



# *Predicting the Fuel Efficiency of 1970's Vintage Cars*

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Rice University  
Data Analytics

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## 1. INTRODUCTION

As 1970 dawned the world's cars averaged 149 horsepower and 17 miles per gallon... gas was cheap and the roar of the engines drowned out Elvis Presley and Creedence Clearwater Revival on the radio.

October 1973 brought the Yom-Kippur War. Early in the war, the U.S supplied Israel with arms, angering the Arab delegation of OPEC, which responded with an embargo of oil sales to the U.S. and other industrial centers. And so began the decade's first oil crisis that sent oil prices skyrocketing upwards and auto manufacturers scrambled to offer more fuel efficient cars.

Hop in and take a journey throughout the 1970s with us as we first visualize oil prices and fuel efficiency throughout the decade. Then we'll pop the hood and see what changed to bring about an 88% improvement in fuel efficiency by 1982.

Our next stop is with Machine Learning models. As you're flipping through the latest digital copy of Hemmings, debating between a 1970 Pontiac GTO "The Judge" or an iconic 1975 Rolls Royce Silver Shadow, the model will predict the gas mileage you'll experience with your "new" vintage beauty.

[Garage](#) [Visualizations](#) [MPG Predictor](#) [The Mechanics](#) [Under the Hood](#) [About Us](#)

## ***How is your Fuel Efficiency?***

Configure your Engine

Displacement

140

Model Year

1975

Horsepower

90

N° Cylinders

3

Weight

2408

Origin

European

Acceleration

19.5

Make Prediction!

Your Predicted MPG is

MPG

21.8

0 10 20 30 40 50

## 2. DATA

Data is graciously sourced from Kaggle and the University of California, Irvine.

The original data .csv file is relatively clean. It is a small dataset, approximately 400 records, and Excel was used for the minimal cleaning required. Six null values in "horsepower" field were replaced with the manufacturers' specified values for Tableau visualizations. The six values were replaced with median values for the machine learning models.

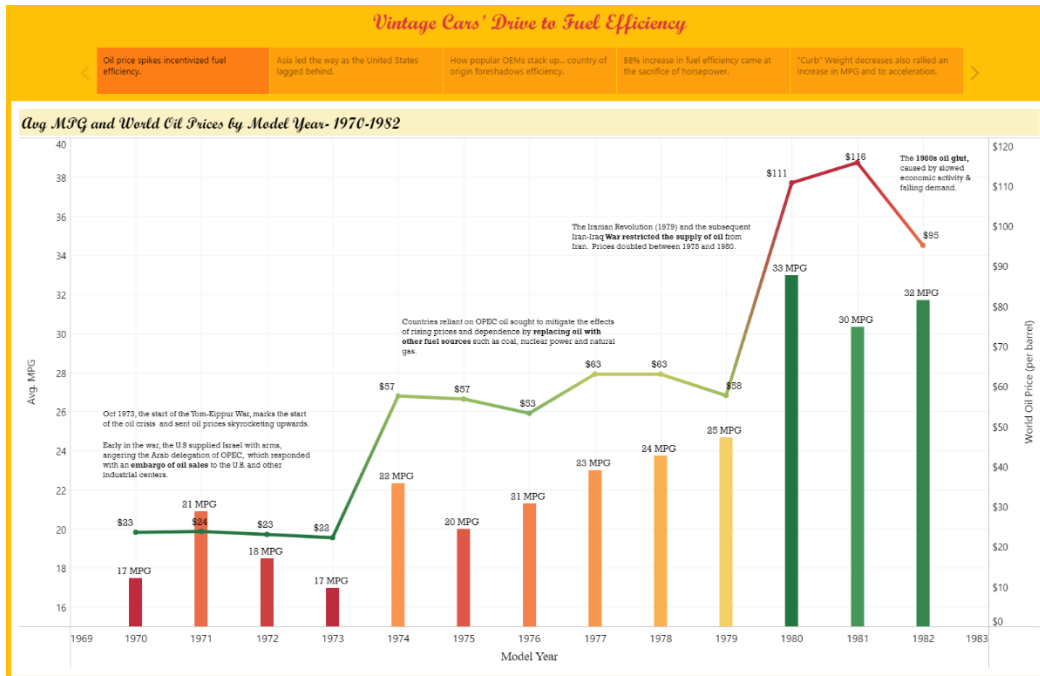
Make and model values were separated into independent fields utilizing Excel's native "text to columns" functionality, for better Tableau visualization prospects. "Make" was listed as unique values to spot misspellings which were then corrected and was capitalized for better tableau visualization. the clean .csv was read into Tableau.

Data fields include make, model, model year, horsepower, engine displacement, engine cylinders, acceleration, fuel efficiency, and vehicle weight.

A second .csv was imported that provides inflation adjusted world oil prices for each of the twelve years.

