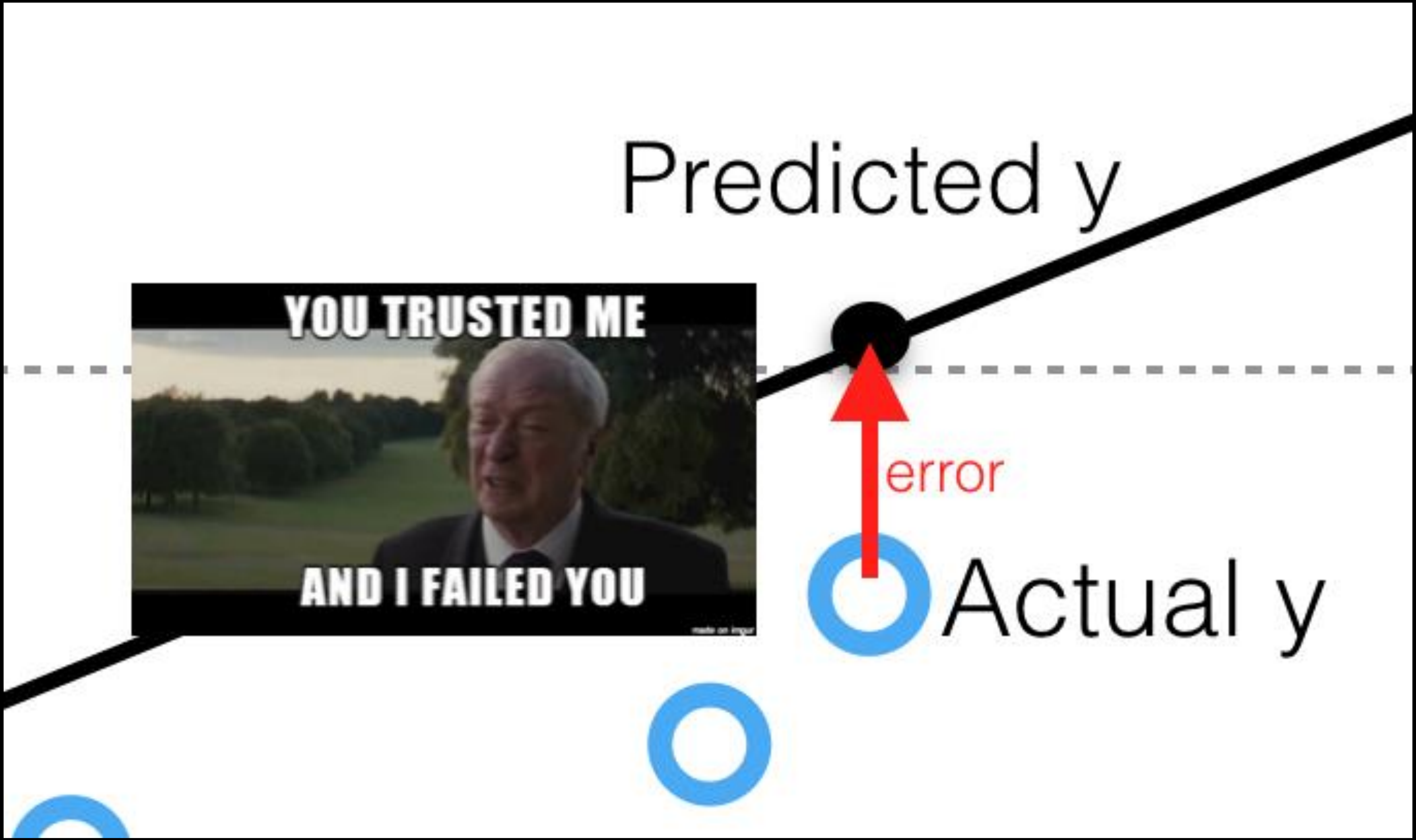
REGRESSION MODEL

CAR PRICE PREDICTION WEB APP

Steven L Truong

Friday, 16/04/2021


Predicted y
YOU TRUSTED ME
AND I FAILED YOU
error
Actual y

INTRODUCTION

❖**MOTIVATION**:

- Buy and sell used cars is always a big decision.
- Create the tools to predict the as closest car’s price as possible.

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- Conclude the best model ready for production.

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❖ **OBJECTIVES**:

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❖ **GOALS**:

- Write the web app and deploy the model to the cloud.

METHODOLOGY

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  - Scrape from cars.com

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  - Scrape from cars.com
- **Tools:**
  - BeautifulSoup, Numpy and Pandas
  - Matplotlib and Seaborn
  - Scikit-learn and XGBoost
  - Streamlit and Heroku

METHODOLOGY

Data Scraping and Preparation

- **Use BeaufulSoup to scrape data from cars.com**
- **Clean the data to be ready for EDA**

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Exploratory Analysis

- Exploratory Data Analysis
- Look at the features’ correlations for insights before modeling.

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Modeling

- Build baseline models.
- Cross validation and choose the final model.

