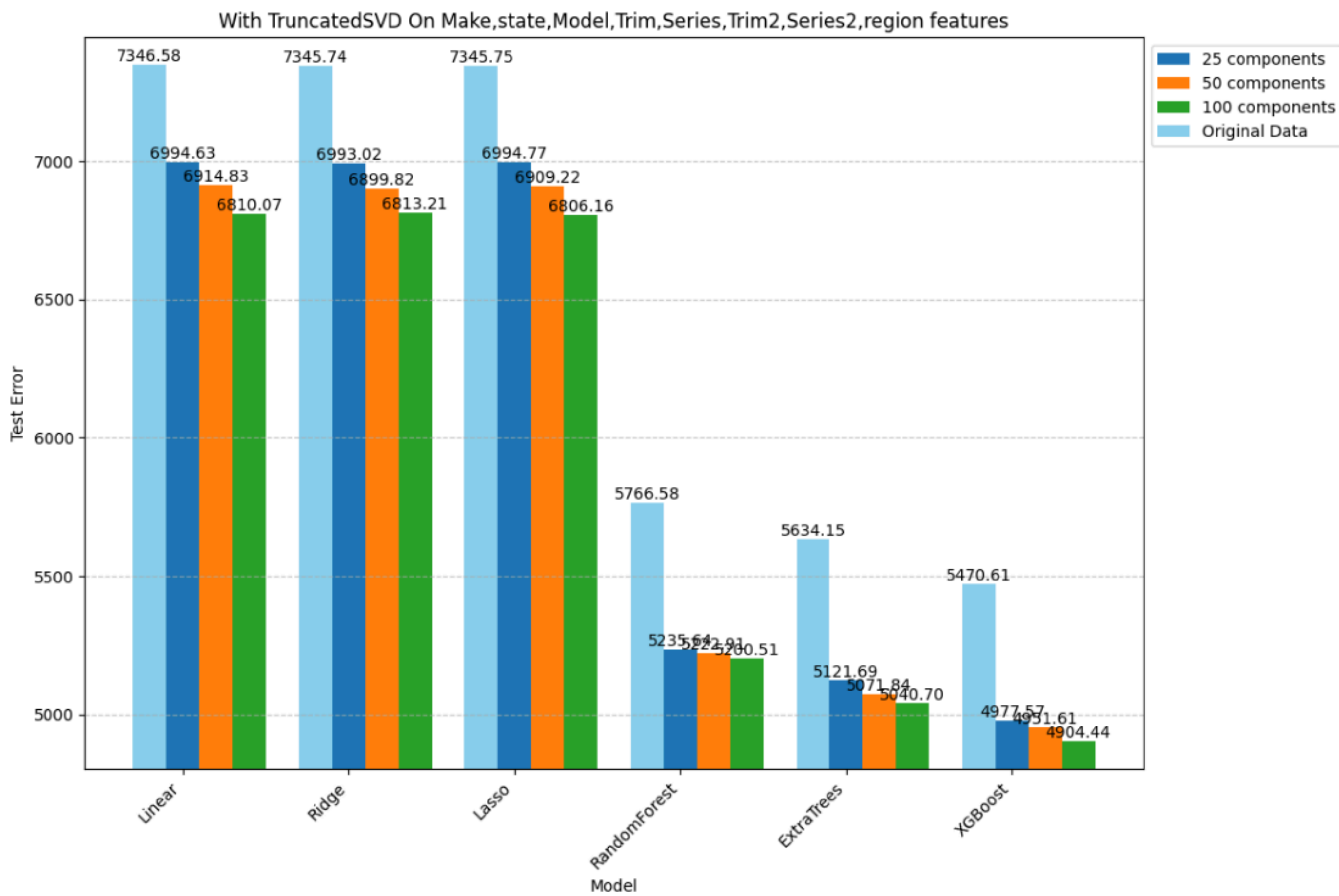
[2021 Median state Income]



	feature	unique_vals
4	Series	1748
3	Trim	1737
2	Model	815
7	region	399
6	Series2	184
5	Trim2	76
0	Make	57
1	state	51

New Features

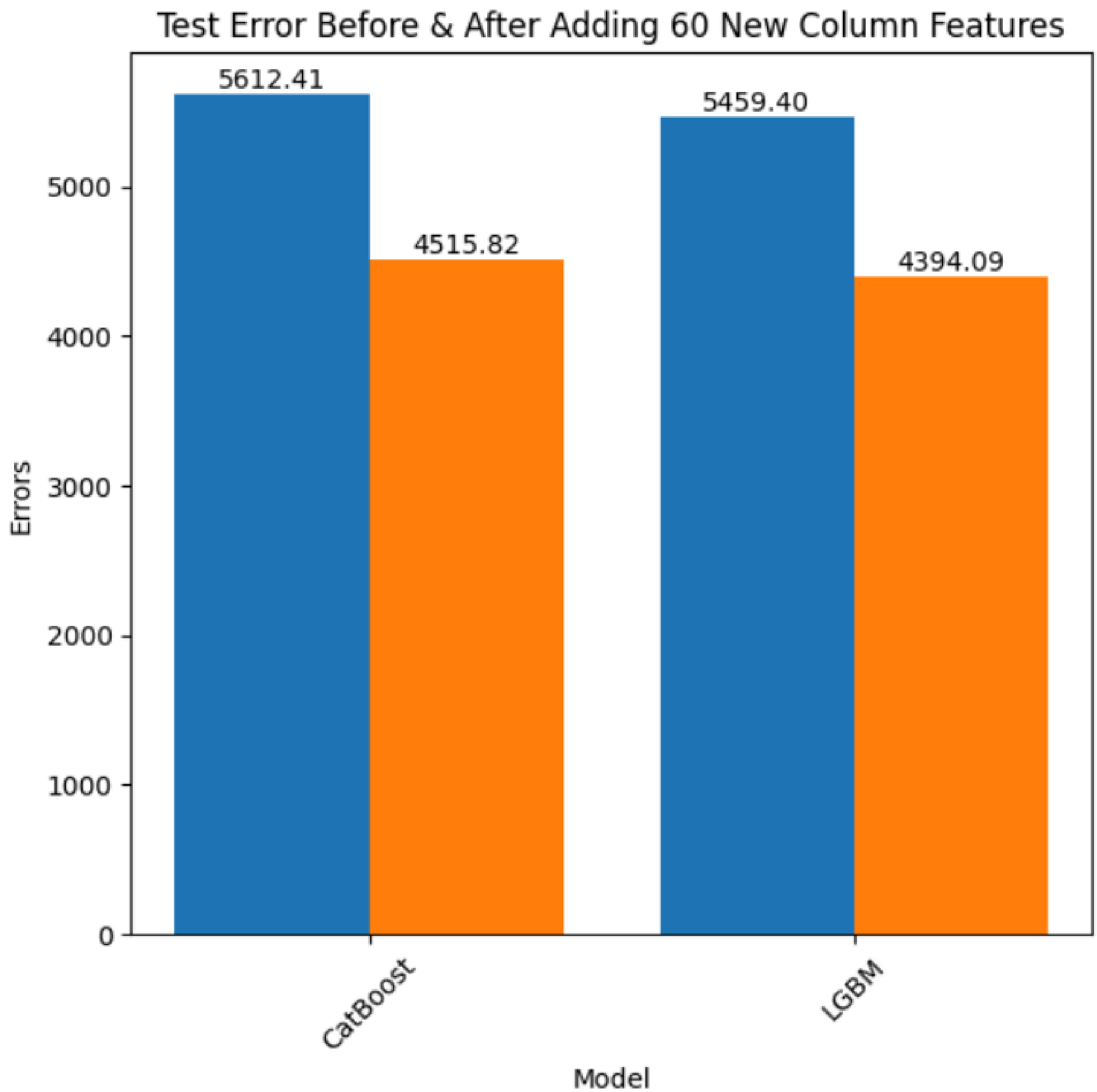
These columns introduced **5,067** new features. TruncatedSVD ‘squashed’ the variance of these columns into < 100 components, and the results were compared to the results without these features, seen above.