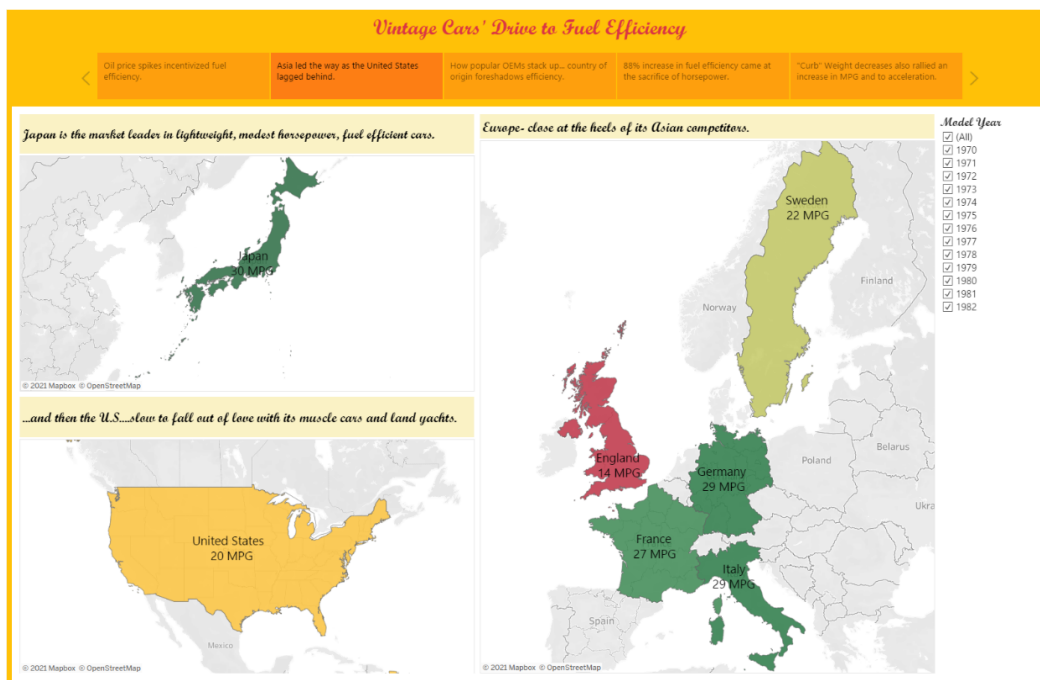
## 3. TABLEAU VISUALIZATIONS

Ten worksheets each have a visualization. The visualizations are brought together on six dashboards which are then presented as a story. The main filter serves to retrieve data for each year unless the data is presented as a time series. The story captions summarize each dashboard and guide the user through the dashboards.

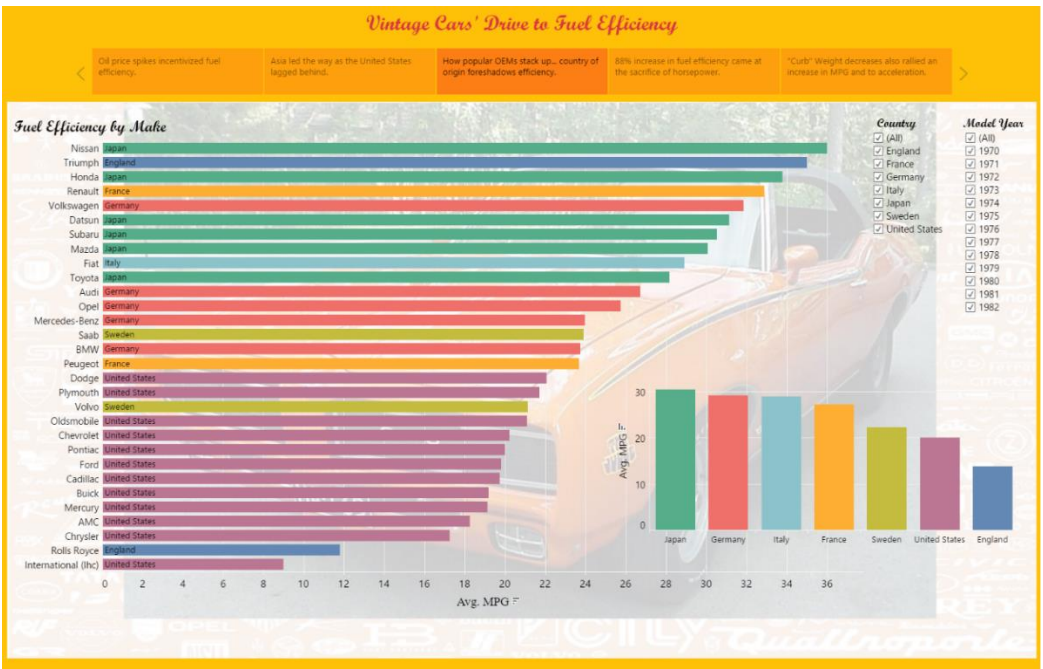


Next the user explores how country of origin influences fuel efficiency. Asia is the frontrunner for the time period with the United States and England trailing the pack.

