

EAGLE FANG DATA CONSULTING

Team 36: Final Presentation

Authors: Andrew Bartels, Jason Young, Matt Palmer, Ngoc Nguyen, Shawn Azzu

Where have all the cheap cars gone?

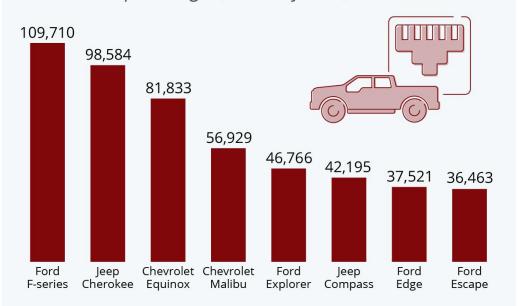
- Customers no longer have an upper-hand
- In the past, the moment a car was driven off the lot, the price would immediately depreciate.
- ► A car's price would be cut in half after just 3 years.
- ► This is no longer the case.

Problem/Background

- Huge Microchip Shortage over the past few years has resulted in decreased car production for new models
- This has increased the price of new and used cars, but has turned more buyers to look at the secondhand market

The U.S. Car Models Worst Hit By The Microchip Shortage

Estimated number of vehicles taken out of production due to microchip shortages (as of May 2021)



Source: Automotive News via Car and Driver









Project Task and Introduction

- ► Penske Motorgroup, LLC has hired Eagle Fang Data Consulting to investigate arbitrage opportunities in the used car market
- ➤ Our task is to create models that will predict used car prices in various regions in the U.S
- ► We have built in app that will enable our clients to easily identify and compare prices



Automotive

Research and Background

- Our Research has shown us that when keeping the mileage, model, and year constant, location has an impact on car price in two ways:
 - ▶ Impact on car based on environment: weather and terrain
 - Car Price fluctuation based on regional economics:
 - Regional Economic Variables indirectly influences cars' value and the overall state of the usedcar market
 - With this knowledge we utilize multiple linear regressions, regressing price on regional and economic variables
- ► The Cost of Driving comes from gas and general maintenance and car price depreciation is exponential within the first 2 to 3 years
 - From then, decline in price is seen to be more gradual
 - ▶ The depreciation is related to miles on the car, we have this variable as Odometer

Approach and Methodology

Data Preparation and Cleaning

- Primary Cars Dataset contains 426,880 observations and 22 explanatory variables.
- The complementary datasets that we combined with our car table include economic data pulled from the 2020 census as well as outdoor recreation data by state from 2021.
- For the first step of the cleaning process, we wrote the tables to an SQLite3 database for lightweight storage and efficient use between team members.

Approach and Methodology

Cleaning Challenges

- Handling NA Values (1,688,231 NA values!)
- Mapping income to cities extract ZCTA codes
- Extracting missing information like Manufacturers & Models from description
- Discrepancies (ex. old vehicles with low mileage)

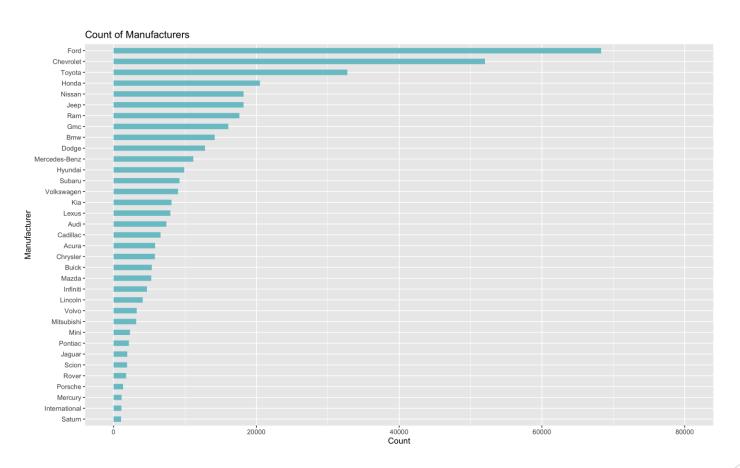
Year Manufacturer	# NA Values	% <u>of</u> Observations	Amt. Recovered	
Year	1,205	28%	1,184	
Manufacturer	17,646	4.13%	11,975	
Paint color	130,203	30.5%	37,758	

