Case Study: Risky Dealer Risk Assessment by an Explainable Model

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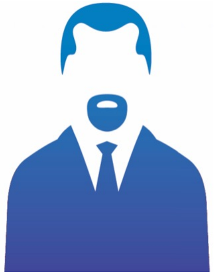
- M.Sc. in Statistics, The University of Georgia
- Data Scientist Intern, Cox Automotive (vAuto)
- Been a Teaching Assistant and a Lab Instructor since 2015.
- Worked in Equifax, State Farm as a Data Scientist

Research:

- Responsible Data Science

Problem Description



Buyer

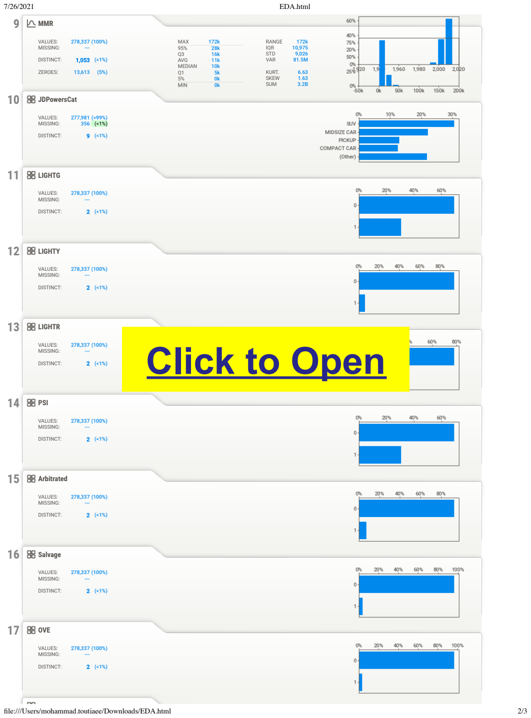
Not Risky (0)

Risky (1)

DealShiled

- Affects buyer's transactional history
- Loss of investor's capital and interest
- Damages reputation as a responsible guarantor
- Can potentially affect car's sale price

EDA



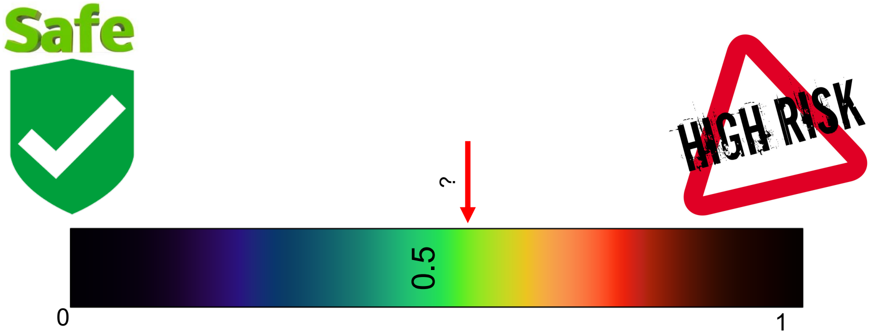
Missing Values	Treatment
CarMake (2)	Added to UNKNOWN
JDPowersCat (356)	Imputed by Mode(SalePrice, CarMake, CarYear)
Autocheck_Score (9320)	Imputed by Mode(SalePrice, CarMake, Mileage)
ConditionReport (~200K)	Imputed by NN(SalePrice, CarMake) Apply t-statistic to check for difference
Returned (~250K)	Removed in training

Dirty Values	Treatment
CarMake	Group similar records Example: B M W => BMW
ConditionReport	Group by similar Mean(SalePrice, CarMake) Example: A, A3 => 20

Feature Engineering

- Original Dataset: 22 Predictors
- One-hot Encoding: JDPowersCat, CarMake, SellingLocation, DayOfWeek
- Added extra engineered features:
    - Number of Distinct Seller per Buyer
    - Number of Purchase per Buyer
    - Avg SalePrice per Buyer
    - Number of Days Since Last Purchase per Buyer
    - etc
- Total features: 291
- Target Variable: Risky or Not Risky (1=Risky, 0=NotRisky)

