Final Presentation Of Used Car Trading Price Prediction

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https://github.com/Christy9615/DATA1030FinalProj



I. Project Recap

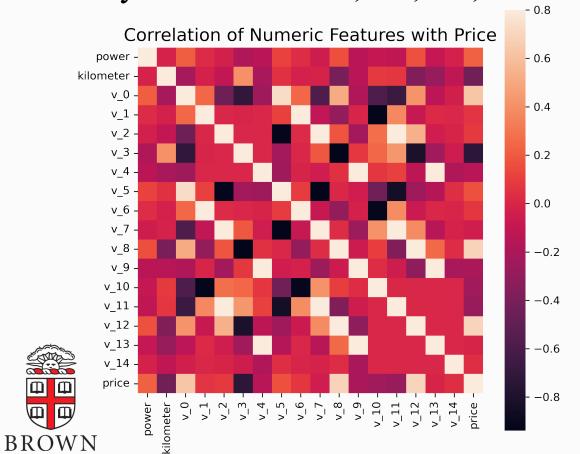
- Dataset Overview --- Used Car Trading Price Prediction
- Project Goal: Predict the trading price of used cars in the test dataset (Regression)

Categorical	seller/ OfferType/ bodyType/ fuelType/ gearbox/ notRepairedDamage regDate/ creatDate/ regionCode/ model/ brand
Continuous	'power', 'kilometer', 'v_0', 'v_1', 'v_2', 'v_3', 'v_4', 'v_5', 'v_6', 'v_7', 'v_8', 'v_9', 'v_10', 'v_11', 'v_12', 'v_13', 'v_14', 'price'

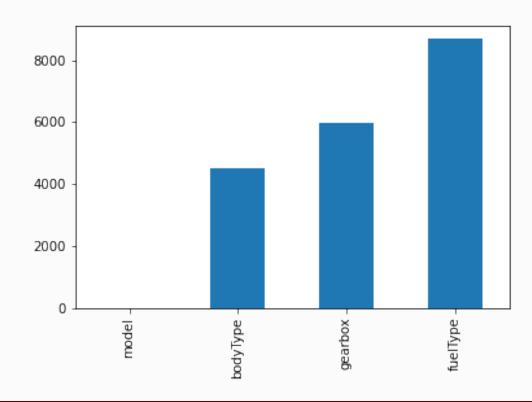


I. Project Recap (EDA)

> Pay attention to V0, V3, V8, V12



➤ Missing value: Using mode 0 to fill the missing value



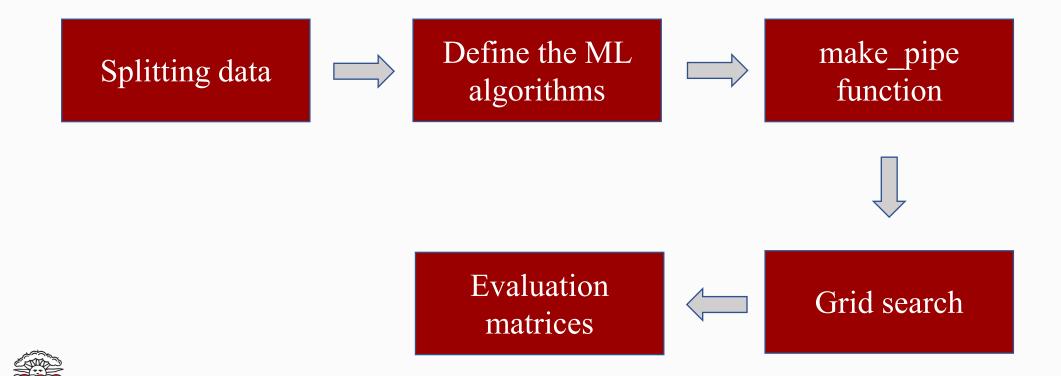
I. Project Recap (Preprocessing)

- > Feature Engineering
 - > Generate new features
 - Example shows below
 - > Preprocessing features with MinMax and OneHot Encoder



II. Cross Validation (CV Pipeline)

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II. Cross Validation (Algorithms, Parameters)

- ➤ 6 Regression

 Algorithms are tried
- Parameters tunedare listed in thetable

Model Name	Parameters tuned
Linear Regression with L1 regularization	Alpha: np.logspace(-5,5,25)
Linear Regression with L2 regularization	Alpha: np.logspace(-5,5,25)
K-Neighbor Regressor	n_neighbors:1,11,30,100
LGBM(Light Gradient Boosted Machine) With gbdt (gradient Boosting Decision Tree)	max_depth: -1,1,2
XGBoost	max_depth: 2,3,4,5,8 subsample: 0.75, 0.8
Random Forest	Not tuned