Variable	# NA Values	% <u>of</u> Observations	Amt. Recovered
Туре	92,858	21.75%	23,214
Drive	130,567	30.59%	12,998

Exploratory Data Analysis

Strategy: Select top 5 Manufacturers

Focus on cleaning the data so that we could build clean visualizations and have accurate models



Analysis and Visualizations

Strategy: Create Regional Comparison

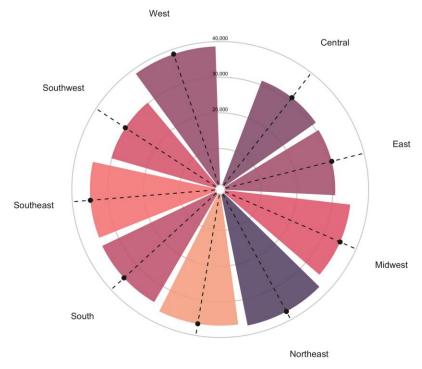
Ultimately, we wanted our client to be able to compare vehicle prices between different parts of the country

We segmented the dataset into 9 key regions:

- 1. West
- 2. Southwest
- 3. Central
- 4. Pacific Northwest
- 5. Northeast
- 6. Southeast
- 7. Midwest
- 8. South
- 9. East

Average Price for 2018 Ford F-150

Comparison Between US Regions

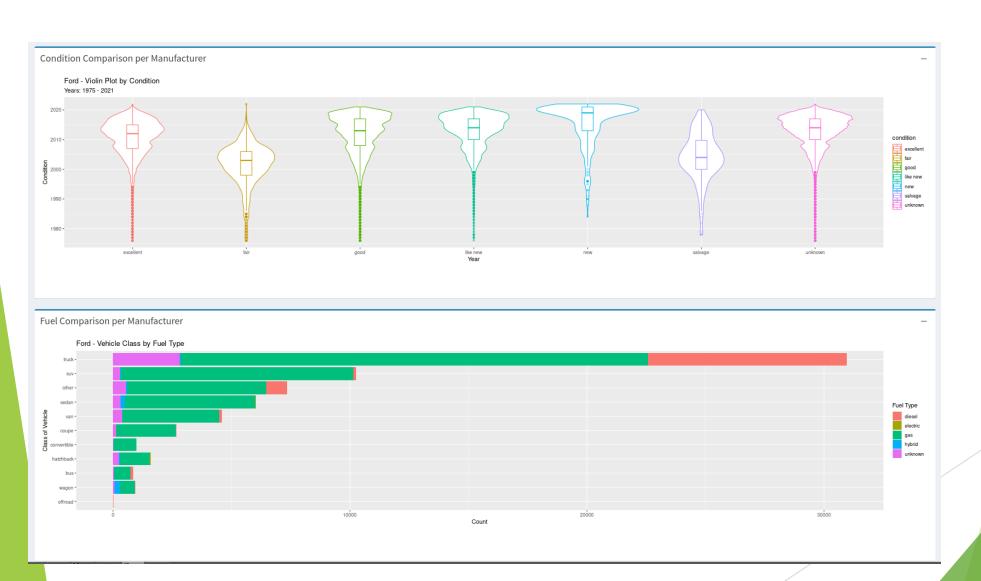


Pacific Northwest

Num	ber of Veh	icles	
100	200	300	

Analysis and Visualizations

Strategy: Build a tool that can compare vehicle attributes



Comparing Regression Models

Model_Comparison():

```
Model_Comparison <- function(df, list_of_tuples)</pre>
  # split dataframe into training, validation, and test sets (60-20-20% rule)
  train_size = round(0.6 * nrow(df), 0)
  valid_size = round(0.2 * nrow(df), 0)
  test_size = round(0.2 * nrow(df), 0)
  shuffled_rows <- sample(nrow(df))</pre>
  df = df[shuffled_rows, ]
  train_data = df[1:train_size, ]
  valid_data = df[(train_size + 1):(train_size + valid_size), ]
  test_data = df[(train_size + valid_size + 1):nrow(df), ]
  # Create the empty output dataframe for comparison
  output_df <- data.frame(matrix(ncol = 4, nrow = 0))</pre>
  colnames(output_df) <- c("Model", "R^2 on Validation Data", "Best Model?",</pre>
