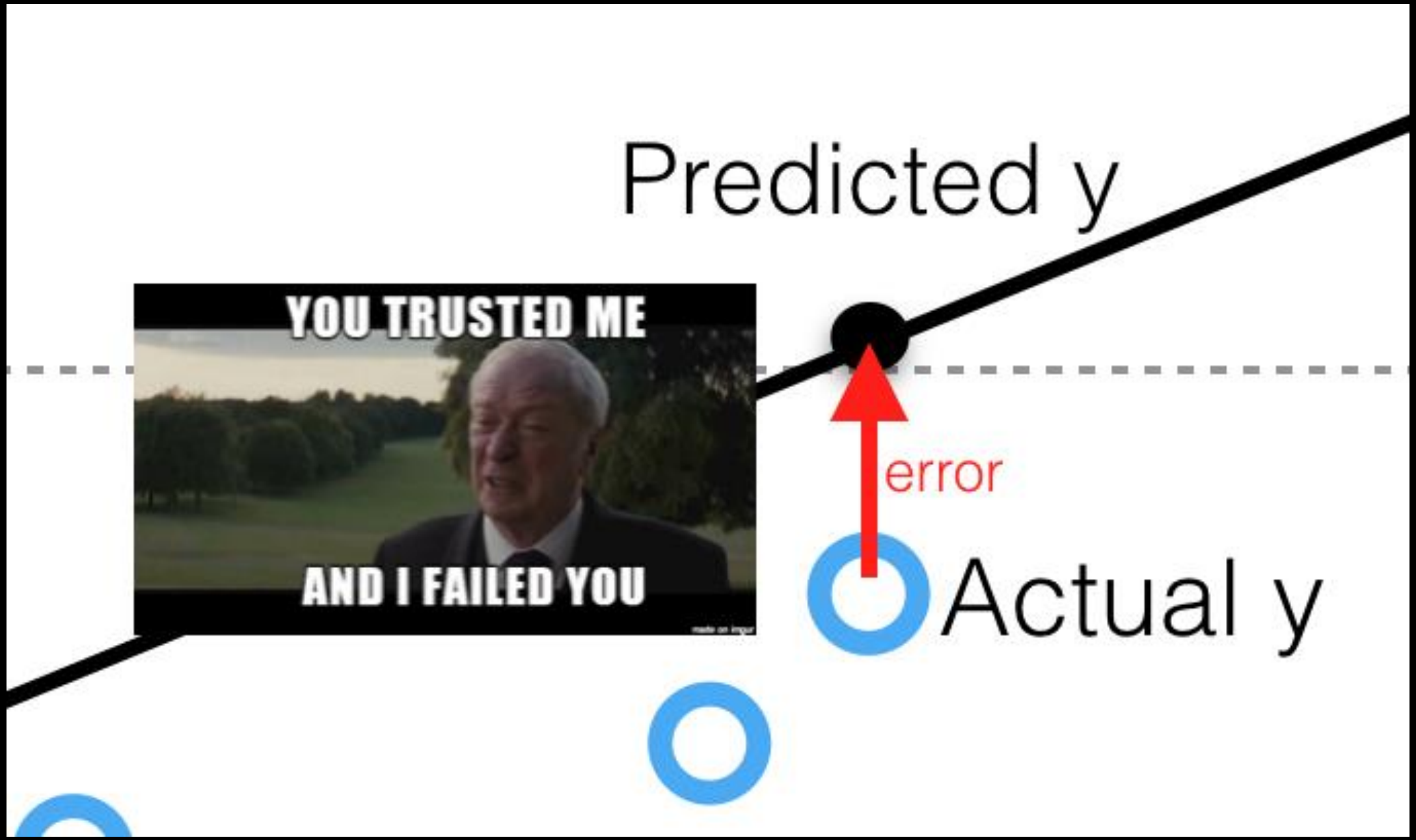
REGRESSION MODEL

CAR PRICE PREDICTOR 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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❖ **OBJECTIVES**:

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❖ **GOALS**:

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

METHODOLOGY

- **Data source:**
  - Scrape from cars.com

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USED

2019 Chevrolet Equinox 1LT

34,354 miles

$19,995 GOOD DEAL

HOT CAR

DELIVERY AVAILABLE | VIRTUAL APPOINTMENTS

Sold by Cash for Cars San Jose, CA 95128

(4.5) 2 Reviews

Basics

Fuel Type: Gasoline
City MPG: 26
Highway MPG: 32
Drivetrain: FWD
Engine: 1.5L I4 16V GDI DOHC Turbo
Mileage: 34,354
Exterior Color: Summit White
Interior Color: Jet Black
Stock: 3558
Transmission: 6-Speed Automatic
VIN: 3GNAXKEV4KL116752