III. Results (Model Scores)

➤ LR with L1: 0.742

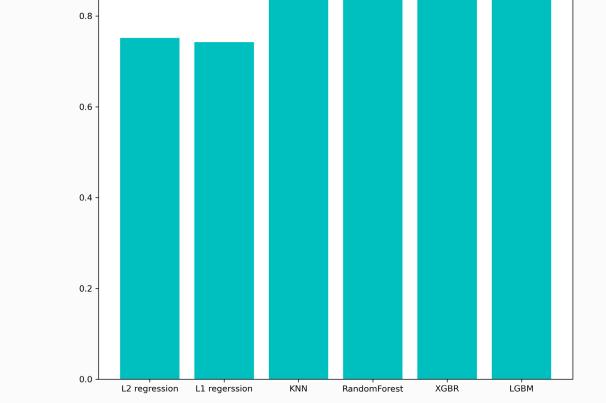
➤ LR with L2: 0.751

➤ K-Neighbor: 0.937

> Random Forest: 0.957

➤ XGBoost: 0.969

➤ LGBM: 0.967



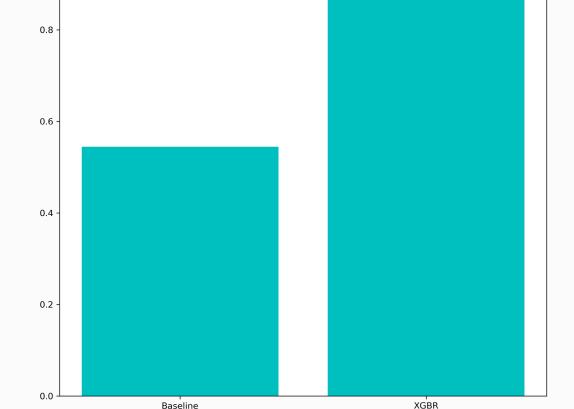
Average R2 score of each model



III. Results (Model Scores)

➤ Baseline: 0.55

➤ XGBoost: 0.969

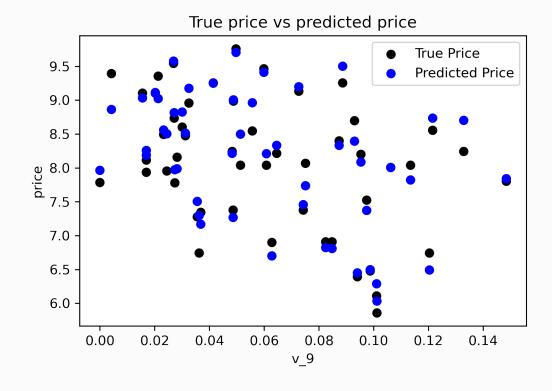


R2 score of XGBR compares to baseline score



III. Results (Models Inspection)

➤ LR with L1 model: First 50 points. The predicted price are generally away from the true price





III. Results (Global Feature Importance)

➤ Global Feature Importance of

Random Forest

Feature	Weight
new3-0	0.2692 ± 0.0013
new0-3	0.2471 ± 0.0012
new12*year	0.0213 ± 0.0007
new8*year	0.0173 ± 0.0003
new8+3	0.0130 ± 0.0001
notRepairedDamage	0.0120 ± 0.0002
kilometer	0.0108 ± 0.0003
new3+8	0.0102 ± 0.0001
v_14	0.0079 ± 0.0001
new11*year	0.0060 ± 0.0001

➤ Global Feature Importance of

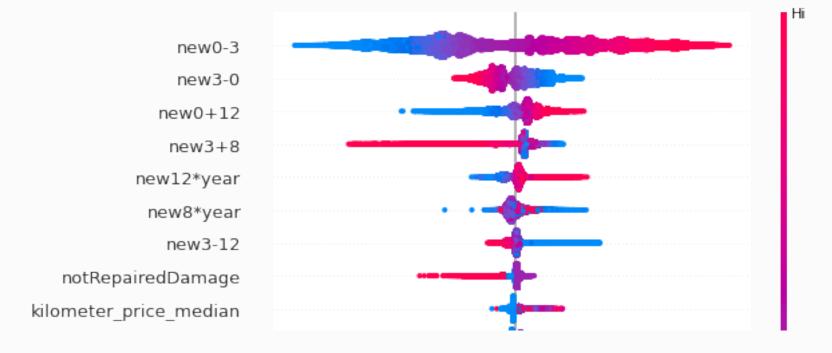
XGBR

reasone eer _pr ace_meason	0:002020
new0*12	0.002930
new12*year	0.005344
new3-12	0.006653
new3-8	0.008650
new12-3	0.008883
new8-3	0.018331
new12-8	0.021881
new0+12	0.032838
new8+3	0.038139
new12+0	0.041154
new3+8	0.206456
new0-3	0.257088
new3-0	0.321593
dtype: float32	



III. Results (SHAP)

➤ Part SHAP plot of XGBR





IV. Outlook

- ➤ Use LGBM rather than XGBoost
- > Tunes Alpha in XGBR
- ➤ Using model stacking combine XGBR and LGBM
- ➤ Buy a 28-cores computer



V. Reference

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- 1. "天池_二手车交易价格预测数据分析." 开发者的网上家园, www.cnblogs.com/cgmcoding/p/13279789.html.
- 2. 零基础入门数据挖掘 二手车交易价格预测赛题与数据-天池大赛-阿里云天池. tianchi.aliyun.com/competition/entrance/231784/information.
- 3. Lundberg, S. (2020, October 6). *Interpretable machine learning with XGBoost*. Medium. Retrieved December 10, 2021, from https://towardsdatascience.com/interpretable-machine-learning-with-xgboost-9ec80d148d27.
- 4. Andrew Lukyanenko. (n.d.). *Predicting molecular properties*. Kaggle. Retrieved December 7, 2021, from https://www.kaggle.com/c/champs-scalar-coupling/discussion/96655

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