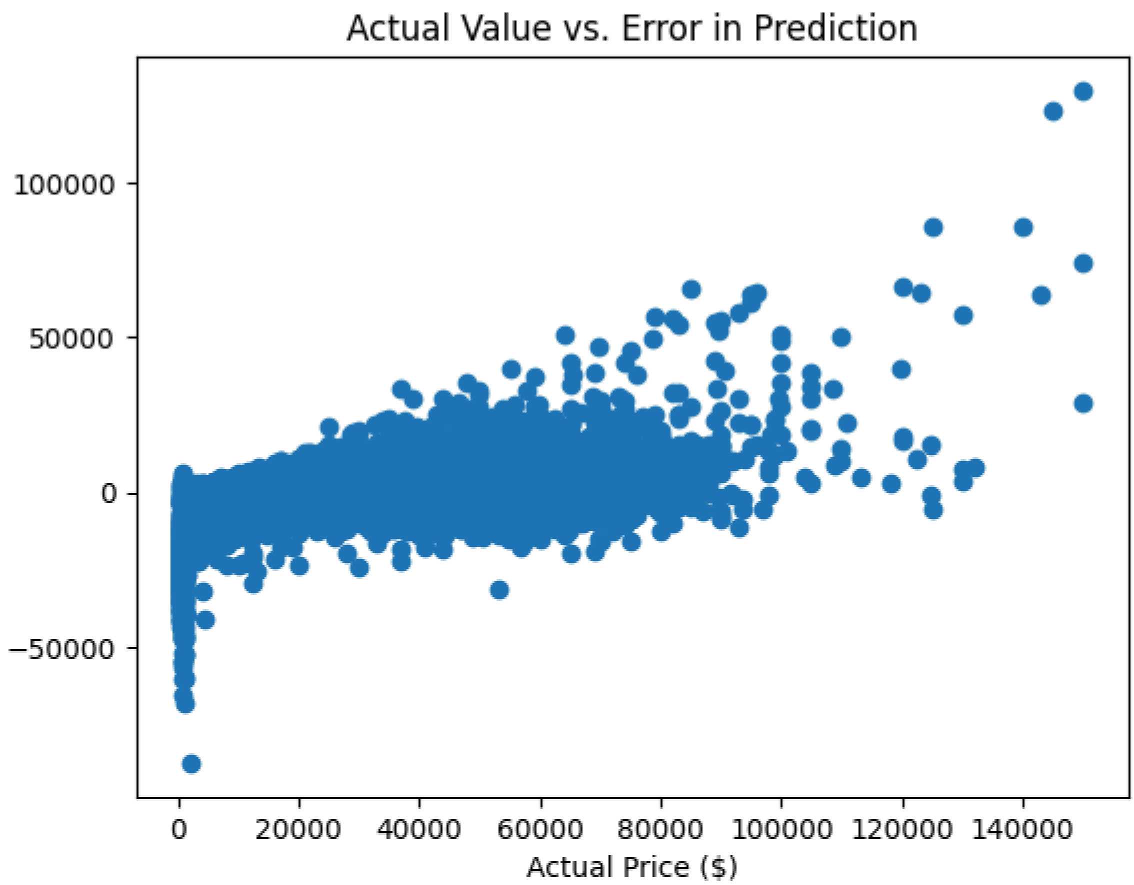


RMSE decreases about 7.5% when squashing variance down to 100 components.

Final Models: CatBoost & LightGBM

- These two models do not require dummy variable encoding.
- CatBoost finds the relationship between categorical variables using integer encoding, which has proven upsides.
- LightGBM performs feature selection within the training process. These are naturally a good fit for the dataset which has a large number of sparse, inconsistent categorical variables.





While it makes sense for errors to increase as the price increases. Vehicles priced below **$5000 should not be estimated to be $50,000** or more. The deviation from the larger trend can be seen in the bottom left of the graph as the dots fall in a straight line.

The dataset came with a ‘description’ column that confirmed the presence of:

1. 'Down Payment' in 'price' Listings

These are generally newer vehicles that are higher-end, and the dealer has listed just a portion of the total price in the 'price' column. Exploring the 'description' column of high percentage errors can confirm there are hundreds of these listings, with errors in prediction sometimes above 4000% and listed prices generally below $3000. These listings are best **removed** from the dataset

2. Significantly Damaged Vehicle Listings

These vehicles show very similar errors as the 'Down Payment' listings. Typically listed for $5000 or less. The description will contain words such as: 'sold as-is', 'doesn't run', or 'for parts'. These listings are best **removed** from the dataset

Other Large Errors:

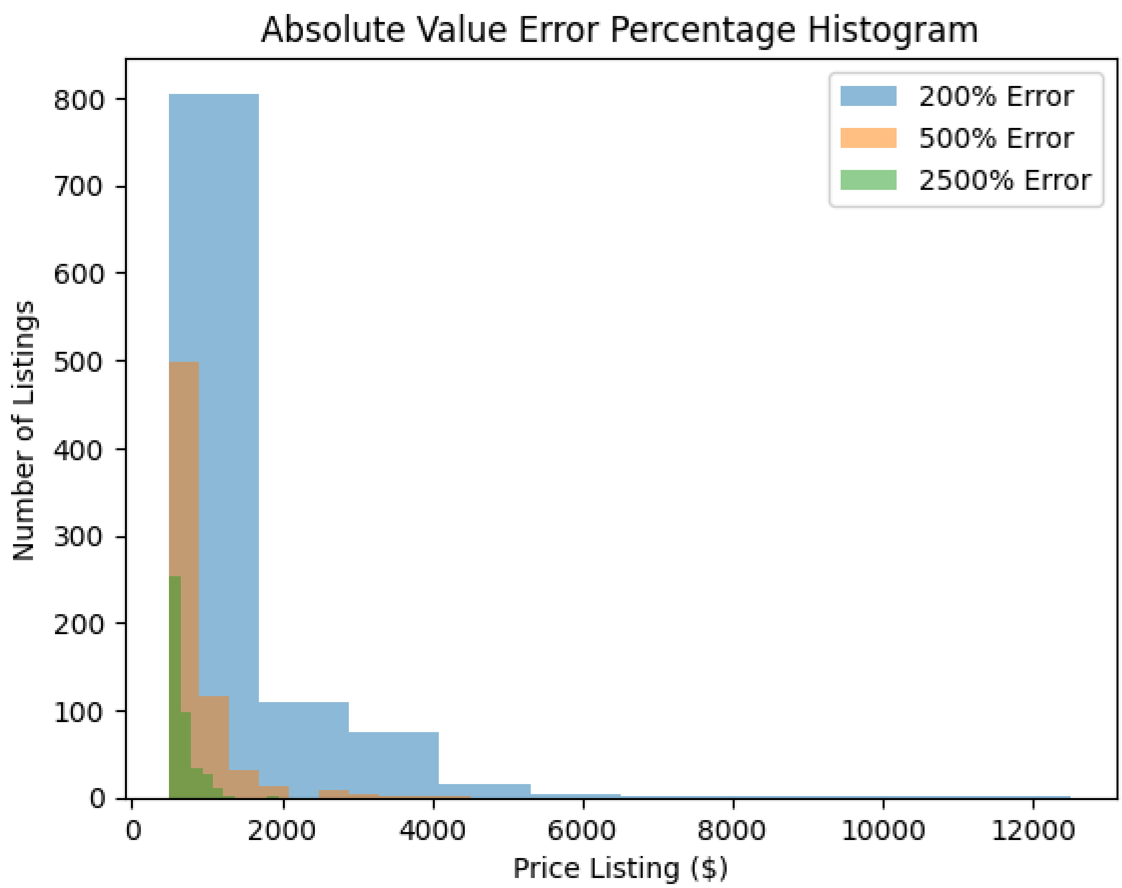
3. Significantly Modified Vehicles

These are vehicles where the car owner put significant investment into upgrading various aspects of the car appearance. The error percentage was not quite as high, with the list price being just a tad above average. Frequently, listings were sports cars and convertibles.