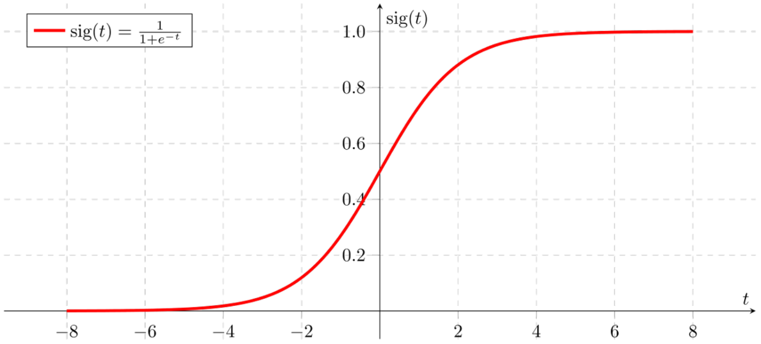
Model Building



		Predicted Class	
		Risky	Not Risky
Actual Class	Risky	TP	FN Type II Error
	Not Risky	FP Type II Error	TN

Model Building

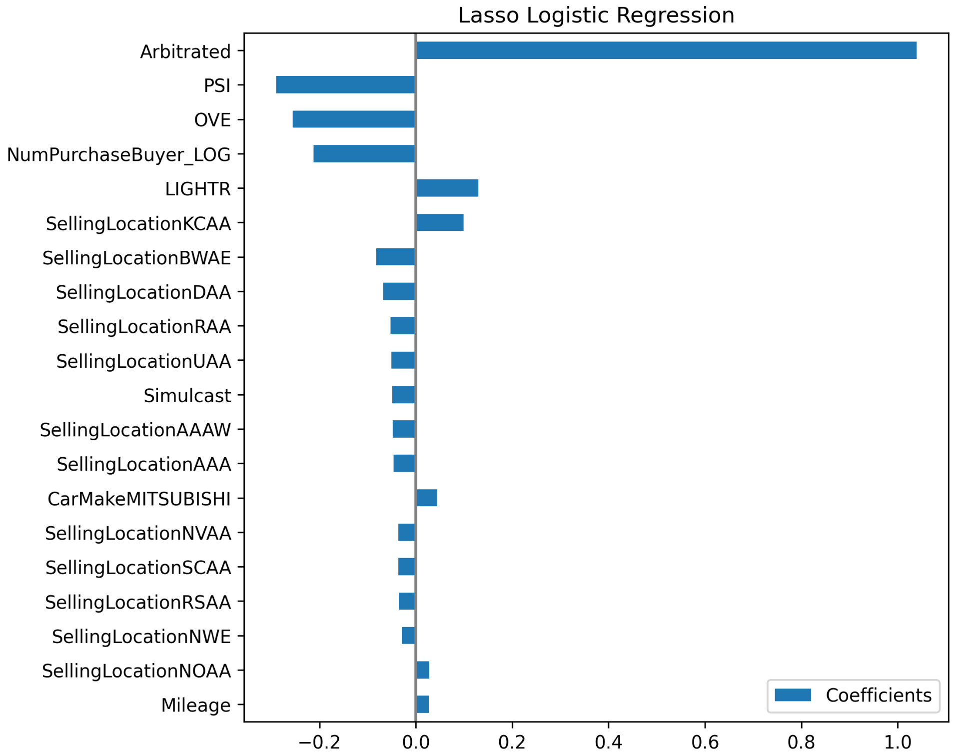
Baseline: Lasso Logistic Regression



AUC Score:
- Train set: 0.82
- Test set: 0.80

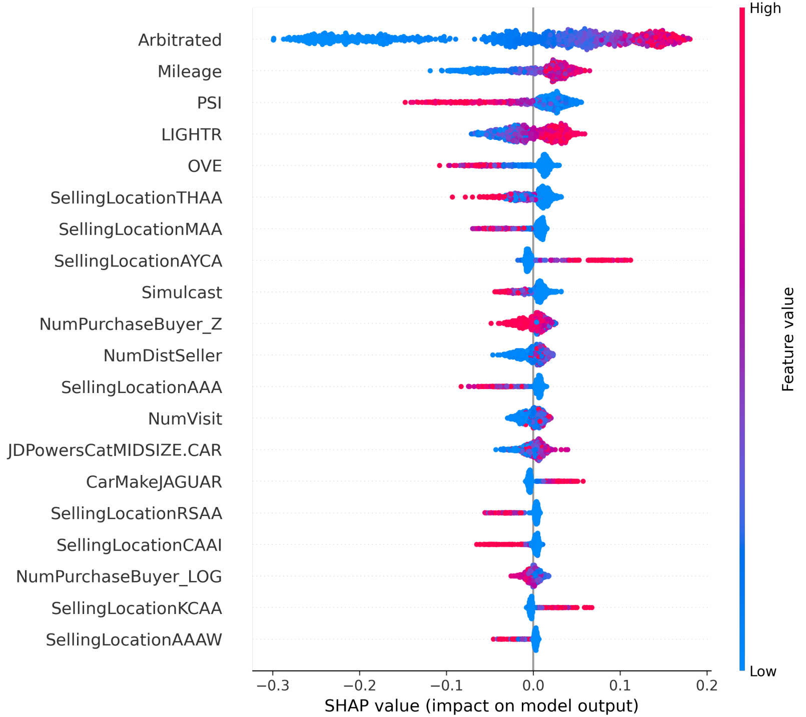
Precision: 0.72
Recall: 0.60
F1-score: 66
No. Selected Vars: 65