Show more details

Convenience

- Keyless Start
- USB Port

Entertainment

- Bluetooth
- Premium Sound System
- Apple CarPlay/Android Auto

Safety

- Backup Camera
- Brake Assist
- Stability Control

Exterior

- Alloy Wheels

METHODOLOGY

Data Scraping and Preparation

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- 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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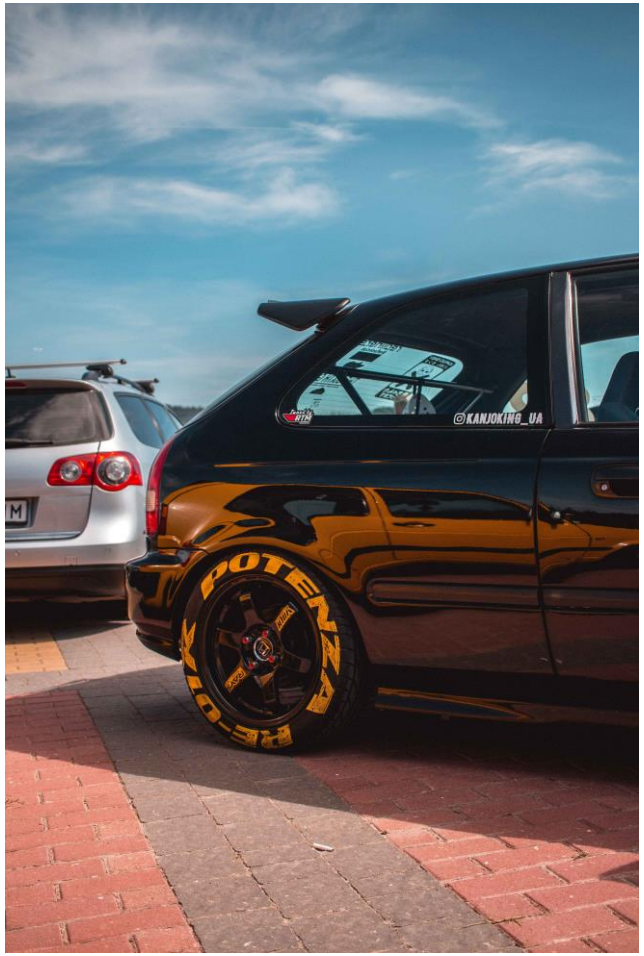
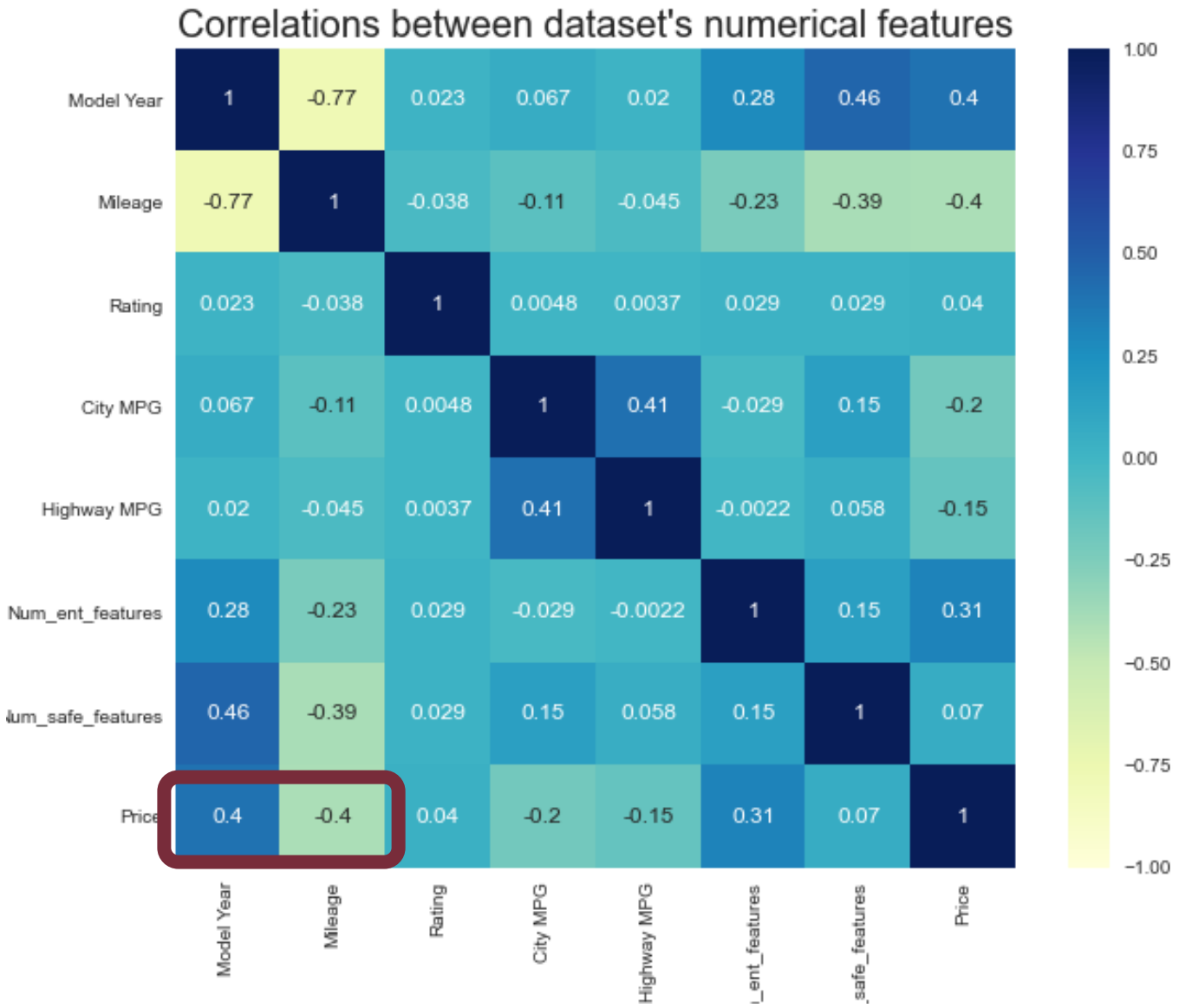