4. Cargo Vans

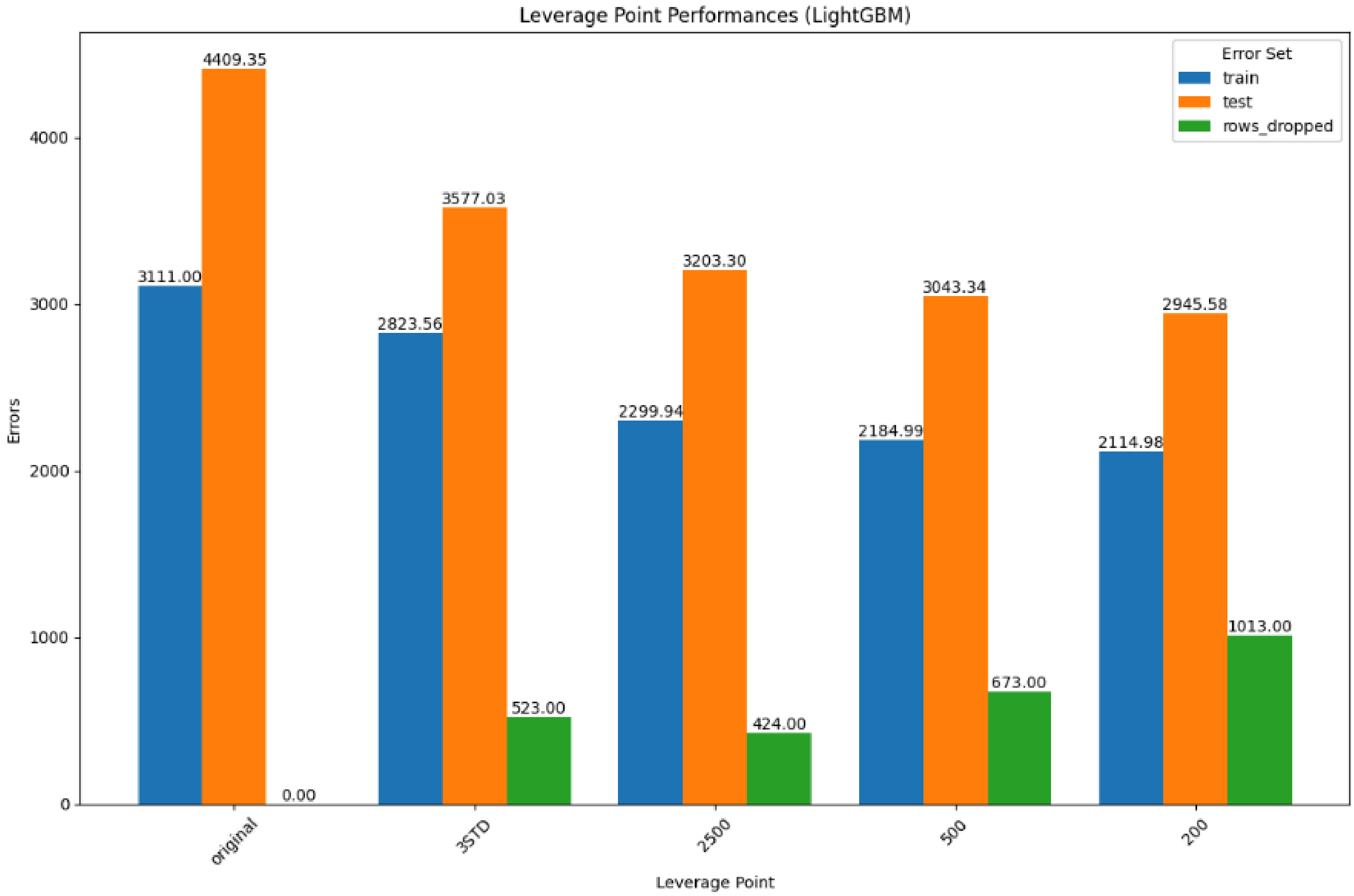
These listings showed high errors as they were a minority of the dataset. It may be that there is a high variance to the depreciation on liveable vehicles such as RVs and Vans, either holding their value despite high miles, or wearing down and requiring significant upkeep investments to maintain the vehicle. Future explorations of this data should involve SMOTE on Vans and Cargo Vans to train on balanced classes.

```
Number of Listings with |200| % prediction error or more: 1013
Number of Listings with |500| % prediction error or more: 673
Number of Listings with |2500| % prediction error or more: 424
```



Spam Detection

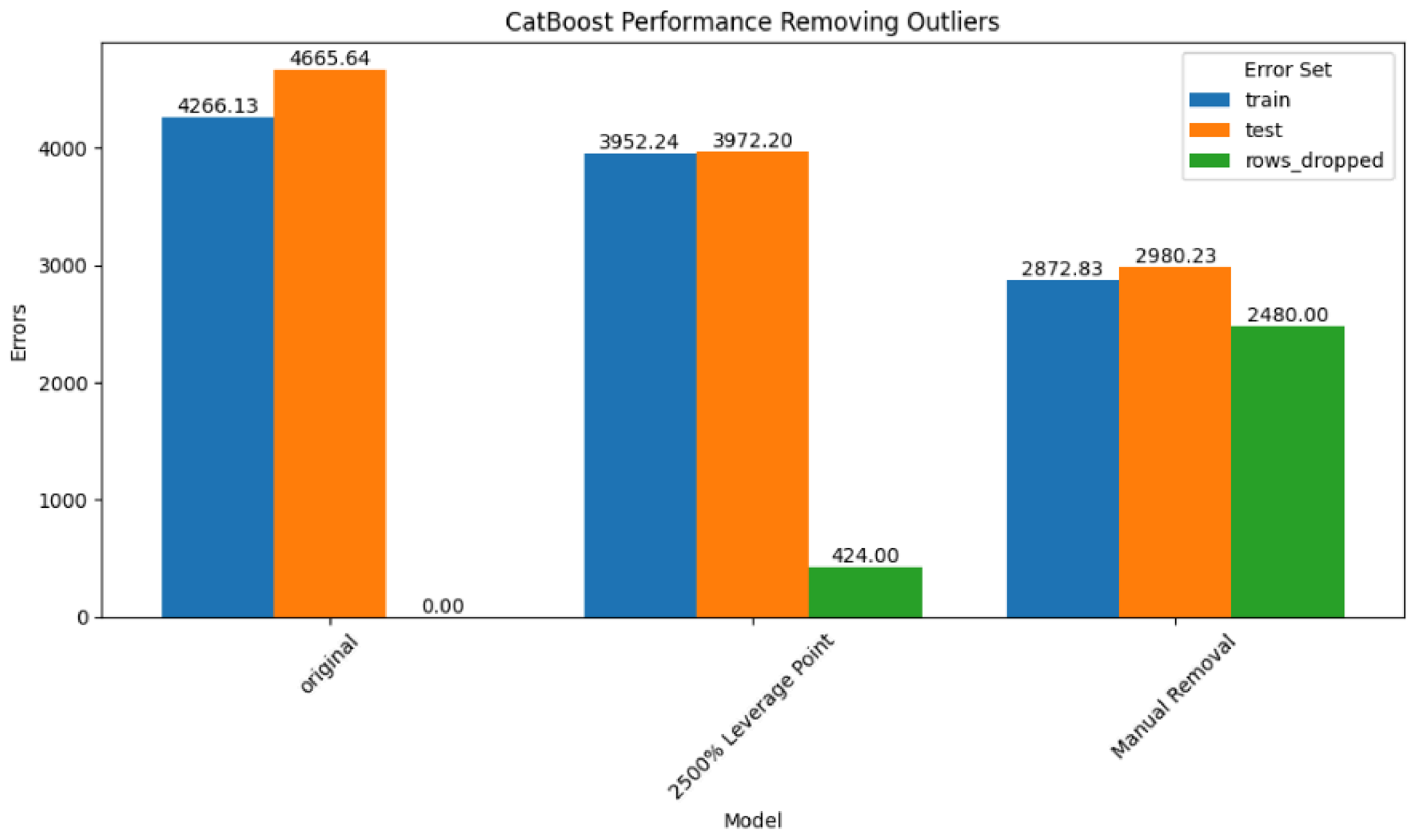
3 Standard Deviations from Mean Absolute Percentage Error
vs.
200%, 500%, 2500% or greater Absolute Percentage Error