Top 20 Variables

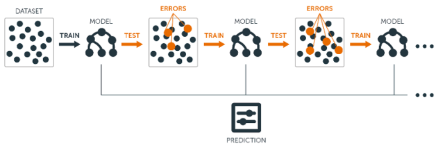


Model Building

Top 20 Variables



Random Forest



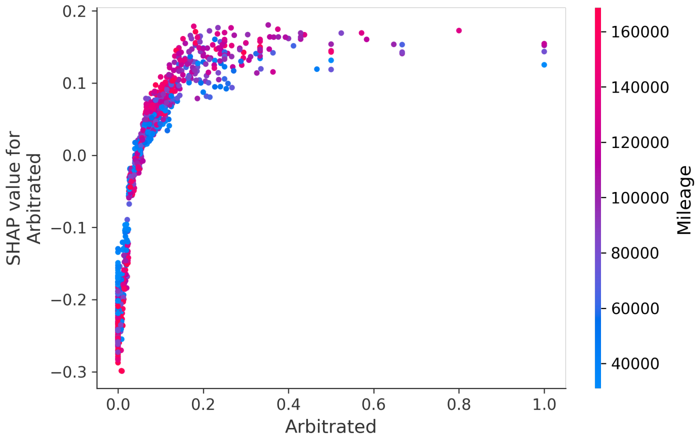
AUC Score:

- Train set: 0.87
- Test set: 0.72

Precision: 0.67

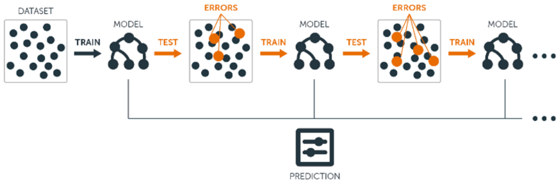
Recall: 0.71

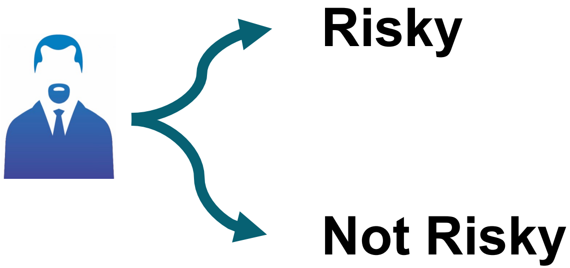
F1-score: .69

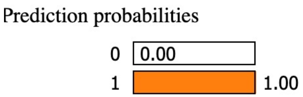


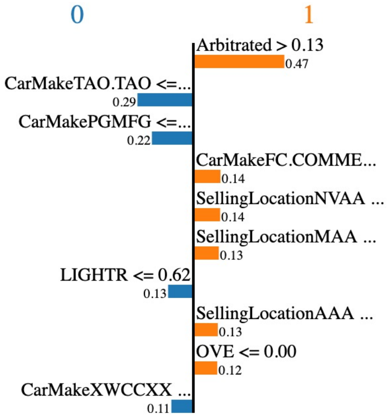
Rejected Application Explanation by LIME

Easy to Implement
Easy to Understand









Feature	Value
Arbitrated	0.40
CarMakeTAO.TAO	0.00
CarMakePGMFG	0.00
CarMakeFC.COMMER	0.00
SellingLocationNVAA	0.00
SellingLocationMAA	0.00
LIGHTR	0.60
SellingLocationAAA	0.00
OVE	0.00
CarMakeXWCCXX	0.00