- 187,168 raw data points were scraped.
- Clean data set has 122,351 rows and 18 columns

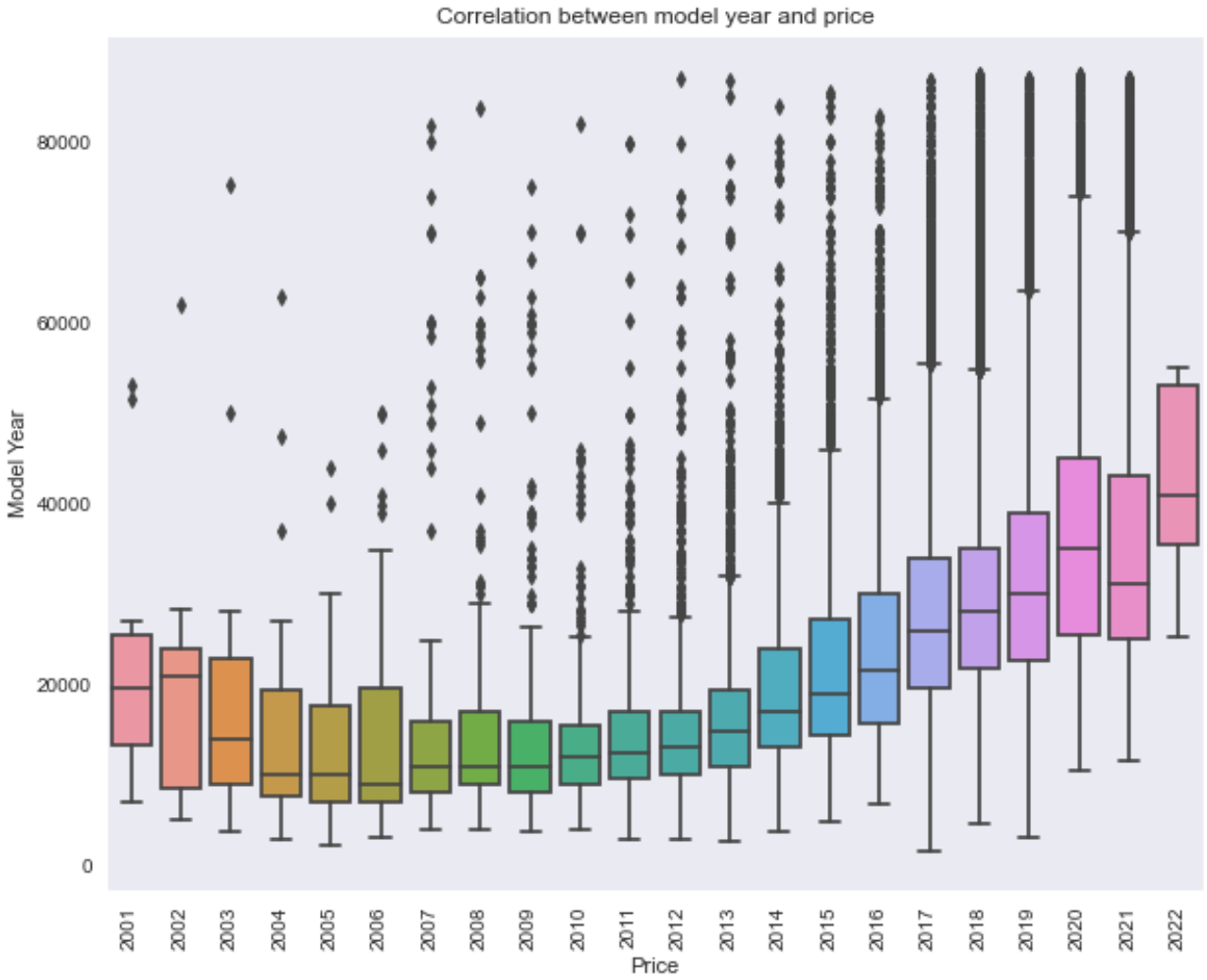
EDA

- 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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  - R^2 for test set: 0.290
- Polynomial Regression Model:
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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):
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In general, they all underfit

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.

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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

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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!

Parameters tuning

- 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: 0.955
  - RMSE = 2788.11
- 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

$35,893

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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

$35,340

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True value

$32,500

CONCLUSION

L1/L2 Regularization

K-Fold Cross-Validation!