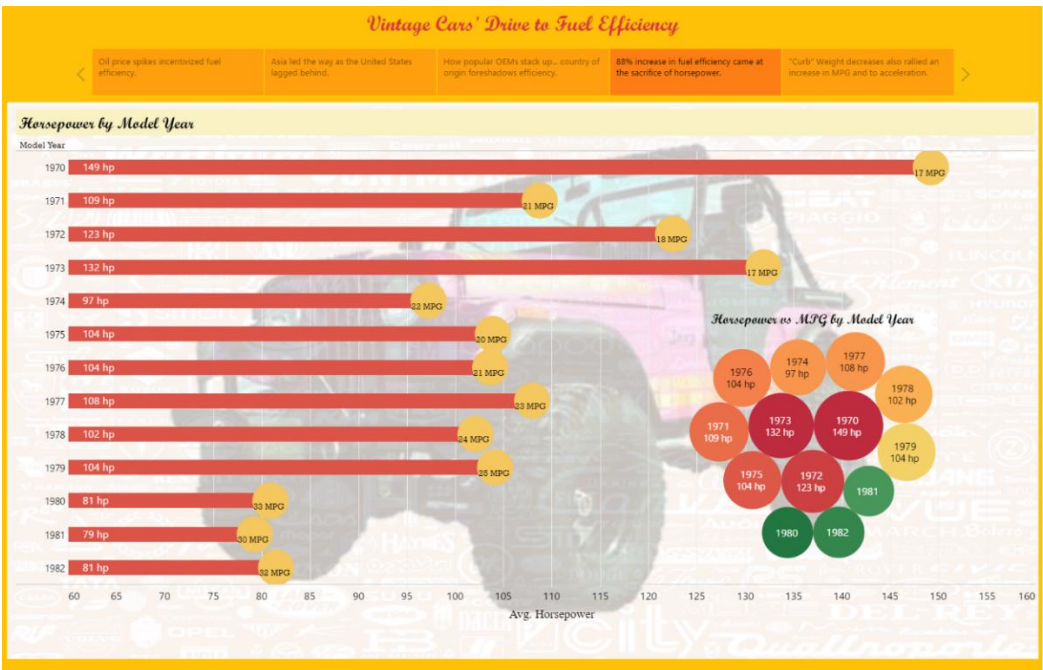
The user can select which year(s) to view and tooltips provides the average metrics for each field by country.



Individual make and fuel efficiency are examined in the third dashboard. The dashboard is generous with labels to provide an easy view of data and, again, tooltips are utilized to provide a wider data view. A summary by country also functions as a legend in the lower right corner.



The user then explicitly views the 46% reduction in horsepower and an 88% increase in fuel efficiency between 1970 and 1982.



Engine metrics roar to life in the final two dashboards. A 28% decrease in weight, a 45% decrease in horsepower, and a 55% decrease in engine displacement contributed to the 88% MPG improvement and a 31% improvement in acceleration.

Blended and dual axis scales allowed the three independent metrics to show with a shared x-axis.



## 4. MACHINE LEARNING

### DATA

The dataset is imported into Jupyter Notebook and read into a pandas dataframe. Data is examined for null values, and pandas “Describe” is used to understand the data prior to machine learning model implementation.