 "R^2 on Test Data")
 # Create empty lists to collect R^2 values
  R_2=c
```

Input:

```
tuple_list =
  list(
    list("Standard LM (car info only)", standard_lm_function_car_only),
    list("Standard LM plus local economic data", standard_lm_function),
    list("Log Age (All Columns)", standard_lm_log_age),
    list("Log Age Log Odometer (All Columns)", log_age_log_odometer)
)
Model_Comparison(cars, tuple_list)
```

Sample Output:

	Model <chr></chr>	R^2 on Validation Data <chr>></chr>	Best Model? <chr></chr>	R^2 on Test Data <chr></chr>
1	Model 1	0.272363884414753	0	NA
2	Model 2	0.369859962701729	0	NA
3	Model 3	0.383760232034281	1	0.389529506010875

Results of Regression Model Comparisons

Model <chr></chr>	R^2 on Validation Data <chr>></chr>	Best Model? <chr></chr>	R^2 on Test Data <chr></chr>
1 Standard LM (car info only)	0.423	0	NA
2 Standard LM plus local economic data	0.459	0	NA
3 Log Age (All Columns)	0.537	0	NA
4 Log Age Log Odometer (All Columns)	0.549	1	0.548

Results of Regression Model Comparisons

Model <chr></chr>	R^2 on Validation Data <chr>></chr>	Best Model? <chr></chr>	R^2 on Test Data <chr></chr>
1 Standard LM (car info only)	0.423	0	NA
2 Standard LM plus local economic data	0.459	0	NA
3 Log Age (All Columns)	0.537	0	NA
4 Log Age Log Odometer (All Columns)	0.549	1	0.548



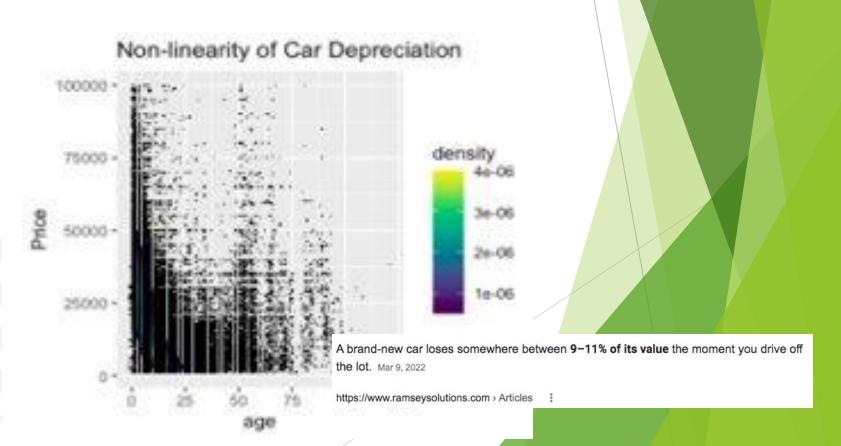
۳	outdoor_rec_by_state	
	index	INTEGER
	State	TEXT
	Total outdoor recreation value a	TEXT
	Percent of total value added1	REAL
	Total outdoor recreation employ	TEXT
	Percent of total wage and salary	REAL
	Total outdoor recreation compe	TEXT
	Percent of total compensation1	REAL