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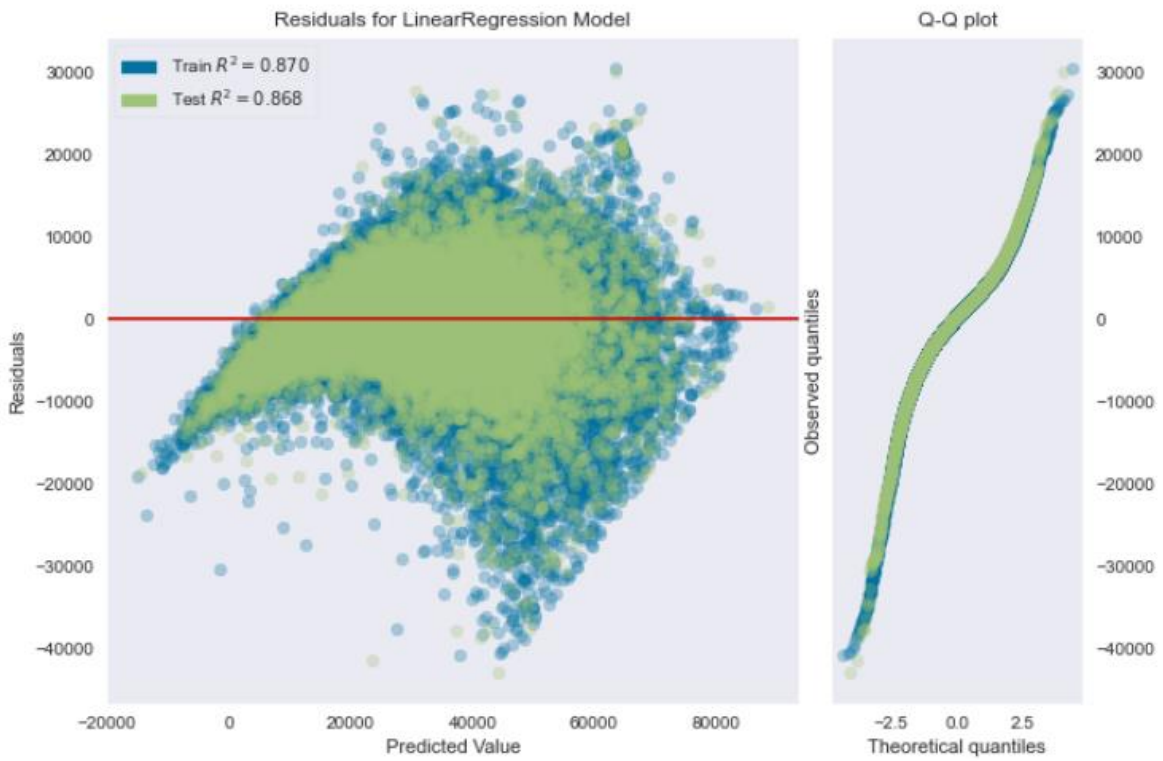
RESIDUALS

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



RESIDUALS

- Extreme Gradient Boosting (XGBoost):
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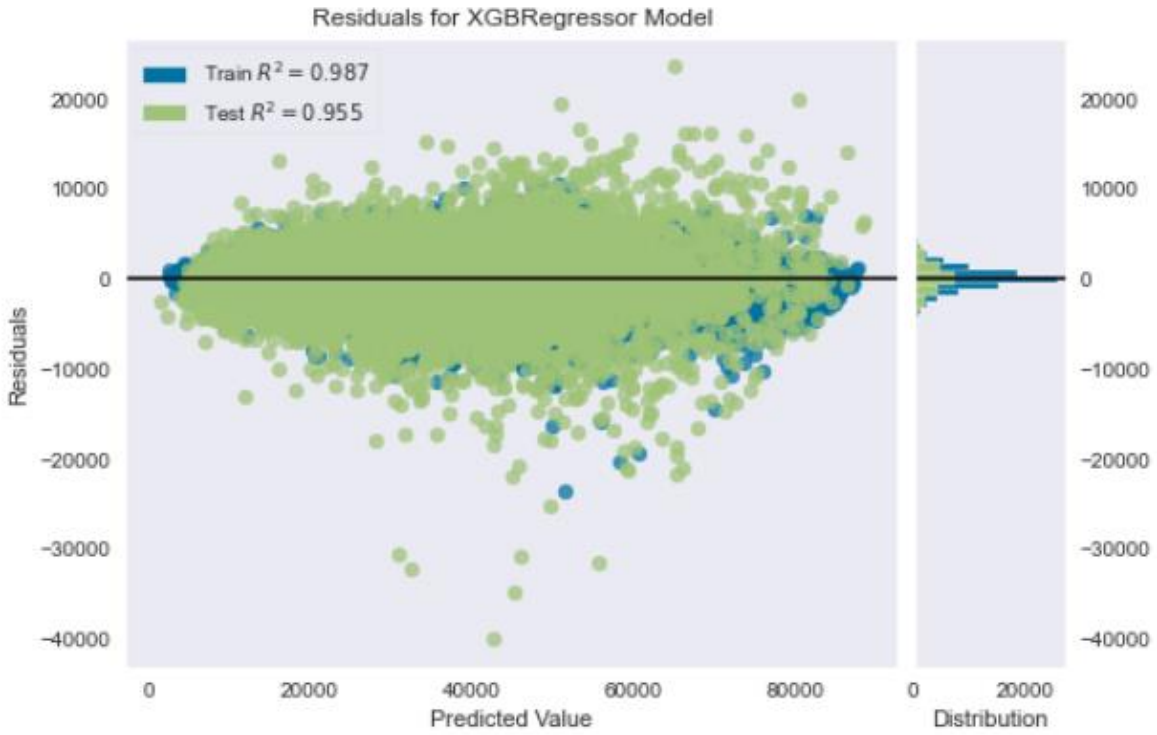
Residuals Plot