#### Data Gathering and Preprocessing

```
# Read csv file using pandas
mpg_df = pd.read_csv('../Data/data.csv')
mpg_df
```

```
t[2]:
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	make	model	country
0	9.0	8	304.0	193.0	4732	18.5	70	1	international (ihc)	1200d	United States
1	10.0	8	307.0	200.0	4376	15.0	70	1	chevrolet	c20	United States
2	10.0	8	360.0	215.0	4615	14.0	70	1	ford	f250	United States
3	11.0	8	380.0	189.0	4648	11.0	70	2	rolls royce	silver shadow	England
4	11.0	8	380.0	189.0	4648	11.0	71	2	rolls royce	silver shadow	England
...	...	...	...	...	...	...	...	...	...	...	...
404	43.4	4	90.0	48.0	2335	23.7	80	2	volkswagen	dasher (diesel)	Germany
405	44.0	4	97.0	52.0	2130	24.6	82	2	volkswagen	pickup	Germany
406	44.3	4	90.0	48.0	2085	21.7	80	2	volkswagen	rabbit c (diesel)	Germany
407	44.6	4	91.0	67.0	1850	13.8	80	3	honda	civic 1500 gl	Japan
408	46.6	4	86.0	65.0	2110	17.9	80	3	mazda	glc	Japan

409 rows x 11 columns

Examination for correlations is made both as a dataframe and a visualization.

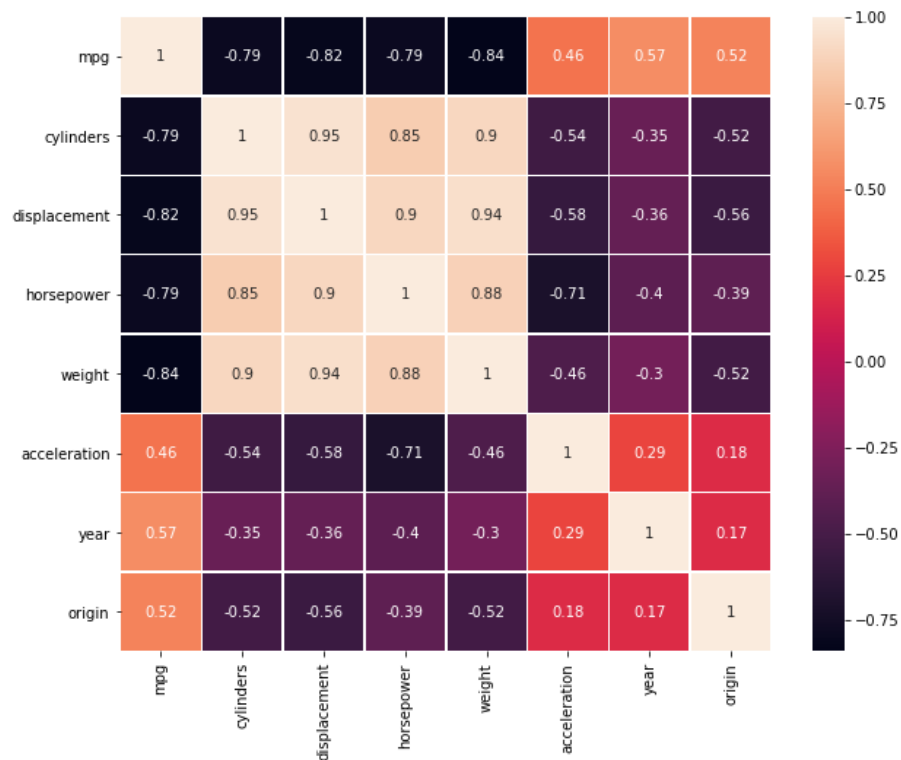
## Correlations

```
: In [11]: linear_feat.corr()
```

11]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
mpg	1.000000	-0.788159	-0.816540	-0.787206	-0.841886	0.456455	0.567691	0.524289
cylinders	-0.788159	1.000000	0.953080	0.849093	0.901268	-0.536239	-0.345548	-0.523433
displacement	-0.816540	0.953080	1.000000	0.903833	0.938297	-0.577335	-0.363767	-0.557914
horsepower	-0.787206	0.849093	0.903833	1.000000	0.876306	-0.712086	-0.399472	-0.393686
weight	-0.841886	0.901268	0.938297	0.876306	1.000000	-0.464254	-0.302058	-0.523480
acceleration	0.456455	-0.536239	-0.577335	-0.712086	-0.464254	1.000000	0.286633	0.175036
year	0.567691	-0.345548	-0.363767	-0.399472	-0.302058	0.286633	1.000000	0.174139
origin	0.524289	-0.523433	-0.557914	-0.393686	-0.523480	0.175036	0.174139	1.000000