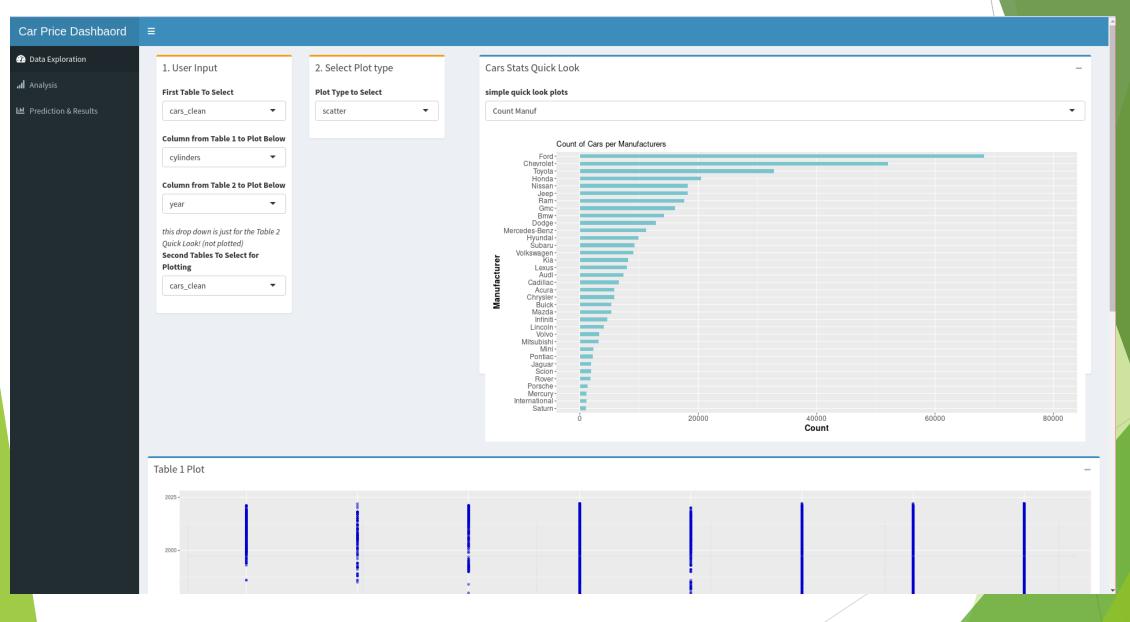
Results of Regression Model Comparisons

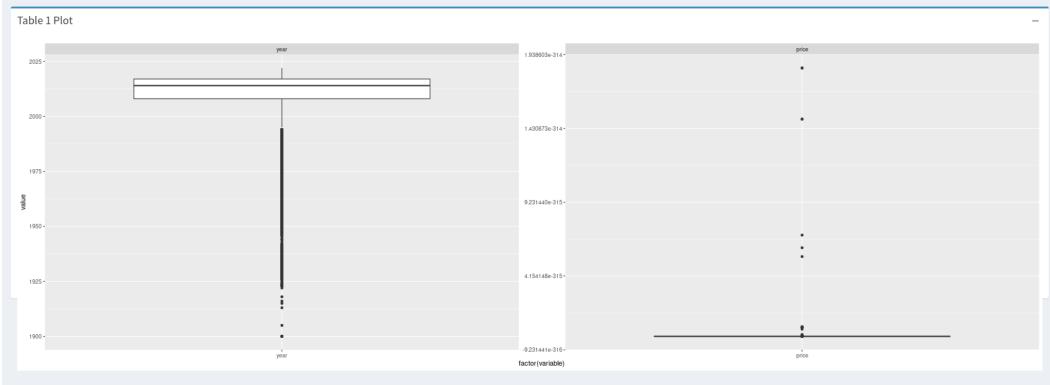
Model <chr></chr>	R^2 on Validation Data <chr>></chr>	Best Model? <chr></chr>	R^2 on Test Data <chr></chr>
1 Standard LM (car info only)	0.423	0	NA
2 Standard LM plus local economic data	0.459	0	NA
3 Log Age (All Columns)	0.537	0	NA
4 Log Age Log Odometer (All Columns)	0.549	1	0.548



outdoor_rec_by_state		
index	INTEGER	
State	TEXT	
Total outdoor recreation value a	TEXT	
Percent of total value added1	REAL	
Total outdoor recreation employ	TEXT	
Percent of total wage and salary	REAL	
Total outdoor recreation compe	TEXT	
Percent of total compensation1	REAL	