DATA CLEANING

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Or we could say “cars cleaning”

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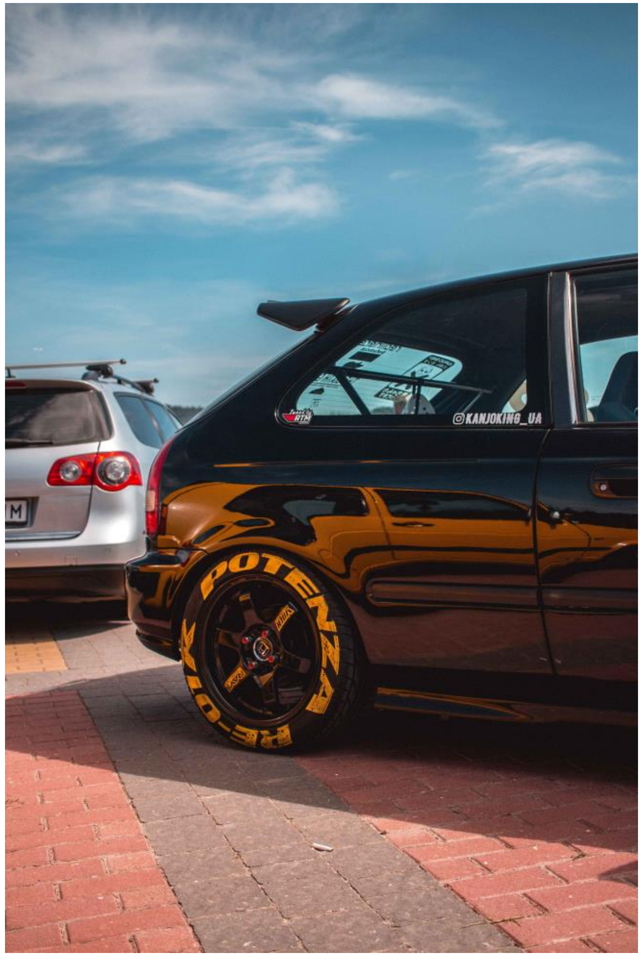
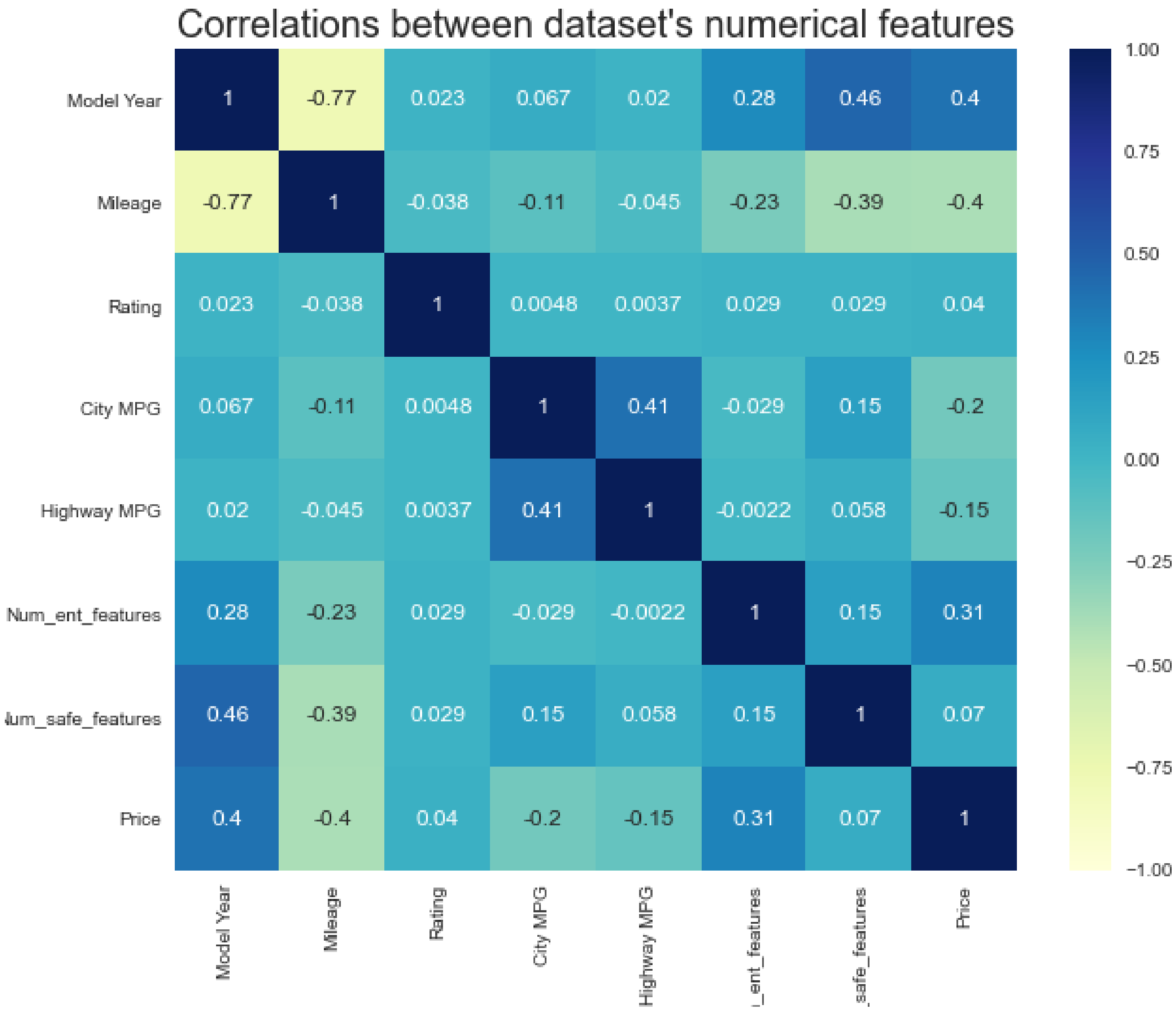


- 187,168 raw data points were scraped.
- Clean data set has 122,351 rows and 18 columns

