

# Predicting Fair Market Value for Used Cars





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connect human potential and co

#### Introduction



#### **Problem Statement:**

- Car buyers/sellers seek a reliable way to estimate prices of used cars.
- Used car pricing is complex due to varying depreciation, mileage, and regional factors.
- Goal: Build a predictive model to estimate used car prices using historical Craigslist listings.

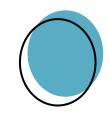
#### **Dataset Used:**

- Source: <u>Kaggle Craigslist Cars & Trucks</u>
- Records: ~426,000 used car listings
- Features: 26 columns incl. make, model, year, odometer, fuel type, etc.

# **Approach:**

 Use XGBoost Regressor (with log-transformed prices and odometer values) to predict car prices





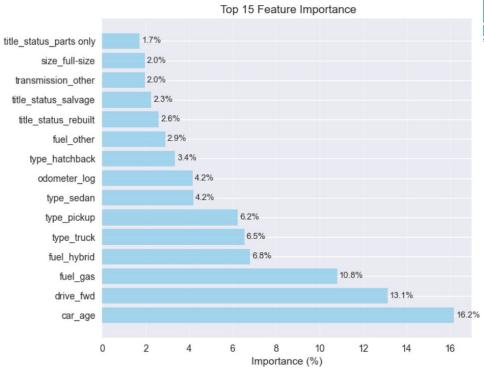
# Price (\$) Log-transformed Price Distribution

Price Distribution

Log transformation is essential for modeling this skewed price data effectively.

Log(Price + 1)

# **Variables Analysis**



The top 15 features contribute ~84.9% of total importance, showing that the model's decisions are concentrated in a few strong signals.

Vehicle age, drivetrain, fuel type, and body type are the strongest predictors of price.

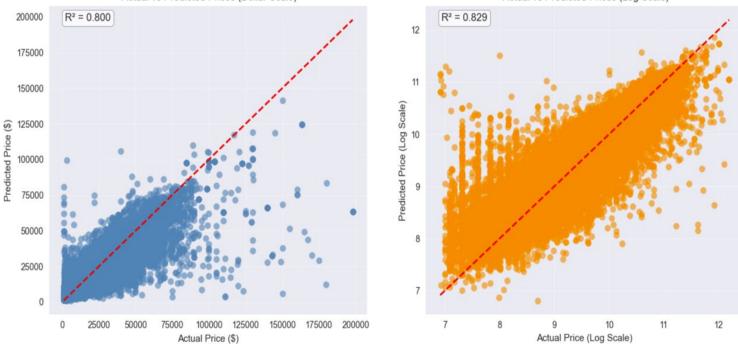


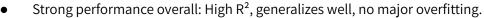
#### **Prediction Analysis**











- Overpredicts slightly on average (~7%).
- Mean Relative Error: +6.6% (train), +7.7% (test) → Slight upward bias model tends to overpredict.
- Predicts directionally well, but not precise for rare/exotic listings.



# **Insights**



# **Challenges**

- Price ranges are very broad (\$0 to nearly \$200K), which makes prediction inherently hard.
- Large memory requirement for Categorical features encoding (therefore used features with considerable unique values).
- Choice of effective new features

### Learnings

- Data Quality is Critical
- Tree-based models (XGBoost) outperformed linear regression.
- Domain knowledge (e.g., "100K+ mileage matters")
- Feature engineering drives performance

# What can be improved

- Improved feature engineering.
- Add Interaction Features:

   Interaction between age ×
   mileage, fuel × type, or
   transmission × drive may reveal
   nonlinear effects.
- Build separate models for economy vs. luxury segments
- Data Quality Improvements:
   example: Better mileage
   normalization (e.g.,
   age-adjusted mileage).





# Thank you!