PREDICTION ERROR

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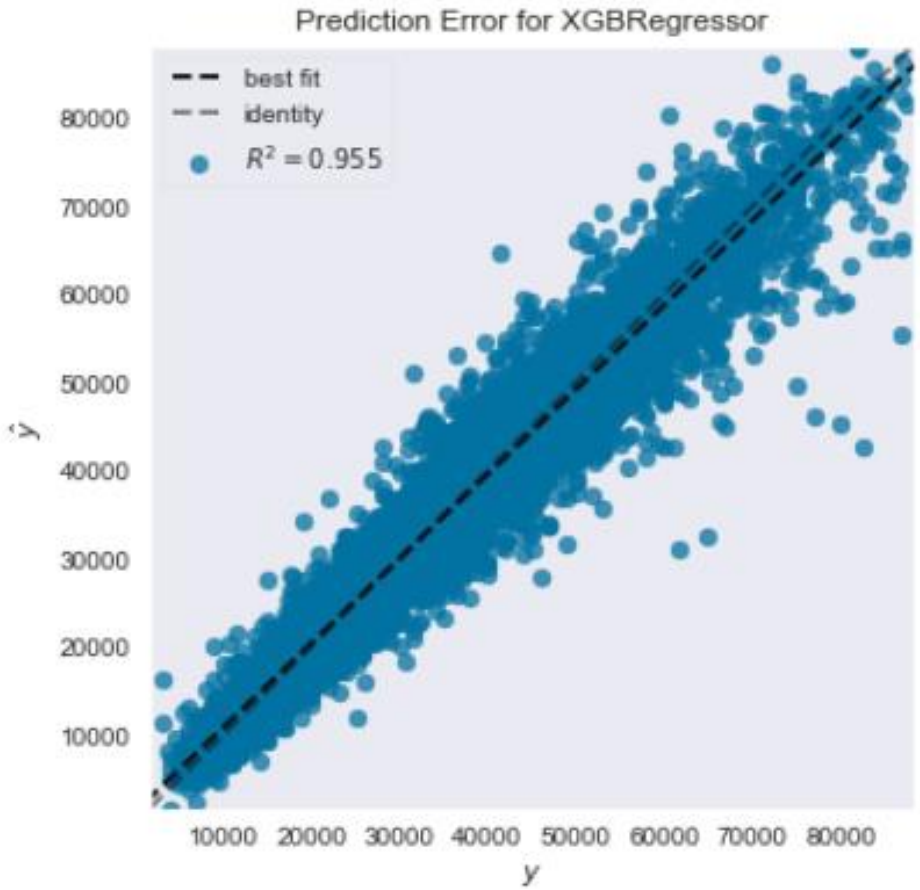
Prediction Error Plot



FEATURE IMPORTANCE

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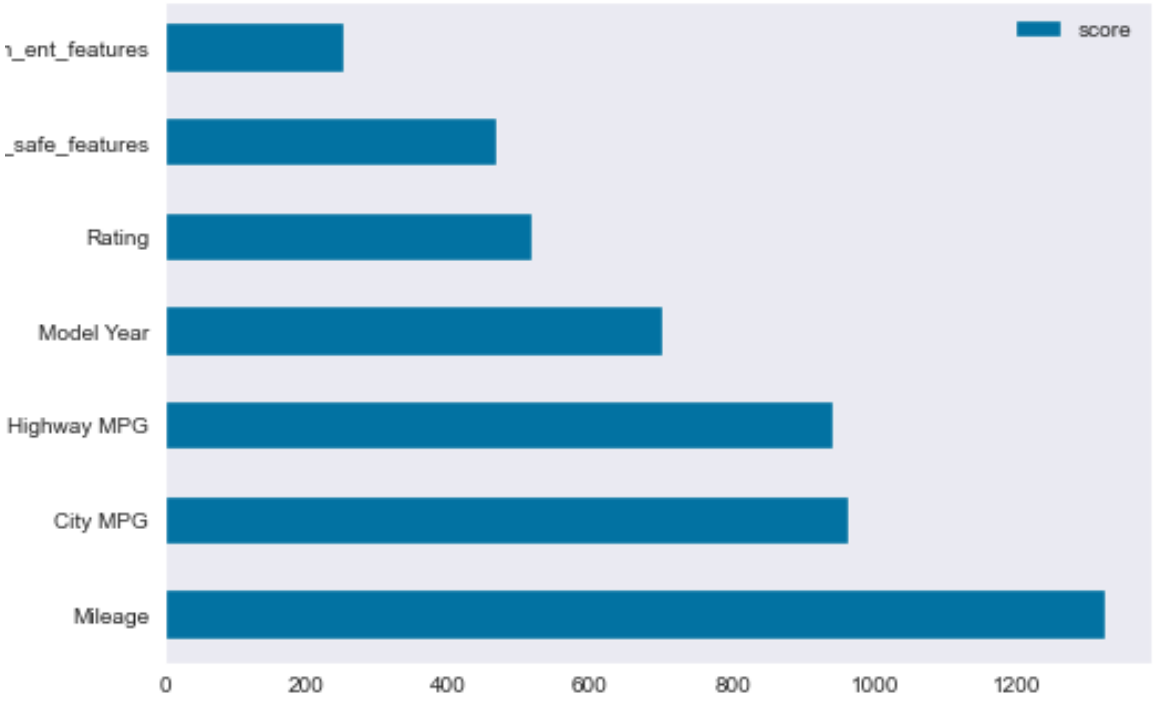