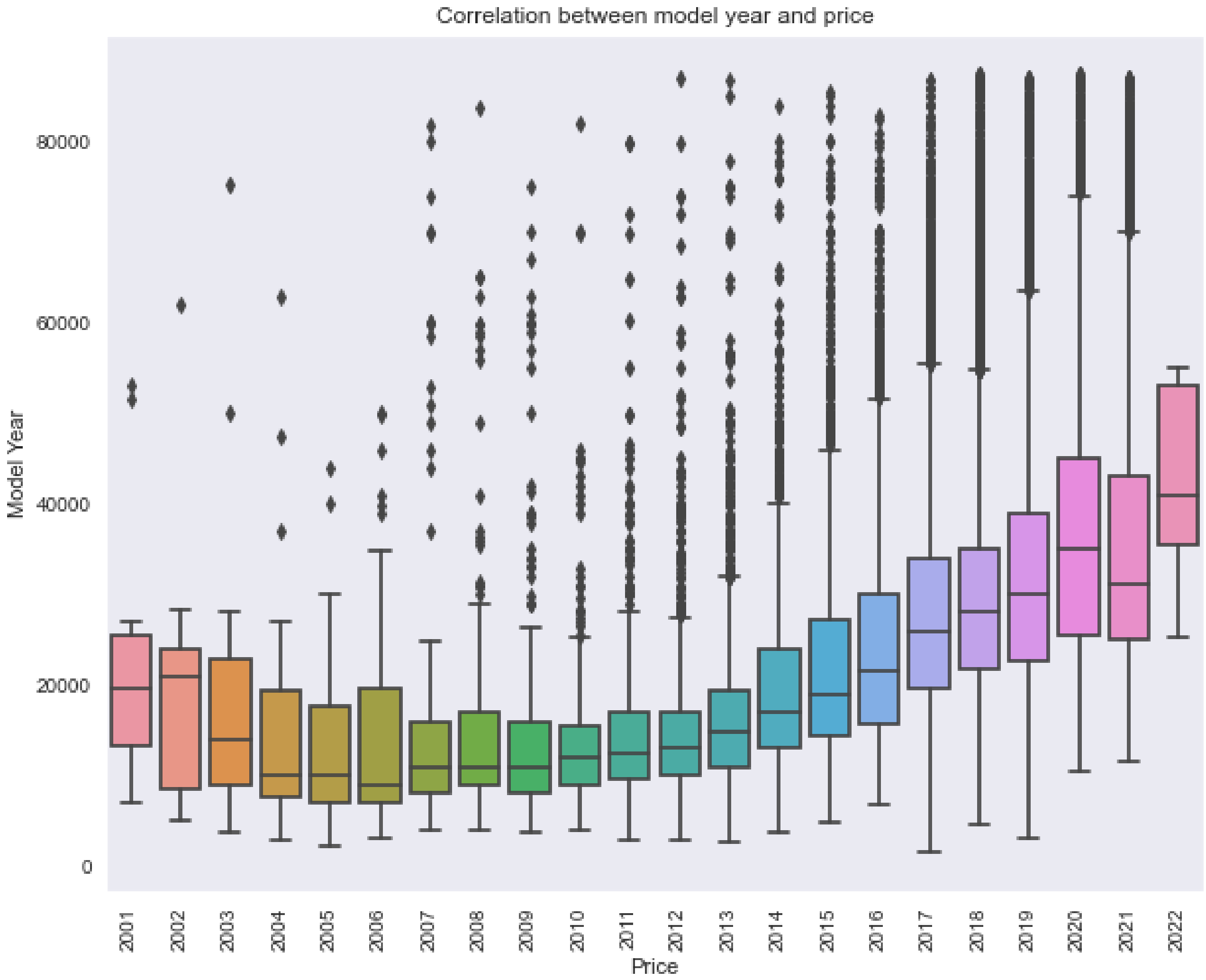
EDA

- Price is positively correlated with Model Year and negatively correlated with Mileage.
- Slightly positively correlated with num_ent_features.
- Not so much for the rest of the features.



EDA

- Price is positively correlated with Model Year.
- There are outliers all over the place.
- Generally speaking, the newer the more expensive car.



MODELS

Pre features engineered.

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- Linear Regression Model:
  - R^2 for test set: 0.290

- Polynomial Regression Model:
  - R^2 for test set: 0.474

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- Random Forest Regressor:
  - R^2 for test set: 0.577
- Gradient Boosted Regressor:
  - R^2 for test set: 0.605
- Extreme Gradient Boosting (XGBoost):
  - R^2 for test set: 0.729

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In general, they all underfit

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MODELS

Work with categorical features!

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Intuitively, car's brand (make) determines the product's price, so let's work on that.

MODELS

Work with categorical features!

- Linear Regression Model:
  - R^2 for test set: 0.505
- Polynomial Regression Model:
  - R^2 for test set: 0.695
- Extreme Gradient Boosting (XGBoost):
  - R^2 for test set: 0.870

MODELS

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We have better results, can we improve our performance?

MODELS

Work with categorical features!

Let’s dummify the entire dataset!

MODELS

L1/L2 Regularization

K-Fold Cross-Validation!