```
: In [11]: plt.figure(figsize=(10,8))  
sns.heatmap(linear_feat.corr(), annot=True, linewidths=.5)  
plt.show()
```



Pair plots, another correlation tool, clearly demonstrates that "cylinders" and "origin" fields do not show a normal distribution as they represent a specific value and can be considered categorical values.

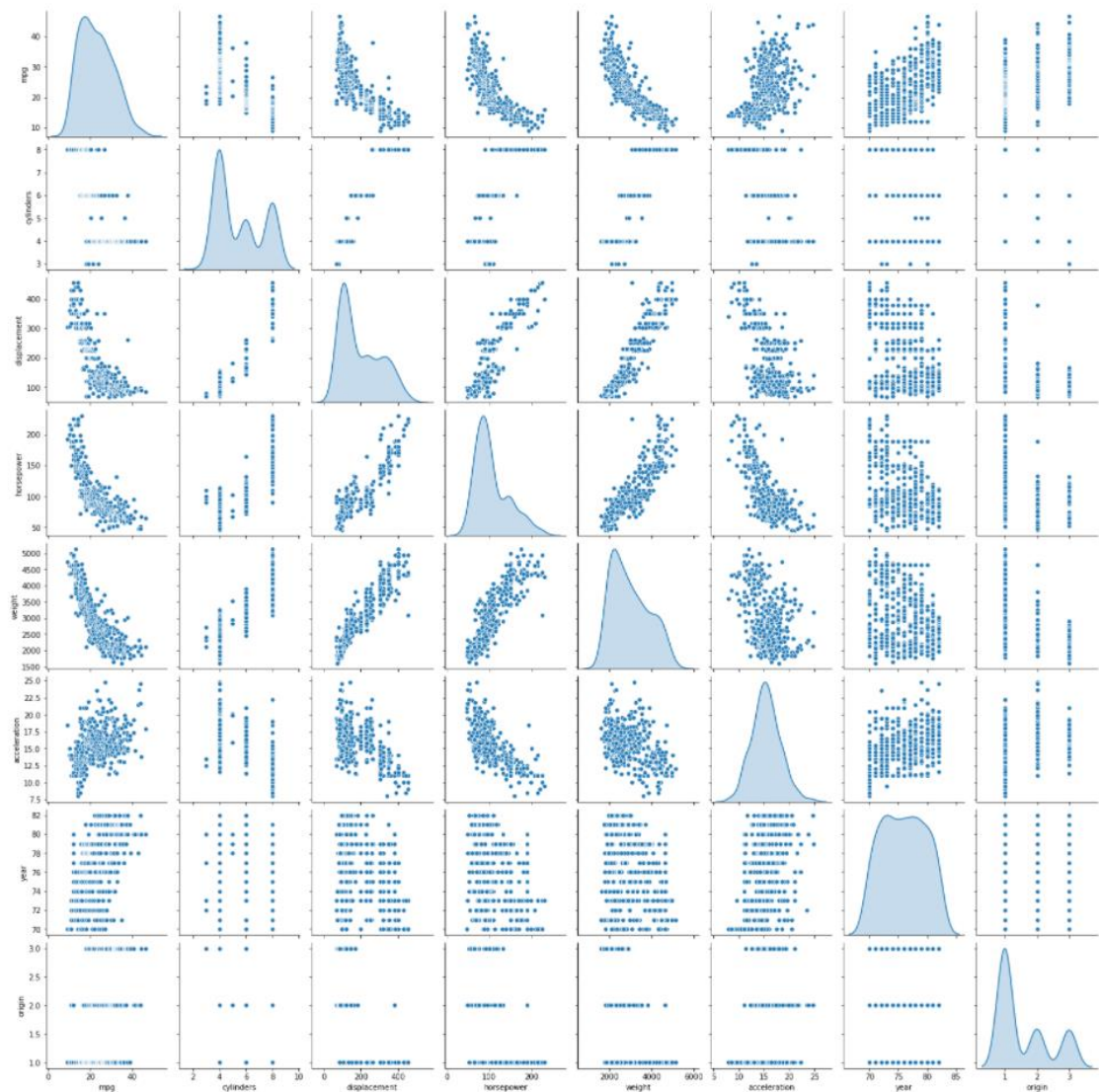