Model Selection

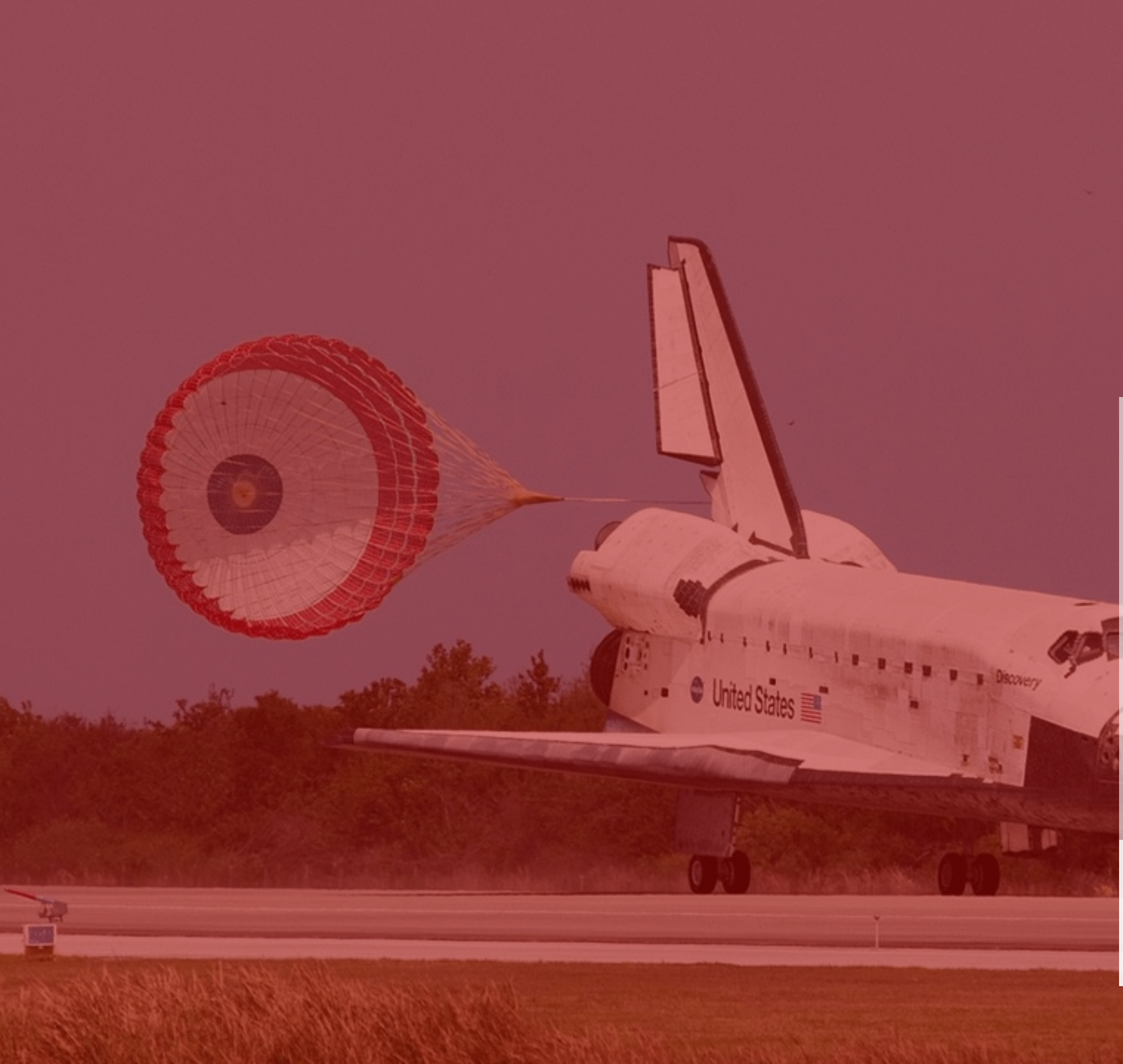
Tr-Ts (67%,33%)	Lasso LR	RF (selected Features)	RF
ROC_AUC	80%	72%	70%
F1-Score	66%	69%	65%

- Interpretable
- Easy to Implement

Conclusion

- Complex machine learning methods need more data (*IEEE BDS' 21*, *MiLeTS' 21*).
- Model debiasing may be required to prevent discrimination (e.g location, age, etc.)
- Interpretation techniques are useful to explain the black box models and provide insights.
- Model's performance can be improved via data augmentation, feature engineering and hyperparameters optimization.
- Toolsets:

jupyter python NumPy LIME R Scikit learn Pandas AIF360



Thank you for your attention!

Questions ...