- Linear Regression Model:
  - R^2 for test set: 0.869
  - RMSE = 4787.90
- Lasso Model:
  - R^2 for test set: 0.866
- Extreme Gradient Boosting (XGBoost):
  - R^2 for test set: 0.920
  - RMSE = 3749.5
- Ridge Model:
  - R^2 for test set: 0.865

PREDICTION

2017 Chevrolet Camaro 2SS

44,953 Mileage, Gasoline engine

City MPG 16 – Highway MPG 25

RWD – Engine 6.2L V8 – 8 speed Manual

Linear Regression Model predicts

$35,235

Extreme Gradient Boosting (XGBoost) predicts

$35,089

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$35,893

True value

$38,395

PREDICTION

2018 INFINITY Q60 3.0t LUXE

18, 719 Mileage, Gasoline engine

City MPG 19 – Highway MPG 27

AWD – Engine 3.0 V6 – 7 speed Automatic

Linear Regression Model predicts

$37,604

Extreme Gradient Boosting (XGBoost) predicts

$35,689

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Extreme Gradient Boosting (XGBoost) predicts

$35,689

True value

$32,500

CONCLUSION

L1/L2 Regularization

K-Fold Cross-Validation!

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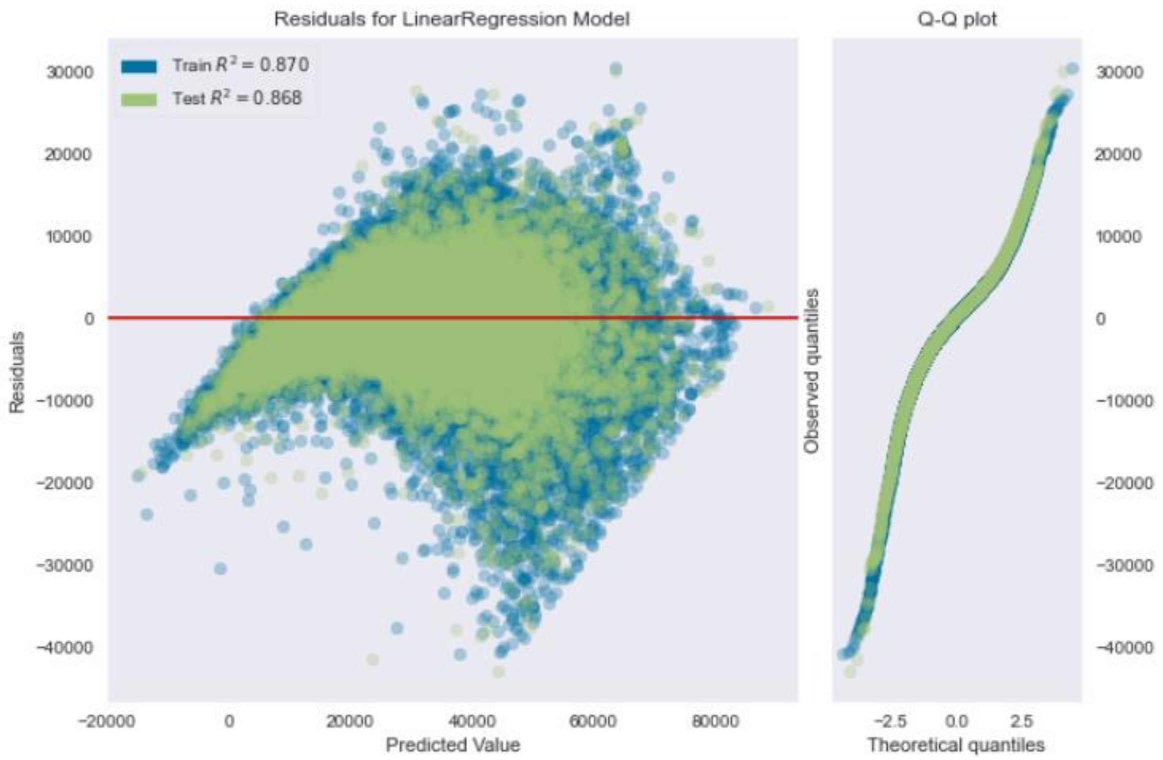
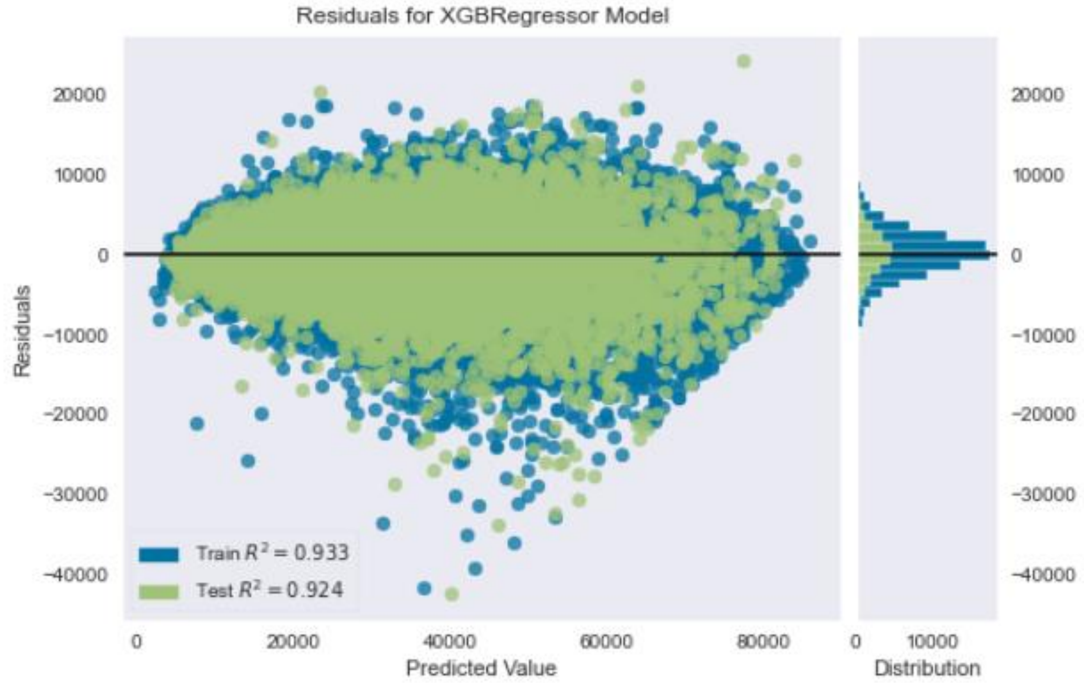
RESIDUALS

