

An ML approach to pricing cars

#### Team 10

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# Have you bought a resale car?

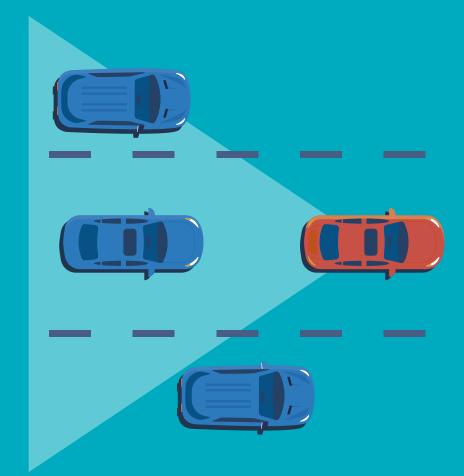
Used car pricing is often ambiguous – it can depend on multiple factors.

However, how these affect the price of the car is often unclear to most potential buyers.

# Our Objective

We seek to build an online platform to bring clarity to buyers in their decision-making process and put them in a better position to negotiate a better price

Let us show you



# **DEMO**

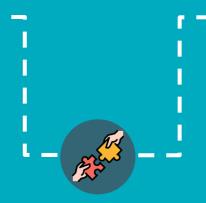
01 02 **DATA** COMPUTER **EDA & Processing** VISION 03 Feature Selection PRICE **PREDICTION** Model Build & Analysis 04 Feature Selection CONCLUSION Model Builds & Analysis Learnings

# About the data

#### Car Images Dataset

- Purpose: Used for computer vision model
- **Source:** Stanford
- **Sample Size:** 16,185
- Feature Size: N/A





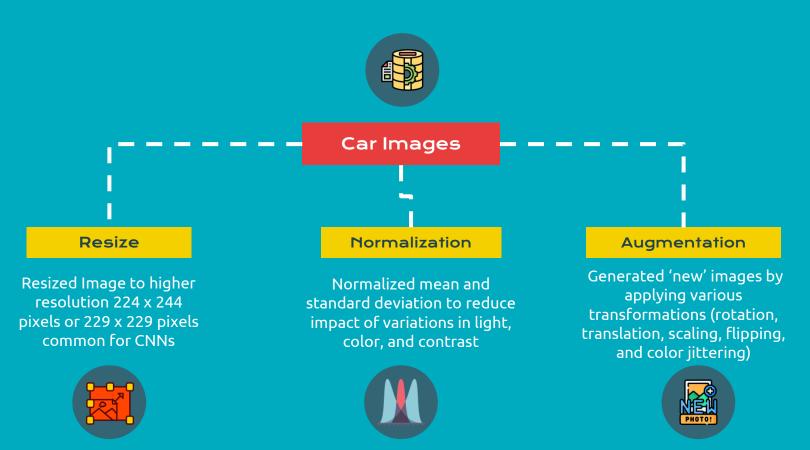


#### **USA Used Cars Dataset**

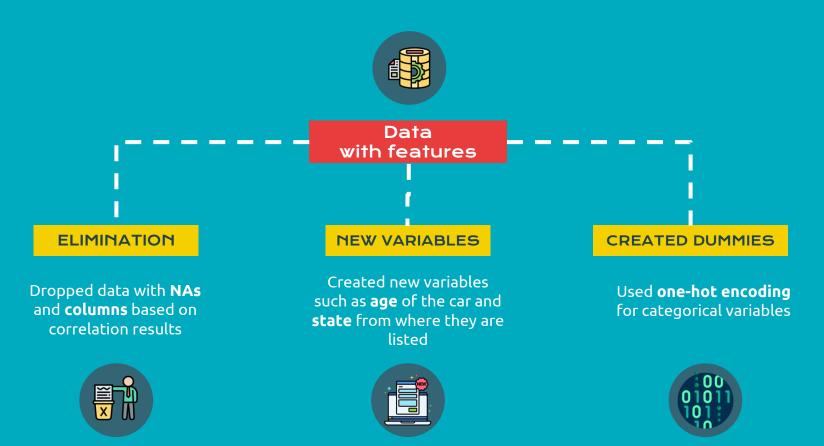
- Purpose: Used for price prediction model
- Source: Kaggle
- **Sample Size:** 3,000,040
- **Feature Size:** 166 features



# CV Multiclass Model data processing



# Data processing for prediction models



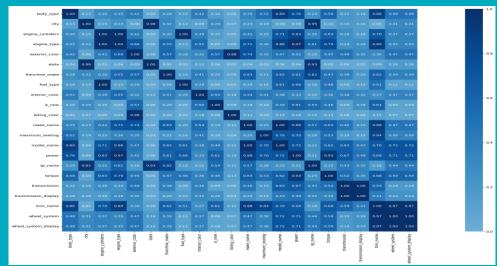
# EDA: CORRELATION ANALYSIS (1/4)