RECAP

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Linear Model

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

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Linear Model

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

Gradient Boosting

0.729 → 1 cat feature → 0.870 → All cat features / Params tuning → 0.955

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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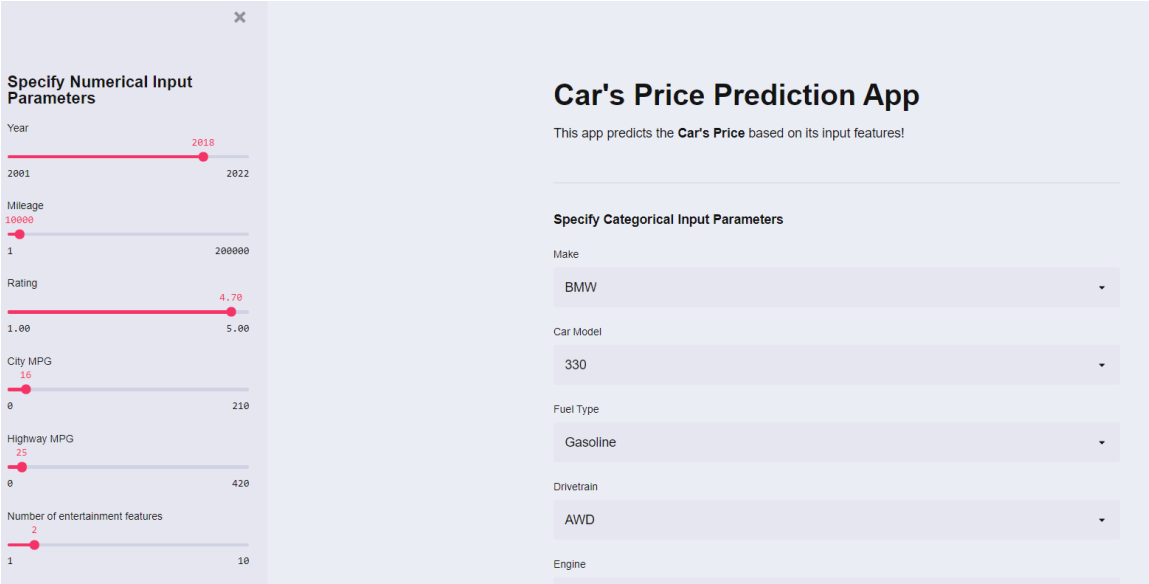