- Linear Regression Model:
  - R^2 for train set: 0.871
  - R^2 for validation set: 869
  - RMSE = 4787.90



RESIDUALS

- Extreme Gradient Boosting (XGBoost):
  - R^2 for train set: 0.932
  - R^2 for validation set: 0.920
  - RMSE = 3749.5



ResidualsPlot(ax=<AxesSubplot:title={'center':'Residuals for XGBRegressor Mo

FEATURE IMPORTANCE

- Extreme Gradient Boosting (XGBoost):
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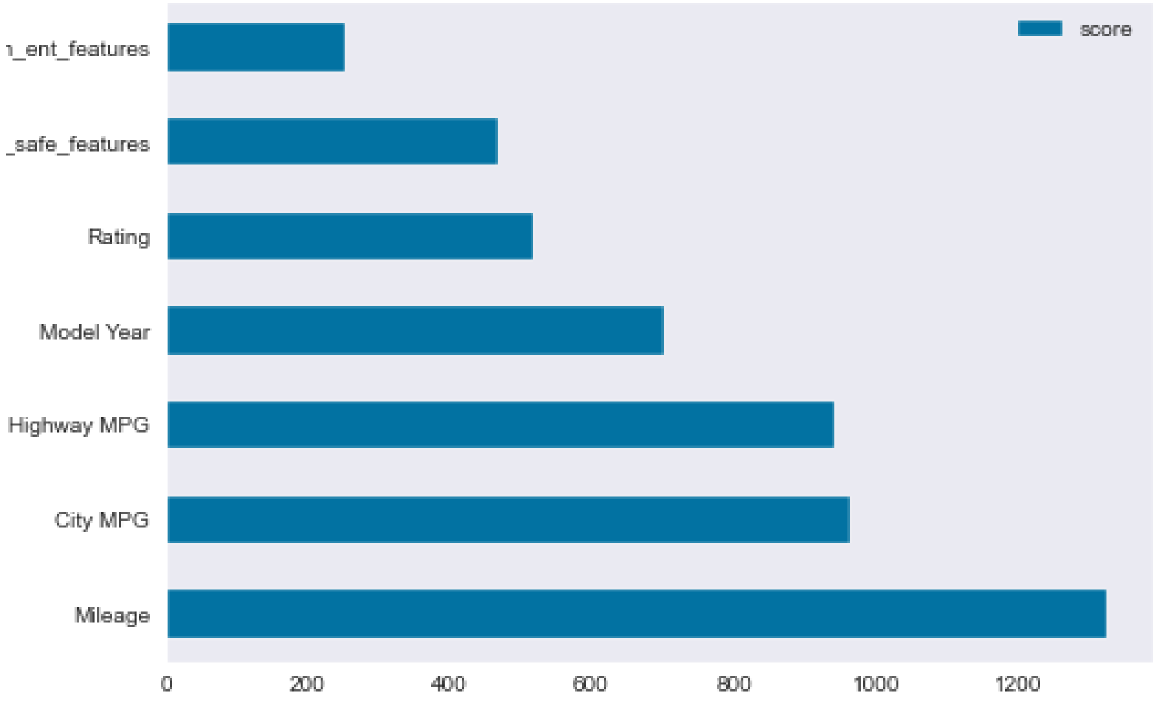
  - R^2 for validation set: 0.920
  - RMSE = 3749.5



RECAP

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Linear Model

0.290 → 1 cat feature → 0.505

0.505 → L1/L2/5-Fold CV → 0.869

0.505 → All cat features → 0.869

RECAP

Linear Model: 0.290 → 1 cat feature → 0.505 → L1/L2/5-Fold CV, All cat features → 0.869

XGBoost: 0.729 → 1 cat feature → 0.870 → All cat features → 0.920

WHAT'S NEXT?

Orignal question?

BUILD THE INTERACTIVE WEB APP AND DEPLOY IT TO THE CLOUD!

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https://car-predictor-regression.herokuapp.com/