```

M ##pairplots to get an intuition of potential correlations
sns.pairplot(mpg_df[["mpg", "cylinders", "displacement", "horsepower", "weight", "acceleration", "year", "origin"]], diag_kind="hist")

```

|: <seaborn.axisgrid.PairGrid at 0x297e154cfd0>



## TRAINING THE MODEL

Training of the data begins with dropping columns determined to be categorical in nature. 30% of the data was used as a test set.

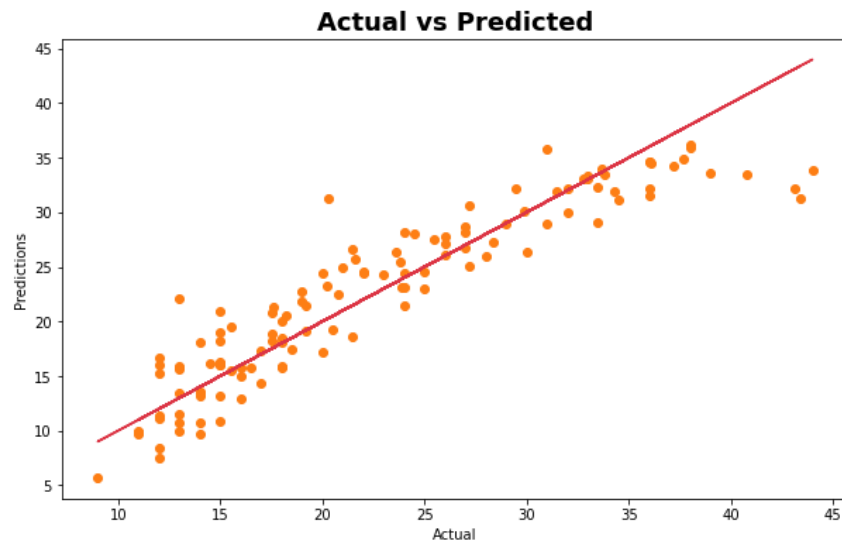
## MODELS

Linear models explored include Linear, Ridge, Lasso, and ElasticNet.



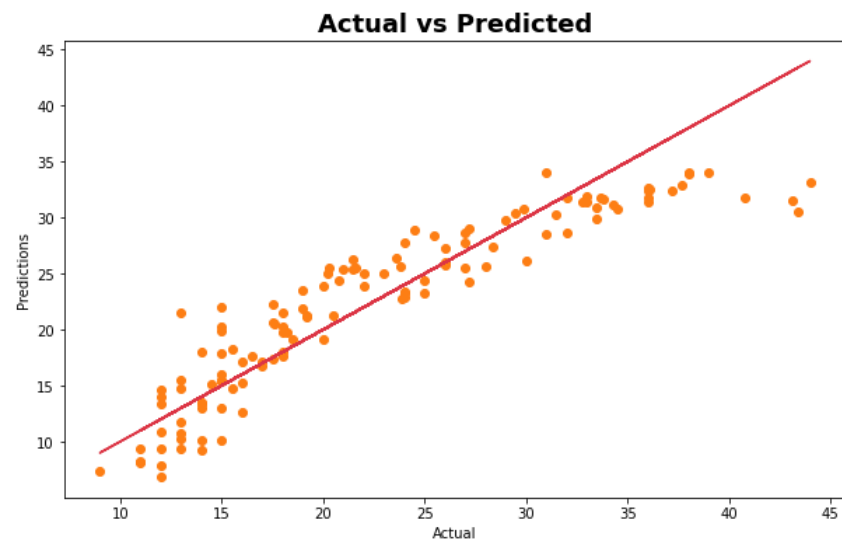
## Linear model:

Model Evaluation Report  
The In Sample R2 Score: 0.8455826329089134  
The In Sample RMSE: 2.9674327357677006  
  
The Out Sample R2 Score: 0.8507259859040834  
The Out Sample RMSE: 3.3691296516747364



## Elastic Net model:

Model Evaluation Report  
The In Sample R2 Score: 0.803633557413395  
The In Sample RMSE: 3.3463121323221747  
  
The Out Sample R2 Score: 0.8346667364178618  
The Out Sample RMSE: 3.5457306168830875



Random Forest models explored are DecisionTree, Random Forest, AdaBoost, and Gradient Boost.

Random Forest:

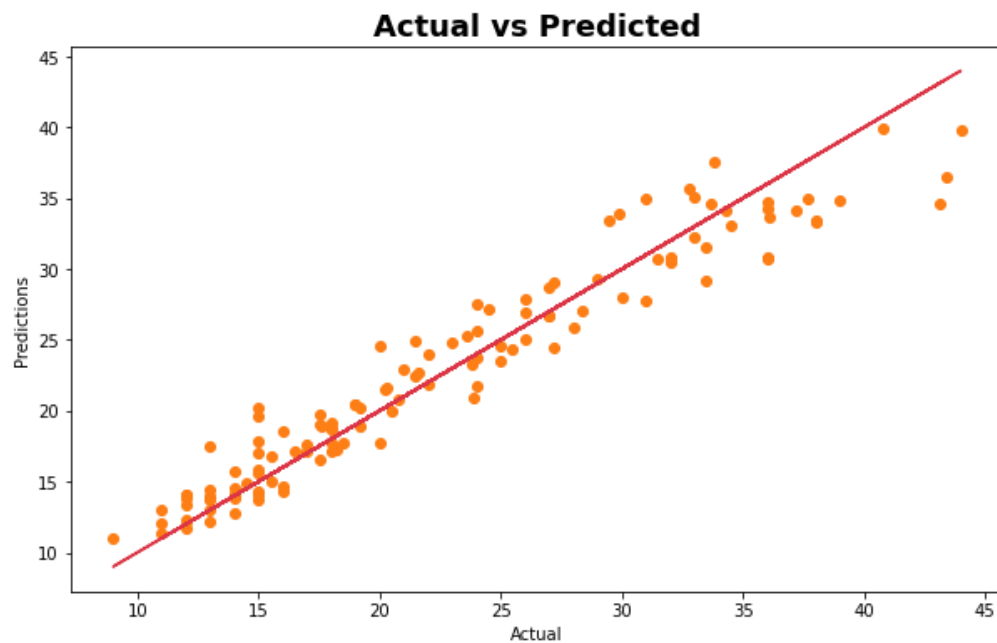
Model Evaluation Report

The In Sample R2 Score: 0.977772795094775

The In Sample RMSE: 1.1258362765865744

The Out Sample R2 Score: 0.9278229947377916

The Out Sample RMSE: 2.342745149903927

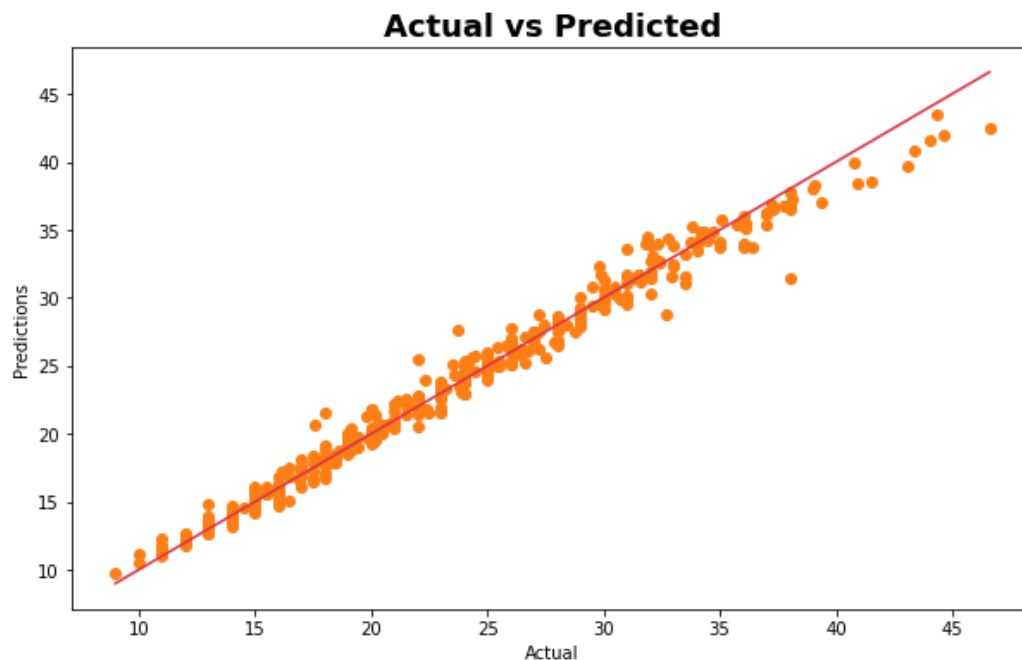


Model results were viewed as a dataframe for easy comparison and selection.

	Model	IN SAMPLE RMSE	OUT SAMPLE RMSE
5	RANDOM FR	1.125836	2.342745
7	GRADIENT BOOSTING	1.356529	2.657023
6	ADA BOOTS	2.447871	3.030495
1	RIDGE	3.005916	3.273203
4	DECISION TREE	0.000000	3.282090
0	LINEAR	2.967433	3.369130
3	ELASTICNET	3.346312	3.545731
2	LASSO	3.350587	3.547672

The Random Forest model was chosen because it has the lowest RMSE and does not overfit the in-sample data.