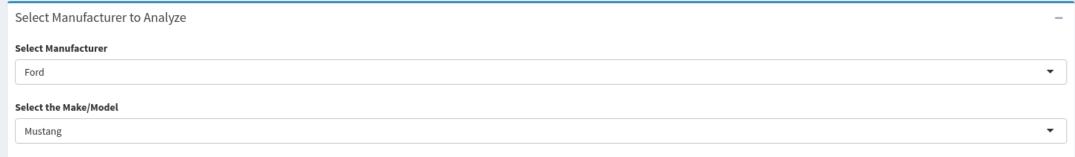


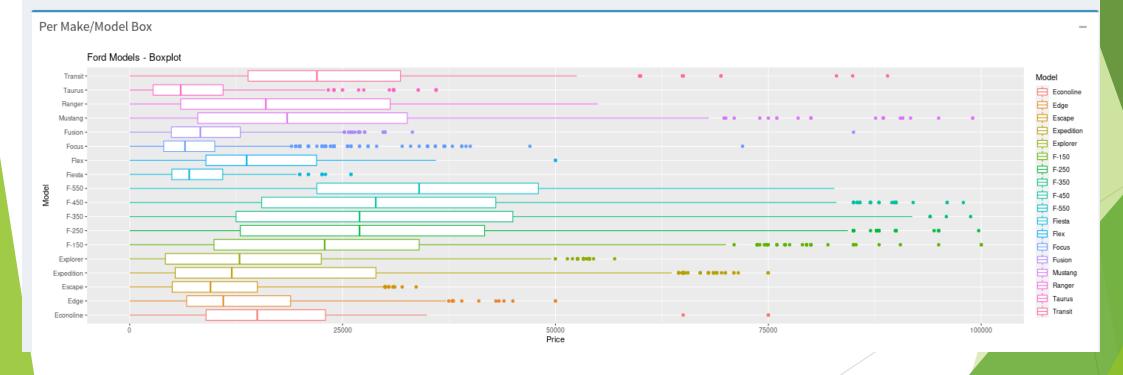
Tabl	e 1 Quick Loc	ok							-
Show	10 v entrie	es					Search	:	
	id ∜	region 🌲	city 🏺	state 🌲	year 🌲	manufacturer $\mbox{$\phi$}$	model 🌲	condition $\mbox{$\phi$}$	cylinders 🔷
1	7316814884	auburn	Auburn	al	2014	Gmc	Sierra 1500 Crew Cab Slt	good	8 cylinders
2	7316814758	auburn	Auburn	al	2010	Chevrolet	Silverado 1500	good	8 cylinders
3	7316814989	auburn	Auburn	al	2020	Chevrolet	Silverado 1500 Crew	good	8 cylinders

	ow 10 ventries Search:								
	id \$	region 🌲	city \$	state 🌲	year 🌲	manufacturer ϕ	model 🔷	condition	cylinders
1	7316814884	auburn	Auburn	al	2014	Gmc	Sierra 1500 Crew Cab Slt	good	8 cylinders
<u>)</u>	7316814758	auburn	Auburn	al	2010	Chevrolet	Silverado 1500	good	8 cylinders
3	7316814989	auburn	Auburn	al	2020	Chevrolet	Silverado 1500 Crew	good	8 cylinders

Analysis tab contents

This tab contains some more complex visualizations for a specific Manufacturer to ensure the most value and consistent app experience.







Conclusion and Final Thoughts

- Overall, this research project for the Penske Motorgroup was a large success. The visualization for observing and predicting car prices are now available to a larger subset of Analysts to generate business decisions
- Visualizations are informative, responsive and generate value
- Infrastructure for the app, backend, and frontend are simple, sleek and reproducible