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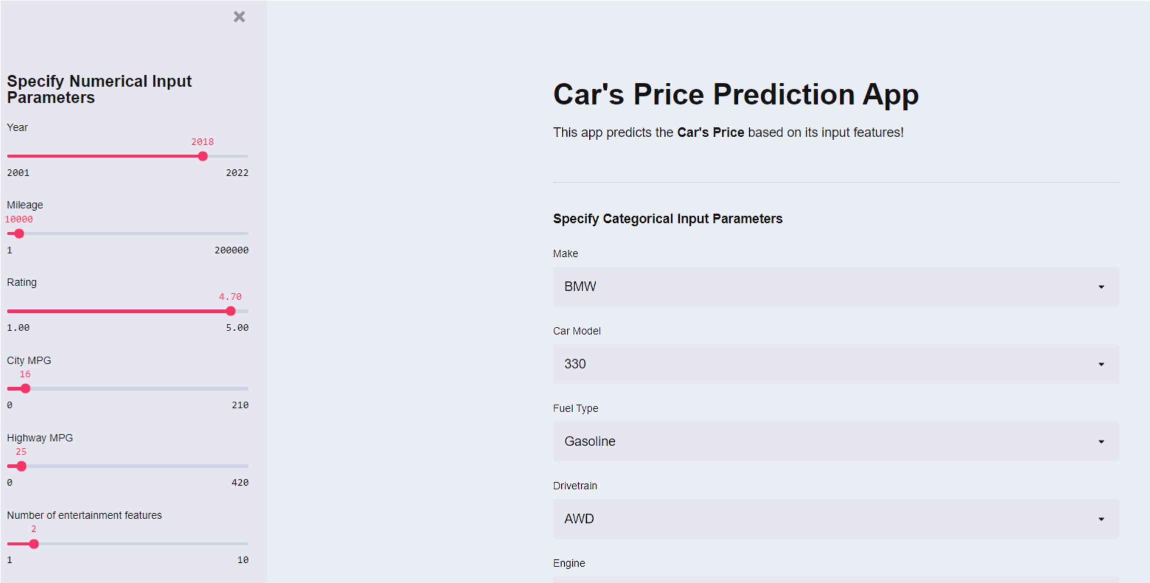