Simply using a >2500% Percentage error threshold **retained 99 more rows** of data, while **improving error reduction by over $300**

Manual Outlier Identification:

By running numerous tests, similar to the above, and inspecting 'description' columns for indications of cars that did not run or cars that were listed as down payment or cars with heavy modifications, **2480** rows were removed.



This **reduced $0.50 in errors per row**.

Notebook: [Modeling]

Feature Importances:

Top 10 Overall Feature	Importance
TractionControl: **Standard**	0.1523
RearVisibilitySystem: **Standard**	0.0674
SemiautomaticHeadlampBeamSwitching: **Standard**	0.0522
BodyCabType: **Crew/SuperCrew/CrewMax**	0.0500
ESC: **Standard**	0.0401
BodyClass: **Pickup**	0.0251
FuelTypePrimary: **Diesel**	0.0257
EngineCylinders	0.0186
VehicleType: **Truck**	0.0120
DayTimeRunningLight: **Standard**	0.0120

Top 5 Makes	Importance
Porsche	0.003383
Jeep	0.002809
Land Rover	0.002344
Mercedes-Benz	0.001840
RAM	0.001834

Top 5 Models	Importance
Porsche 911	0.005904
Jeep Wrangler	0.004085
Acura TLX	0.003151
GMC Sierra HD	0.002492
Cadillac XT6	0.002194

Depreciation Curve Experiment Procedure:

Train model without state, region, state_income.

Based on feature importance of a specific Model/Series/Trim, identify most similar vehicles to each unique vehicle (drop duplicates, subset on: control columns plus series/trim).

'Control' columns: displ, Turbo, VehicleType, GVWR, BodyCabType, EngineCylinders, BodyClass, & ModelYear

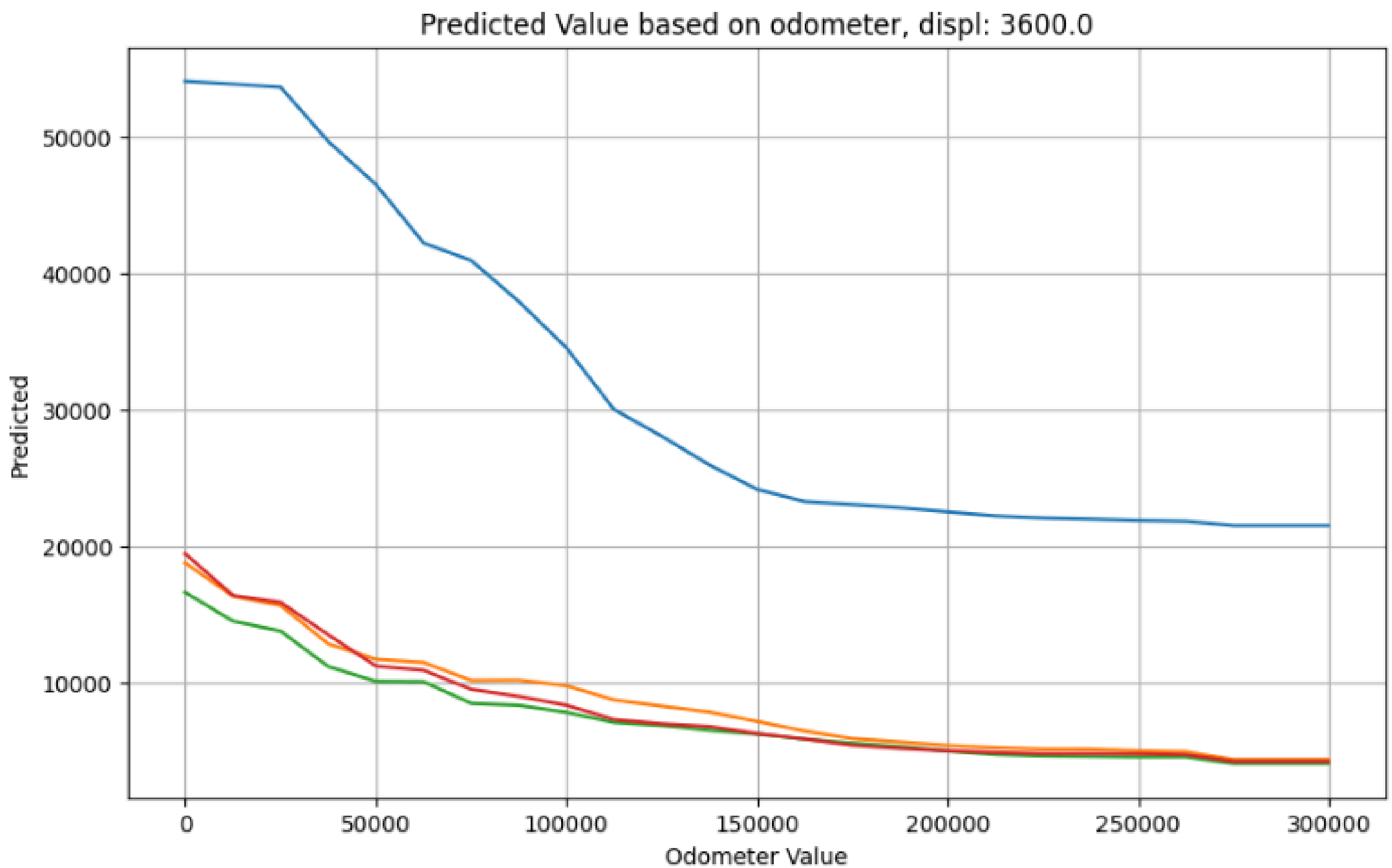
Variable: Odometer: 0 to 300,000 miles, new row every 12,500 miles