```
Model Evaluation Report
The In Sample R2 Score: 0.9837653391708724
The In Sample RMSE: 1.010377387191379
```



## 5. PREDICTING THE PAIN at the PUMP

The pickled model is then used to predict a car's fuel efficiency based on characteristics selected by the user that include model year, engine displacement, horsepower, and vehicle weight.

The website displays the predicted result as both text and as a colored gauge.

## 6. DEPLOYMENT

The project is packaged as a full stack web deployment on Heroku.

The "Garage" page introduces the user to the project. it includes an interactive slideshow with twelve car images from the time period. A navigation bar allows the user to visit several different pages:



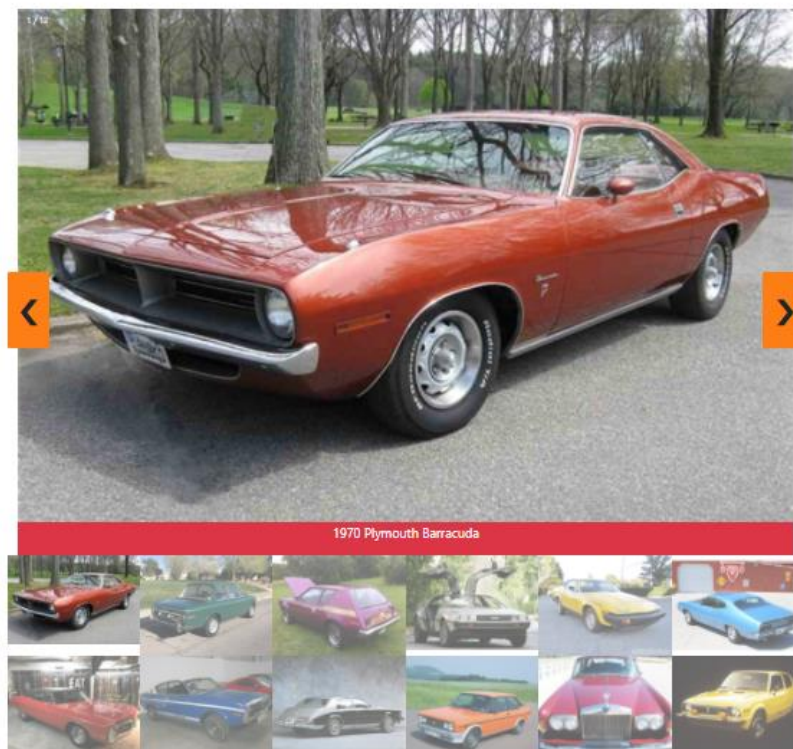
As 1970 dawned the world's cars averaged 149 horsepower and 17 miles per gallon... gas was cheap and the roar of the engines drowned out Elvis Presley and Creedence Clearwater Revival on the radio.

October 1973 brought the Yom-Kippur War. Early in the war, the U.S. supplied Israel with arms, angering the Arab delegation of OPEC, which responded with an embargo of oil sales to the U.S. and other industrial centers. And so began the decade's first oil crisis that sent oil prices skyrocketing upwards and auto manufacturers scrambling to offer more fuel efficient cars.

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- Visualizations - This is the Tableau storyboard
- MPG Predictor - This is the predictive activity
- The Mechanics - This is the explanation of the Machine Learning behind the prediction.

## Machine Learning Analysis

### Introduction

In this project we used various machine learning models, trained and tested the data to see the models ability to predict the MPG (Mile Per Gallon) for a vehicle and tells us about the efficiency of fuel consumption of a vehicle in the 70s and 80s base on other attributes of that vehicle. We used linear, decision tree and random forest models.

### Data Preprocessing

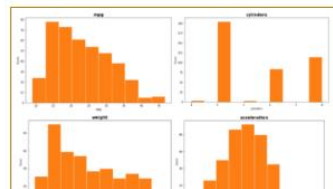
The first step in our analysis was to clean and pre-process our dataset to make ready for our machine learning analysis. The dataset was imported into Jupyter Notebook and read into a pandas dataframe. Data was examined for null values and understood prior to machine learning model implementation.