We check correlation between variables to avoid inputting highly correlated variables into the model

# CorrPlot for continuous variables

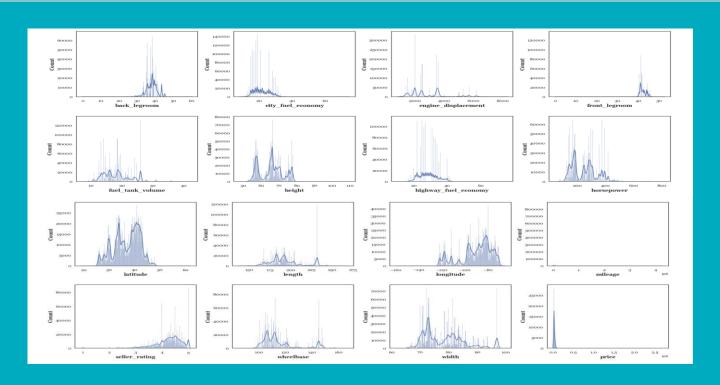


# Cramer's V for categorical variables



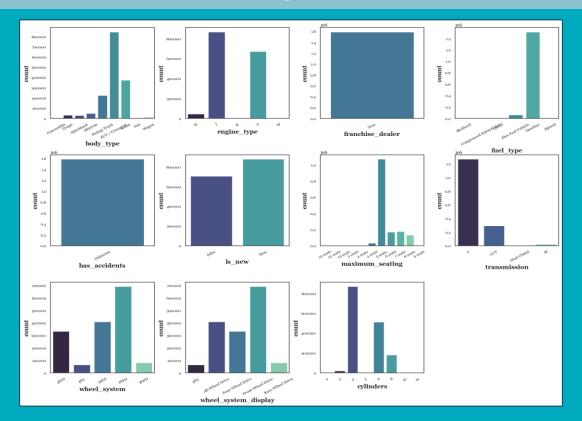
# EDA: CHECKING THE DATA DISTRIBUTION (2/4)

Since the input variables are not normally distributed, data normalization will be required prior to developing the machine learning models



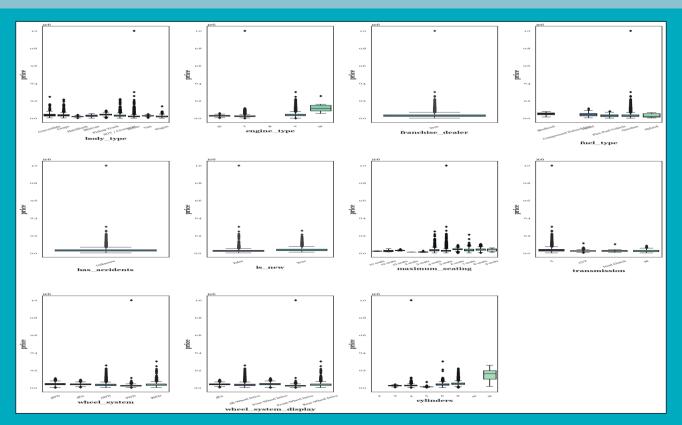
# EDA: CHECKING THE DATA DISTRIBUTION (3/4)

Since the input variables are not normally distributed, data normalization will be required prior to developing the machine learning models



# EDA: CHECKING FOR OUTLIERS (4/4)

We check for the presence of outliers in categorical variables, data normalization will be required prior to developing the machine learning models



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# Process for CV multi-class model selection

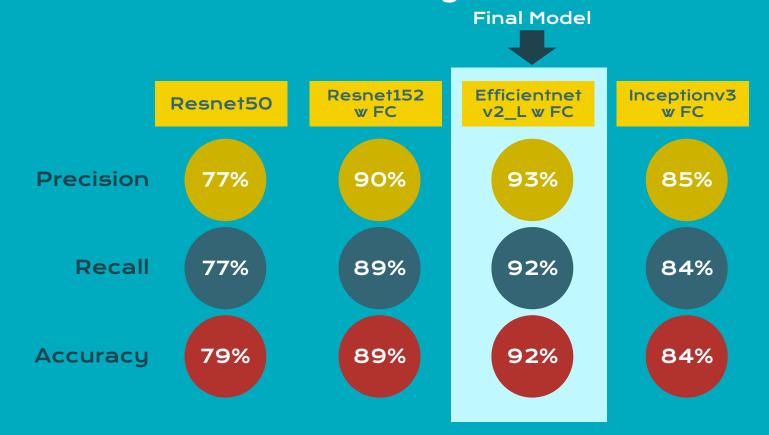


Trained ~100 (20/80) epochs with various torchvision transfer learning backbones: Resnet50, Resnet152, Effcientnetv2\_L, Inceptionv3