Create predictions for each vehicle at each odometer reading

Plot results

Porsche 911

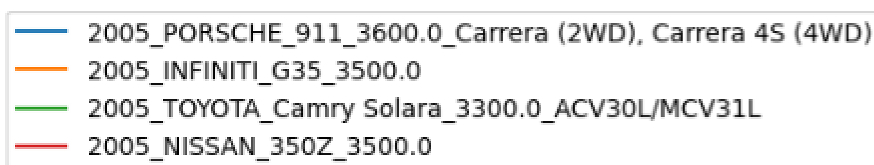
2005



MSRP

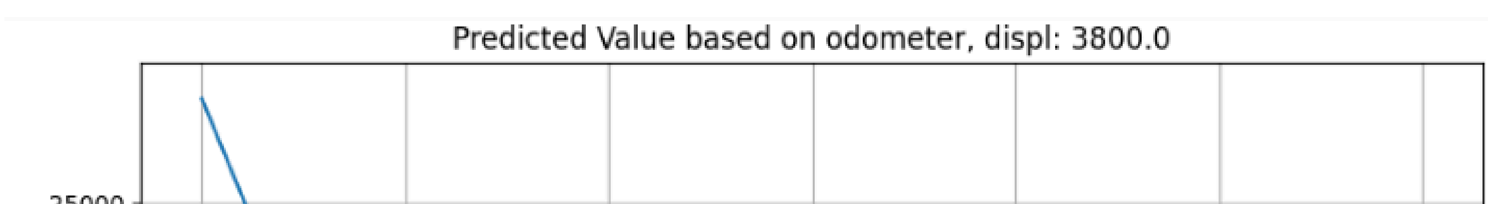
[Porsche 911](#) - $83,400

[Infiniti G35](#) - $30, 700



Jeep Wrangler

2007 - V6



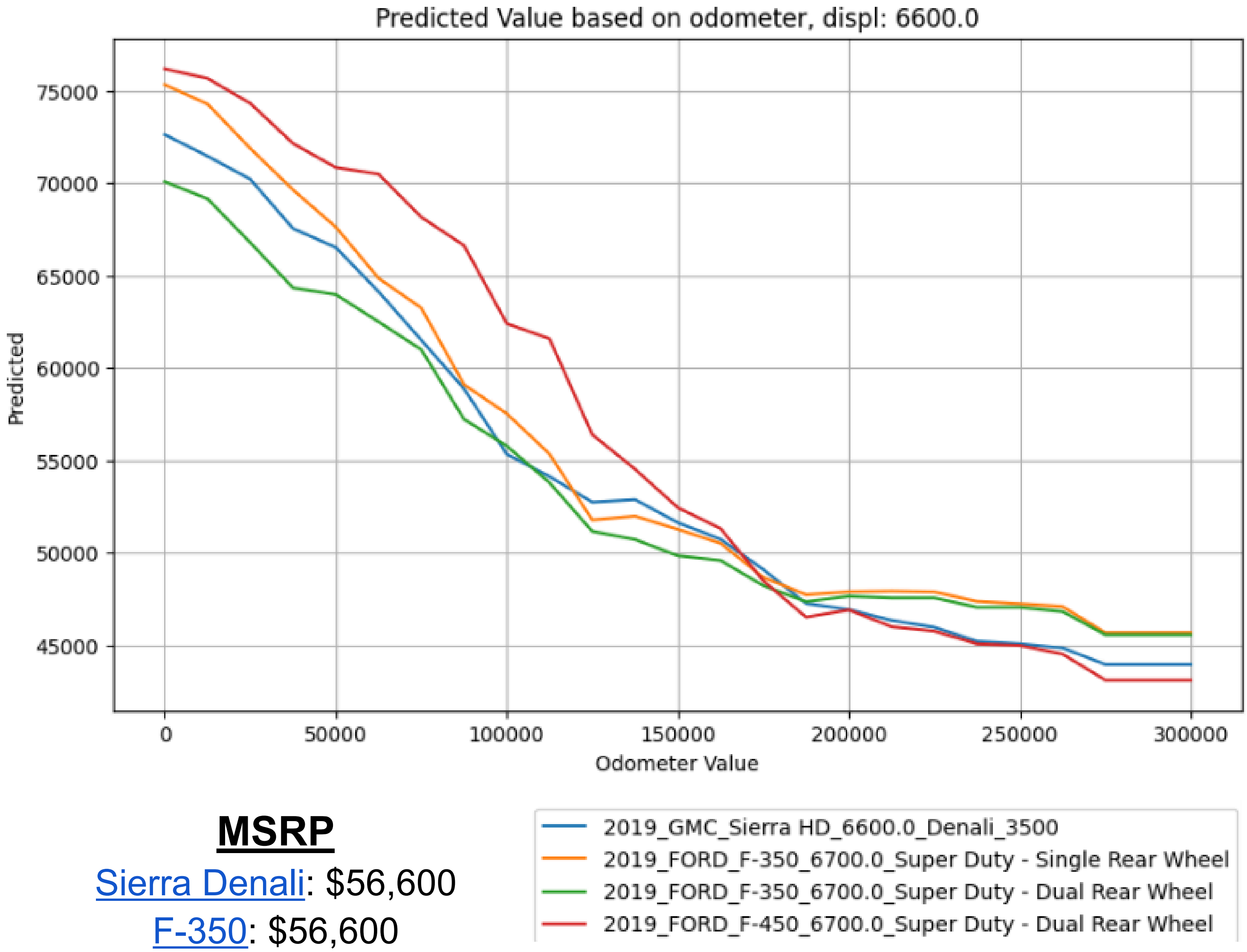
MSRP

Wrangler (Unlimited X): $22,530

Pathfinder: $25,000 - $31,000

GMC Sierra HD

2019 - 6.6L Turbo Diesel



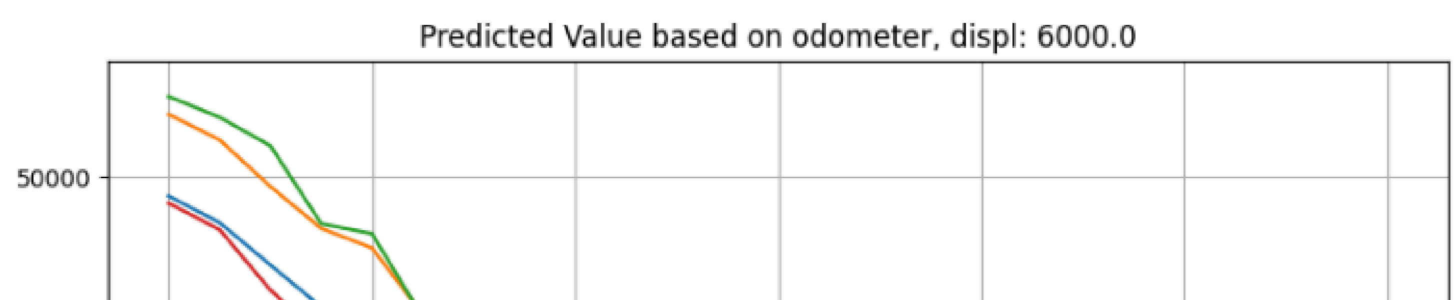
<u>MSRP</u>

Sierra Denali: $56,600

F-350: $56,600

F-450: $56,600

2019 - 6.0L Diesel

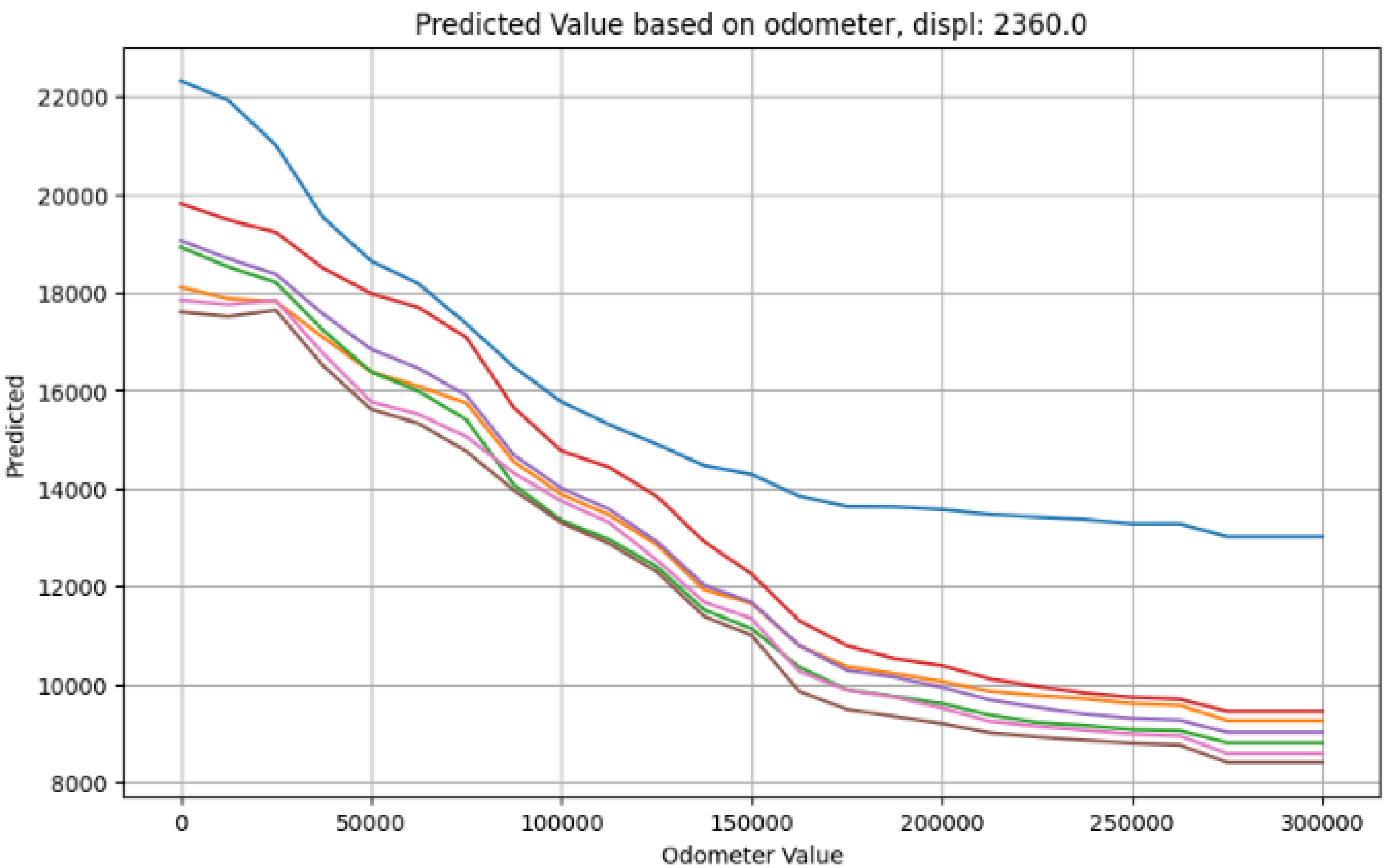


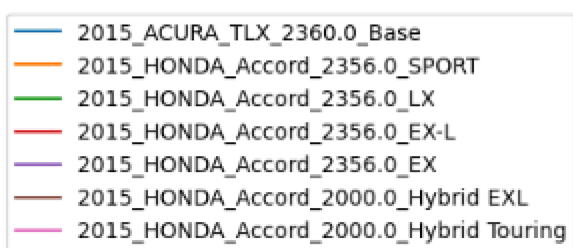
MSRP

Ram 2500 Tradesman: $39,850
Sierra 2500 Fleet: $40,000
Ram 2500 BigHorn: $42,100
Ford F-250 SuperDuty: $43,000