```
# Read csv File using pandas
mpg_df = pd.read_csv('.../data/data.csv')
mpg_df
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	make	model	country
0	16.0	8	304.0	150.0	4752	16.0	76	1	international (JCI)	1955	United States
1	15.0	8	307.0	150.0	4376	15.0	76	1	chevrolet	120	United States
2	18.0	8	340.0	215.0	4913	14.0	76	1	ford	250	United States
3	11.0	8	360.0	180.0	4548	11.0	76	2	volvo 460	volvo 460	England
4	11.0	8	360.0	180.0	4548	11.0	71	2	volvo 460	volvo 460	England
...	...	...	...	...	...	...	...	...	...	...	...
404	43.0	4	80.0	48.0	2326	23.7	80	2	volkswagen	jetta (mk2)	Germany
405	44.0	4	87.0	52.0	2100	24.0	82	2	volkswagen	jetta	Germany
406	44.0	4	80.0	48.0	2085	21.7	80	2	volkswagen	passat (mk2)	Germany
407	44.0	4	81.0	47.0	1990	15.8	80	3	honda	civic 1500 gl	Japan
408	45.0	4	85.0	55.0	2110	17.9	80	3	mitsubishi	glc	Japan

409 rows x 11 columns

To enhance our understanding of the data distribution, we looked at the histogram of numerical features.



- Under the Hood - This is the dataset. This can be filtered by one to three metrics, or searched using the search too. Pagation is an added feature.

## MPG Data

Find your favorite car!

Filter by one or more search criteria:

Model Year (1970-1982)

Make

Country

Filter Table Clear Filters

Show  entries

Search:

Model Year	Make	Model	MPG	Cylinders	Displacement	Horsepower	Acceleration	Weight	Country
1972	AMC	Ambassador Sst	17	8	304	150	11.5	3672	United States
1972	AMC	Matador	15	8	304	150	12.5	3892	United States

Showing 1 to 2 of 2 entries

Previous  Next

- About Us - This is the team that crafted the project.

Tableau is deployed in Tableau Public at:

<https://public.tableau.com/profile/dana.woodruff#!/vizhome/Vintage-Car-MPG/VintageCars?publish=yes>

The website is deployed at: <https://vintagecarsmpg.herokuapp.com/>

Project materials are held in GitHub at:

<https://github.com/jessicapardo/Vintage-Cars-MPG>

...with forks at:

<https://github.com/danawoodruff/Vintage-Cars-MPG>

<https://github.com/BaudOptics/Vintage-Cars-MPG>

## 7. REFERENCES

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