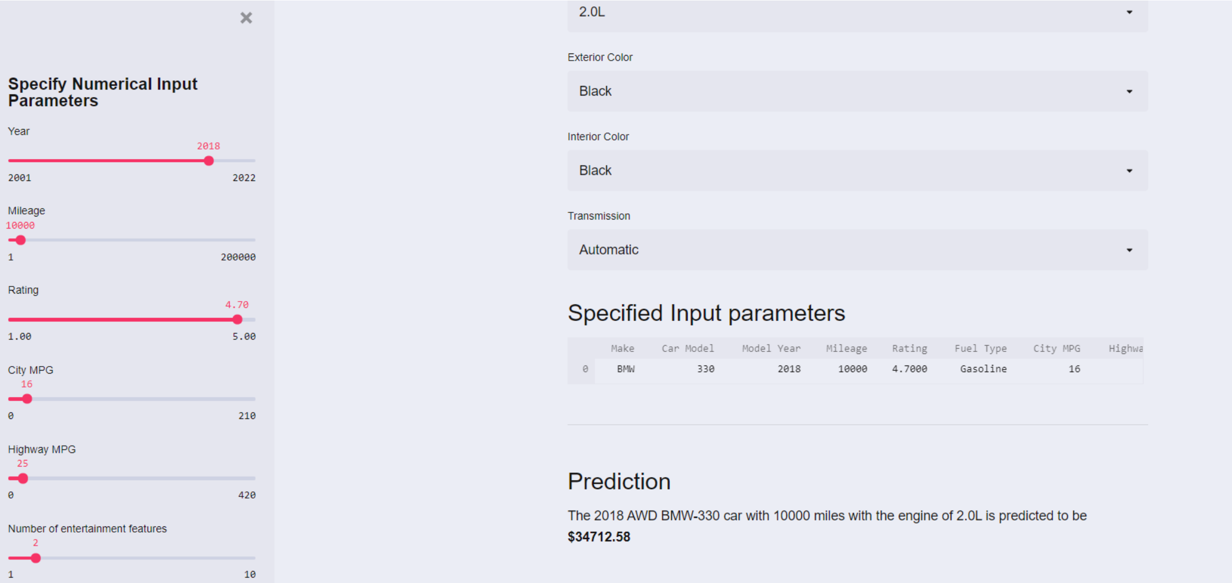

THANK YOU

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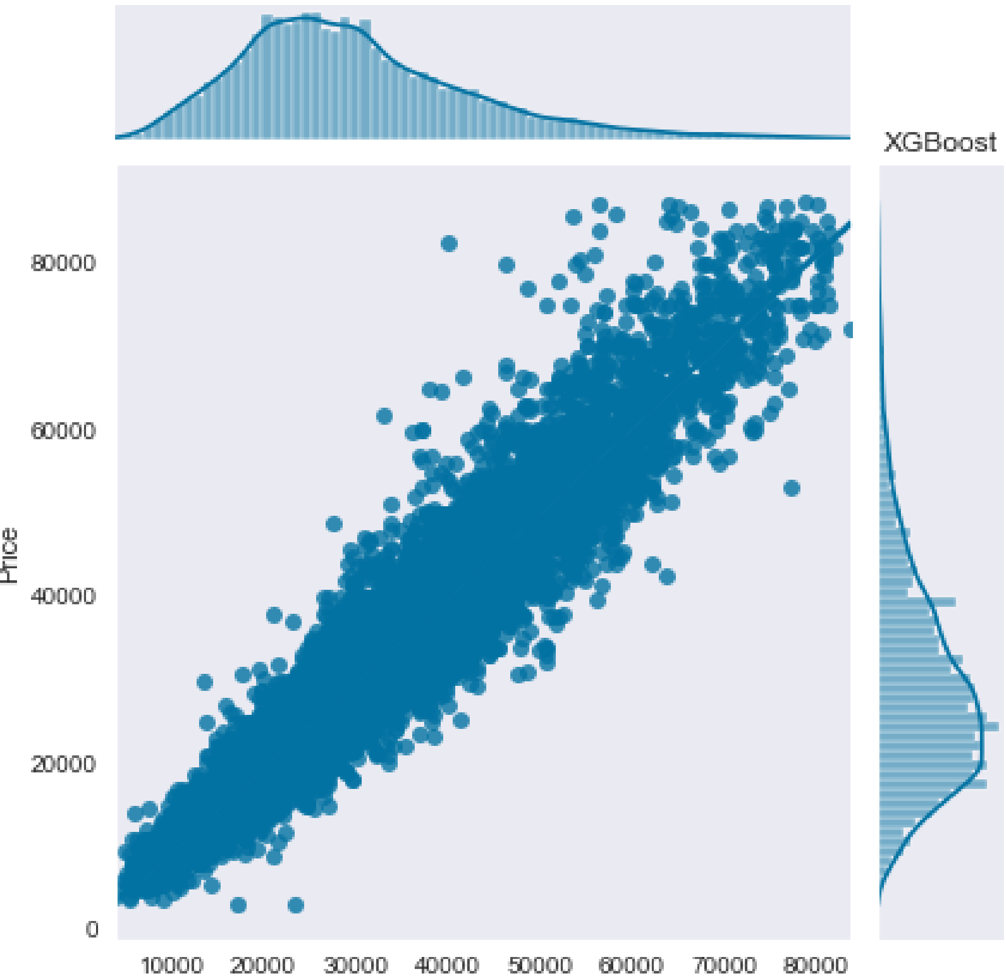
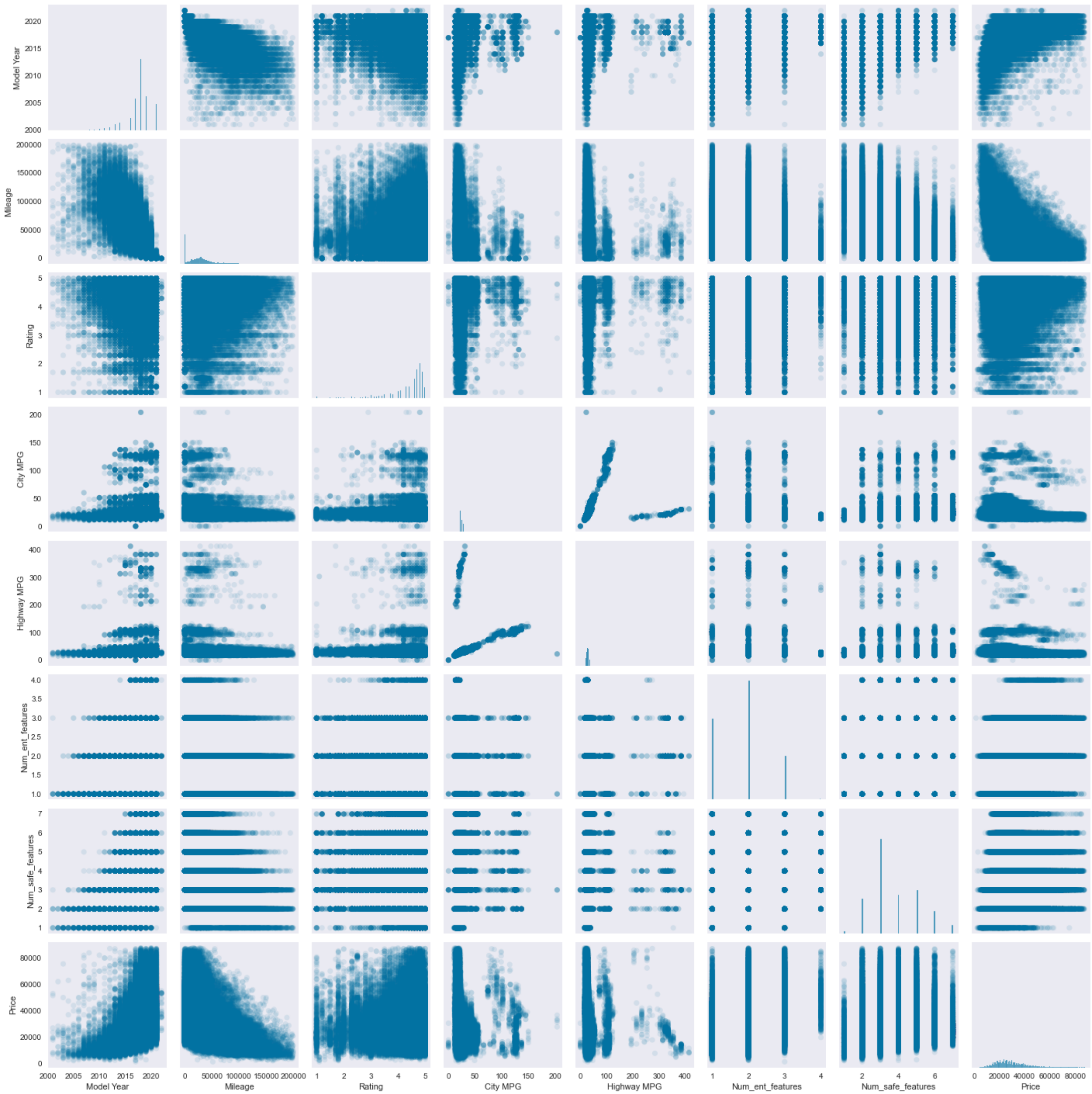
QUESTIONS?