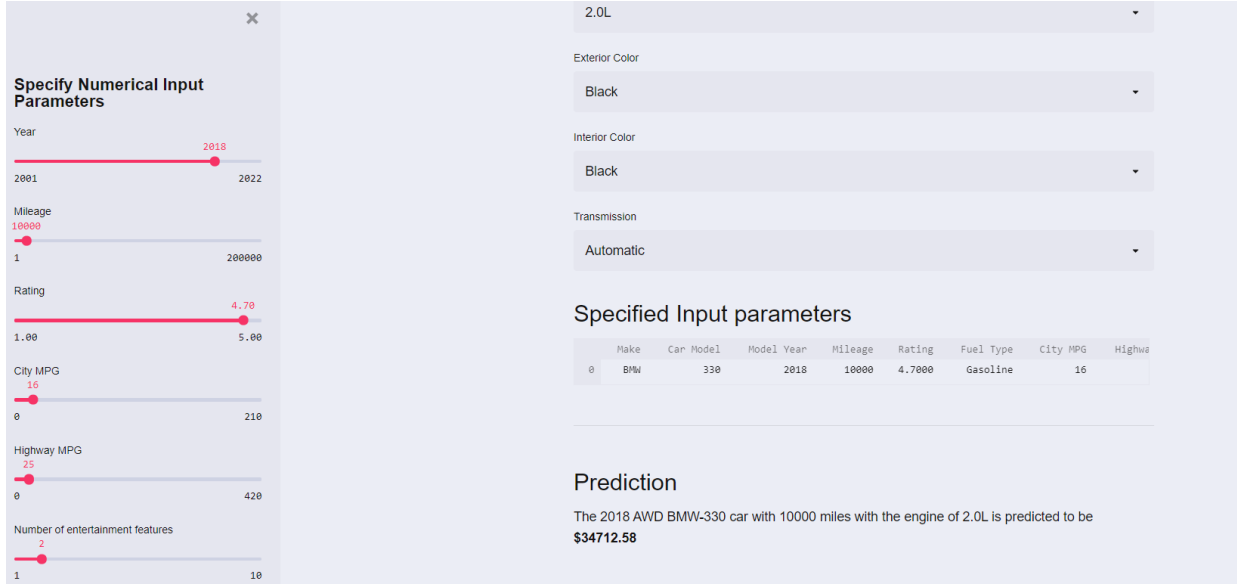

FUTURE WORK

- Incorporate geographic features to determine the price based on location.
- Explore parameters for XGBoost to get better models.

THANK YOU

STEVEN L TRUONG

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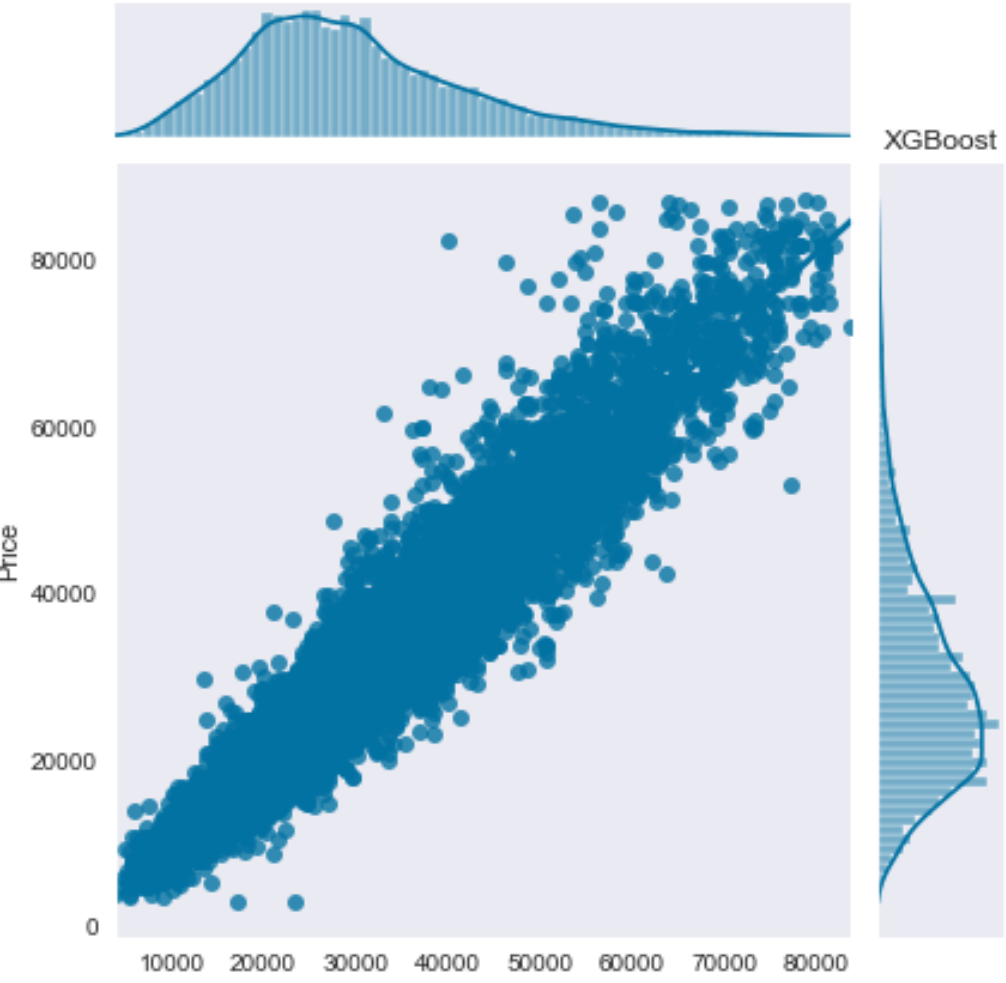
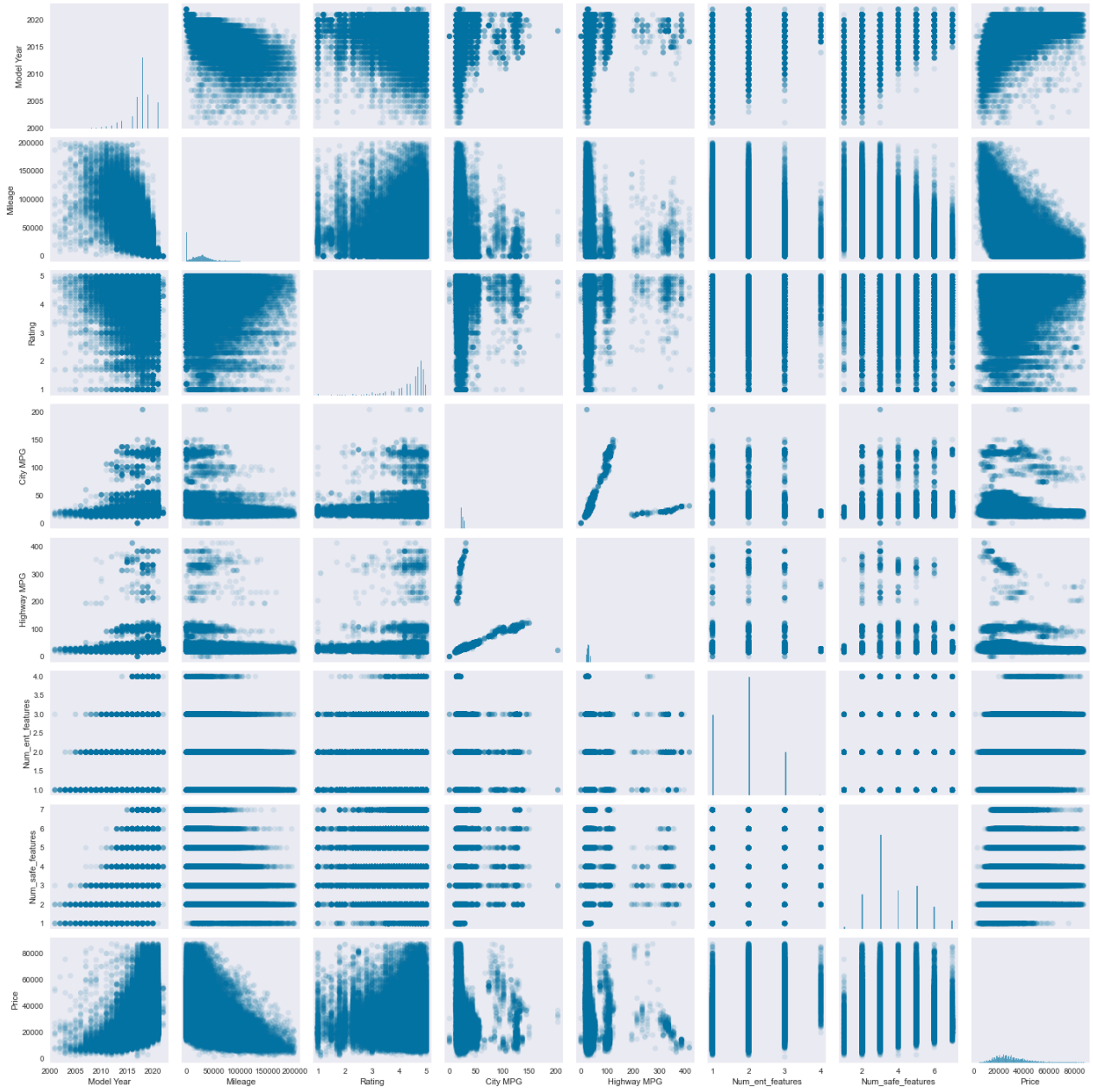
QUESTIONS?