Acura TLX

2015 - V4



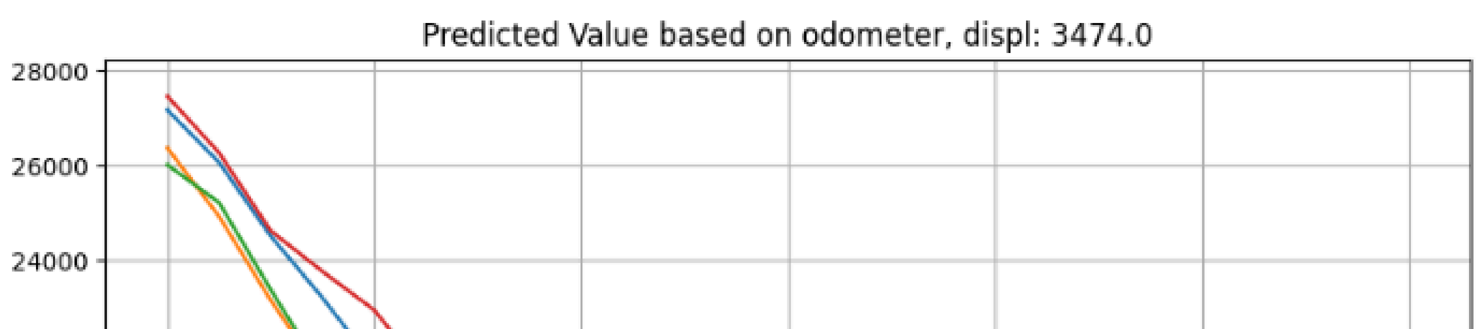


MSRP

TLX: $31,450

Accord EX-L: $28,400

2015 - V6

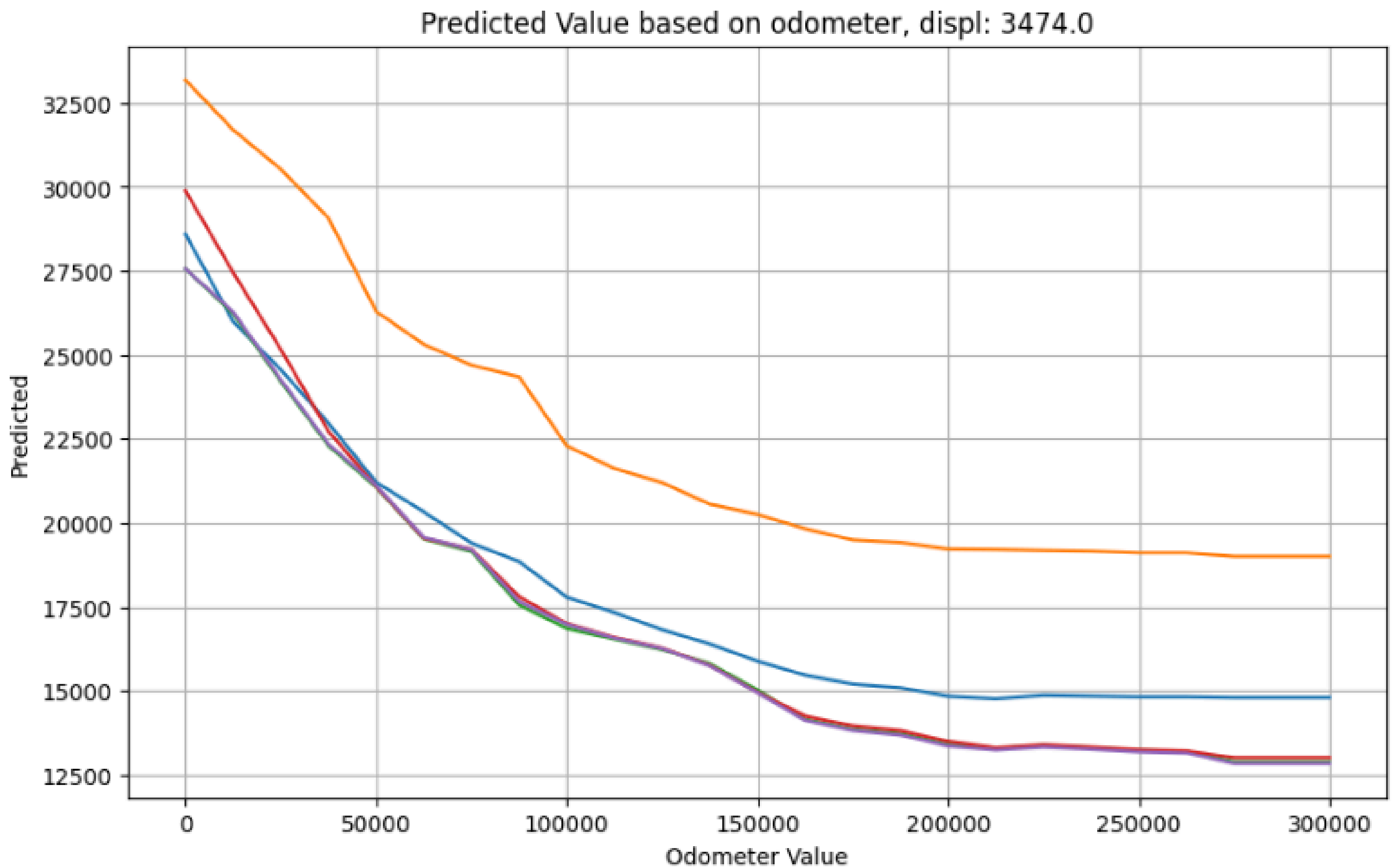


MSRP

RLX: $48,450

TLX: **$35,320**

2016 - V6

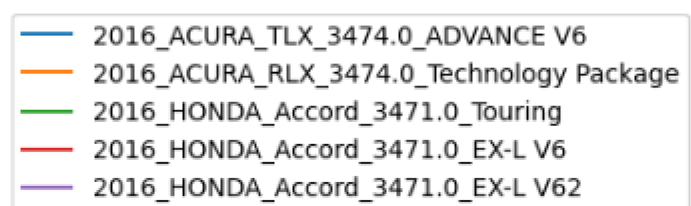


MSRP:

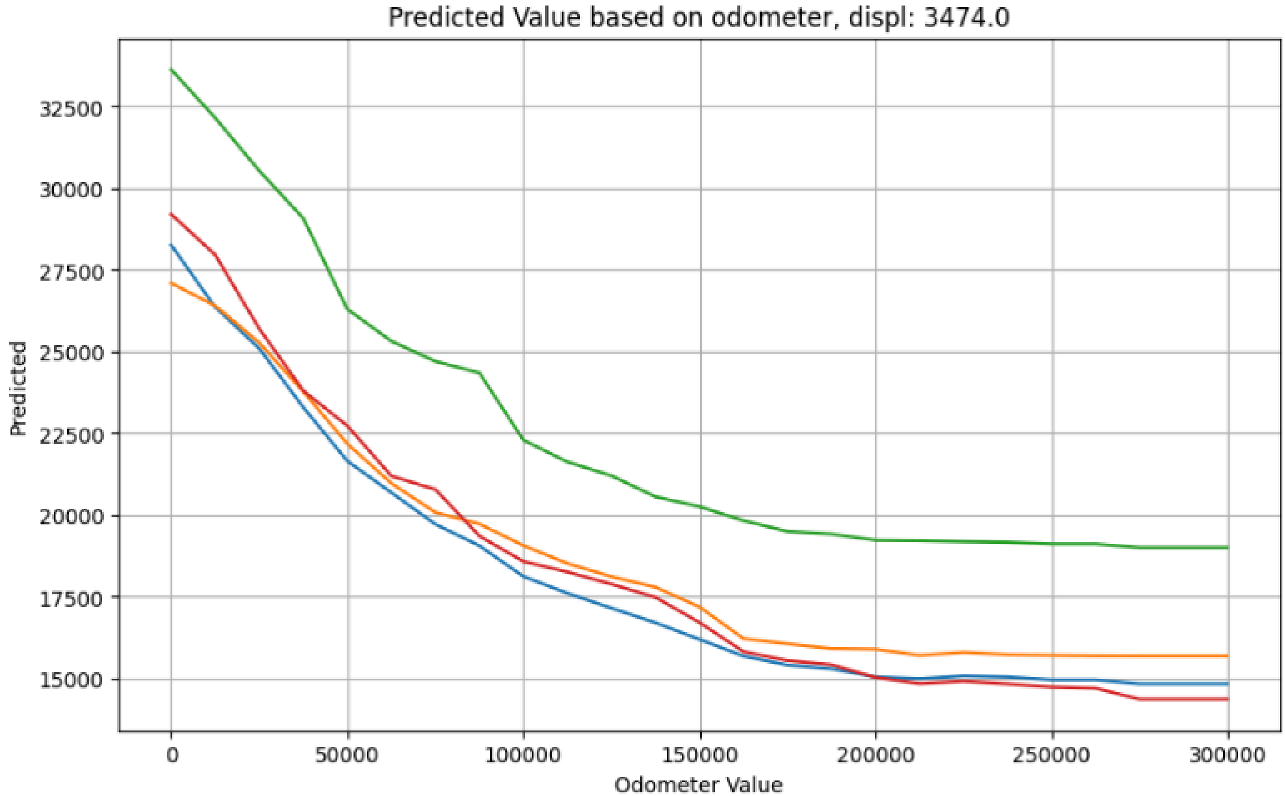
TLX Advance: $42,600

RLX Tech: $54,450

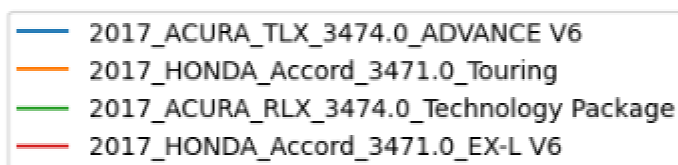
Accord EX-L: $30,740



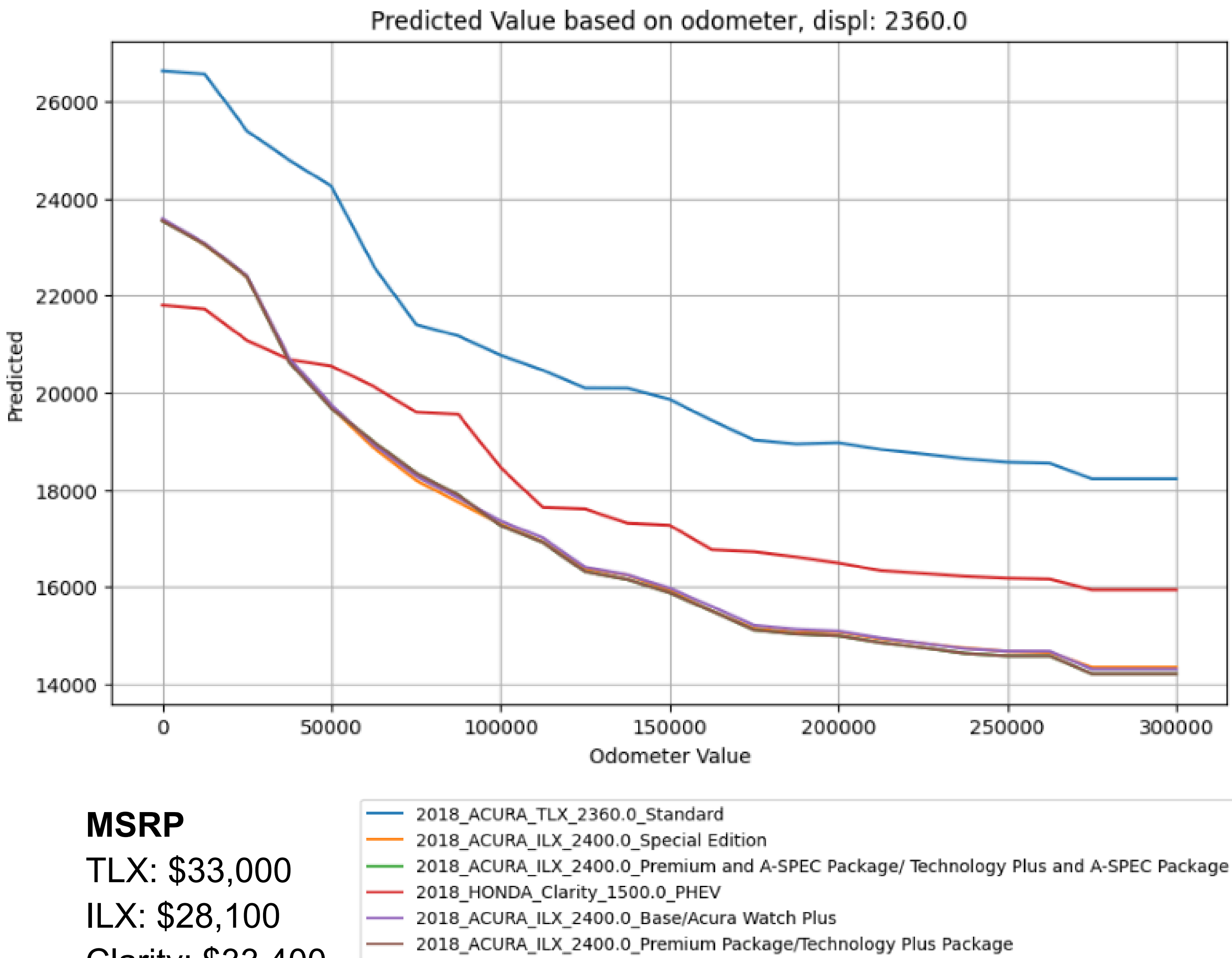
2017 - V6



MSRP:
[TLX Advance]: $42,700
[RLX Tech]: $54,450



2018 - V4



MSRP

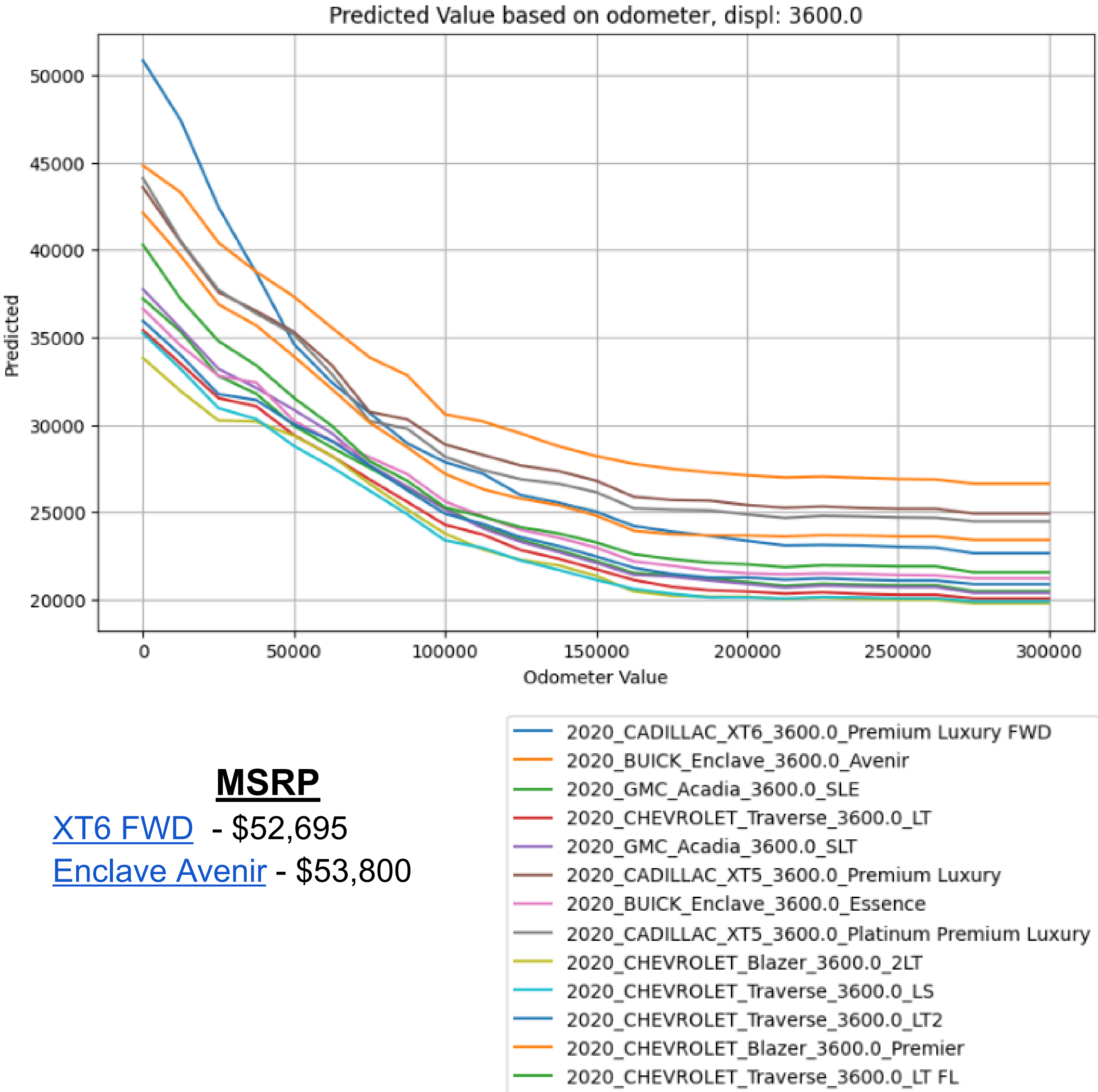
TLX: $33,000

ILX: $28,100

Clarity: $33,400

Cadillac XT6

2020



MSRP

XT6 FWD - $52,695
Enclave Avenir - $53,800

Future Work

Data Cleaning/Engineering: Imputations

Series and Trim offerings can **double** the price of a vehicle, even with the same Make/Model/Year. The VIN API output, for this dataset, had 50% null values. The other problem: some series values were in 'Series' column, some were in 'Series2' columns.

2015 Chevrolet Silverado

Series options:
- 1500,
- ½ Ton,
- 1500 (½ Ton),
- And more!

Trim options:
- LT
- LT (Work Truck)
- Work Truck
- Work Truck/Fleet/Base

The data required so much cleaning per make/model combination and many vehicles had changing trim and series offerings based on generation. This required a lot of research to determine which groupings were the same, such as:
1500 ,½ ton , 1500 (½ ton) => '1500'

Data Scraping

The main reason cleaning Series & Trim column data is important is not for the models predictive capability, but to **obtain new features** for each vehicle such as:
- MSRP
- Fuel Economy
- Horsepower & Torque
- Towing Capacity
- Safety/Luxury Features

MSRP alone would probably **decrease errors** to $1000 or less per car.

Matching up the unique values found from the NHTSA VIN decoding with those found on car specification websites is a task in itself, and would require a lot of time and effort, but would be vital to bring a data-driven car pricing tool to production.

Spam Detection

Looking for keywords such as ‘as-is’, ‘doesn’t run’ or ‘down payment only’ is not sufficient as frequently wordings are more nuanced than these things. Using a spam detection model could be beneficial on the description columns. Frequently, comparing the listed price to the word that comes before ‘down’ as in ‘$200 Down!’ indicated a fake listing.