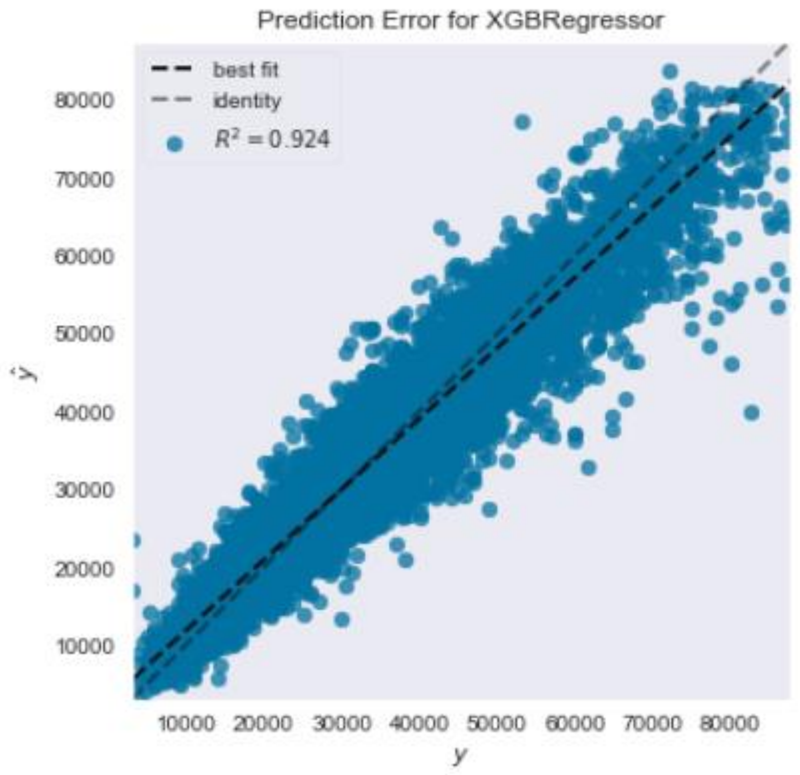
APPENDIX

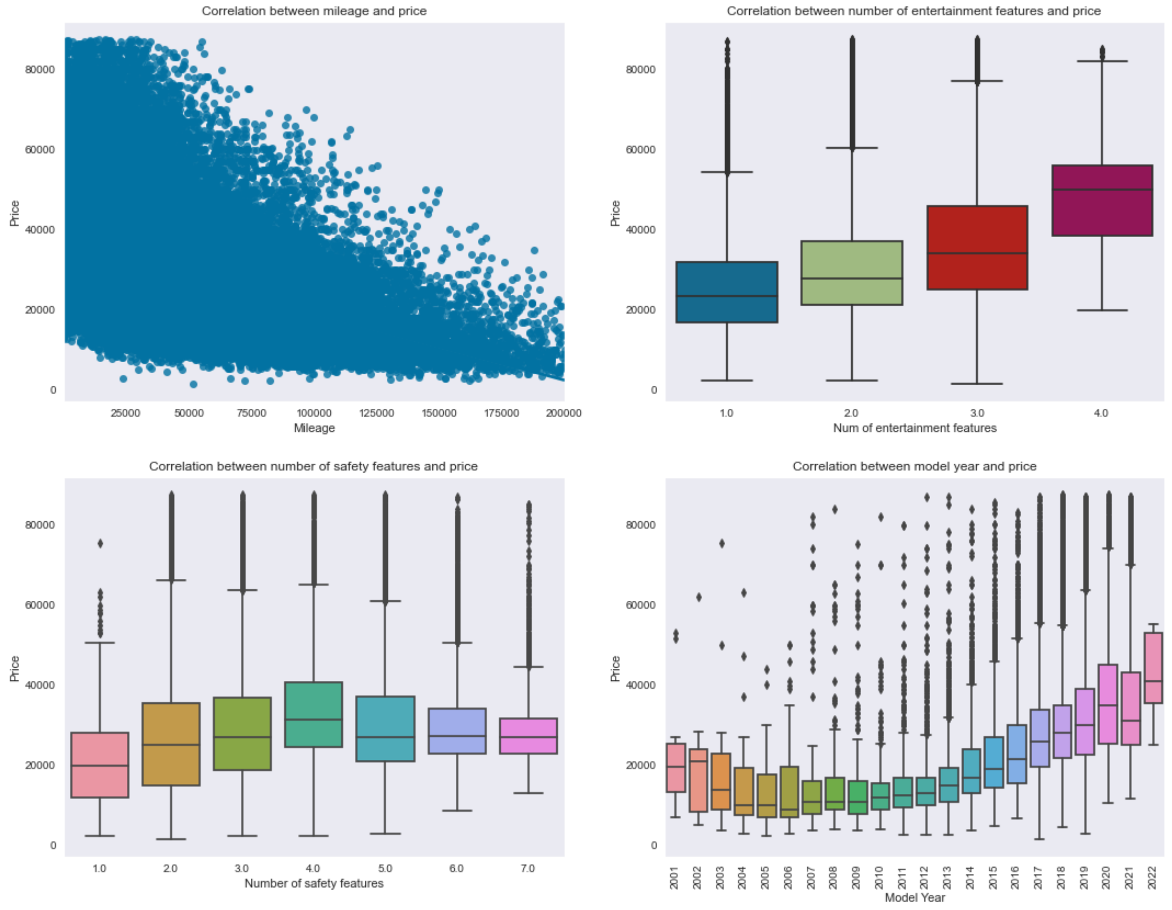

XGBoost
Price
80000
60000
40000
20000
0
10000
20000
30000
40000
50000
60000
70000
80000


Model Year
Mileage
Rating
City MPG
Highway MPG
Num_ent_features
Num_safe_features
Price

APPENDIX

Prediction Error Plot





Documentation on how to use streamlit to build the interactive app : https://streamlit.io/