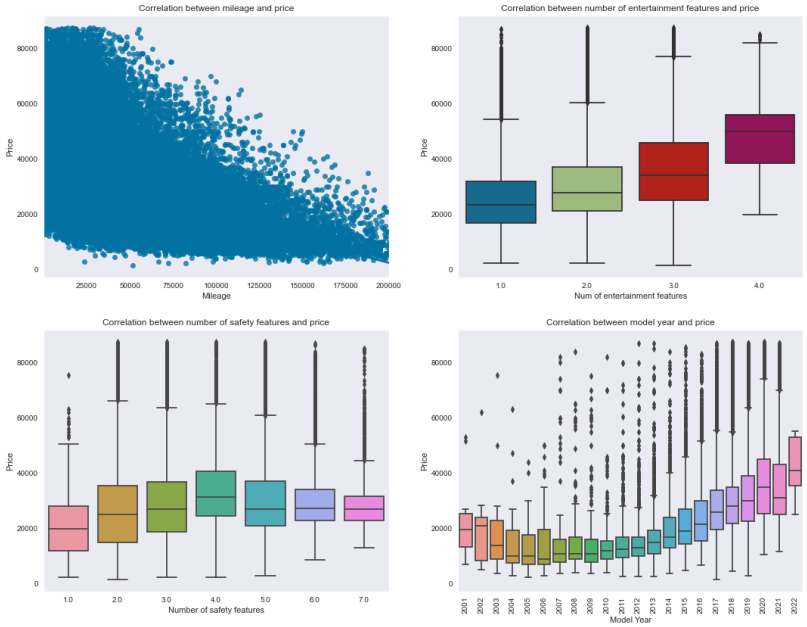
APPENDIX


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


Model Year
Mileage
Rating
City MPG
Highway MPG
Num_ent_features
Num_safe_features
Price

APPENDIX

Parameters of XGBoost to achieve the best results so far.




```
RMSE:  2788.11

R-Squared:  0.9553
```

```
1  xgb_reg_2000
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.3, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=2000, n_jobs=0, num_parallel_tree=1, random_state=0,
             reg_alpha=1, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

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