Saved Model after every epoch, evaluated and selected the best model on precision/ recall/ accuracy

Further trialed the model by varying hyper parameters like learning rate, addition of FC layer & Input resolution

# Trials best model summary



# Final Selected Model

#### **Parameters**

Model Parameters	EfficientnetV2 Depth: 23 layers Width: 4.0 Activation F: Swish Pooling: Adaptive Average Pooling 307 mil parameters	FC Layer Depth: 2 layers Activation F: Relu 598k parameters	
	Optimizer	Adam	
Training Parameters	Learning R	0.001,0.0001	
	LR Scheduler	Cosine Annealing	
	Dropout	0.3	
	Batch size	32	

#### **Classification Report**

	2000	0.98	0.98	0.98	44
Acura Integra Type R		0.98	0.93	0.95	44
Acura RL Sedan		0.82	0.88	0.85	32
Acura TL Sedan		0.79	0.98	0.88	43
Acura TL Type-S		1.00	1.00	1.00	42
Acura TSX Sedan	2012	1.00	0.78	0.87	40
Acura ZDX Hatchback		1.00	0.87	0.93	39
Aston Martin V8 Vantage Convertible	2012	0.90	0.78	0.83	45
Aston Martin V8 Vantage Coupe	2012	0.82	0.78	0.80	41
Aston Martin Virage Convertible	2012	1.00	0.82	0.90	33
Aston Martin Virage Coupe	2012	0.77	0.97	0.86	38
Audi 100 Sedan	1994	0.71	0.90	0.79	40
Audi 100 Wagon	1994	1.00	0.83	0.91	42
Audi A5 Coupe	2012	0.71	0.90	0.80	41
Audi R8 Coupe	2012	0.98	0.95	0.96	43
Audi RS 4 Convertible	2008	0.89	0.92	0.90	36
Audi S4 Sedan	2007	0.96	0.96	0.96	45
Audi S4 Sedan	2012	0.97	0.74	0.84	39
Audi S5 Convertible	2012	0.84	0.76	0.80	42
	•••				
Tesla Model S Sed	lan 2012	1.00	0.97	0.99	38
Toyota 4Runner S	lan 2012 SUV 2012	1.00	1.00	0.99 0.99	40
Toyota 4Runner S Toyota Camry Sed	lan 2012 SUV 2012 lan 2012	0.98 0.95		0.99 0.95	40 43
Toyota 4Runner S Toyota Camry Sed Toyota Corolla Sed	dan 2012 SUV 2012 dan 2012 dan 2012	0.98 0.95 0.97	1.00 0.95 0.91	0.99 0.95 0.94	40 43 43
Toyota 4Runner S Toyota Camry Sed Toyota Corolla Sed Toyota Sequoia S	lan 2012 SUV 2012 lan 2012 lan 2012 SUV 2012	0.98 0.95 0.97 0.97	1.00 0.95 0.91 0.89	0.99 0.95 0.94 0.93	40 43 43 38
Toyota 4Runner S Toyota Camry Sed Toyota Corolla Sed Toyota Sequoia S Volkswagen Beetle Hatchba	ian 2012 SUV 2012 ian 2012 ian 2012 SUV 2012	0.98 0.95 0.97 0.97 1.00	1.00 0.95 0.91 0.89 1.00	0.99 0.95 0.94 0.93	40 43 43 38 42
Toyota 4Runner S Toyota Camry Sed Toyota Corolla Sed Toyota Sequoia S Volkswagen Beetle Hatchba Volkswagen Golf Hatchba	ian 2012 SUV 2012 ian 2012 ian 2012 SUV 2012 ack 2012	0.98 0.95 0.97 0.97 1.00	1.00 0.95 0.91 0.89 1.00 0.98	0.99 0.95 0.94 0.93 1.00 0.99	40 43 43 38 42 46
Toyota 4Runner S Toyota Camry Seé Toyota Corolla Seé Toyota Sequoia S Volkswagen Beetle Hatchba Volkswagen Golf Hatchba Volkswagen Golf Hatchba	ian 2012 SUV 2012 dan 2012 dan 2012 SUV 2012 suck 2012 ack 1991	0.98 0.95 0.97 0.97 1.00 1.00	1.00 0.95 0.91 0.89 1.00 0.98	0.99 0.95 0.94 0.93 1.00 0.99	40 43 43 38 42 46 43
Toyota 4Runner S Toyota Camry Sed Toyota Corolla Sed Toyota Sequoia S Volkswagen Beetle Hatchba Volkswagen Golf Hatchba Volkswagen Golf Hatchba Volvo 240 Sed	dan 2012 SUV 2012 dan 2012 dan 2012 SUV 2012 cck 2012 dck 1991 dck 2012	0.98 0.95 0.97 0.97 1.00 1.00 0.95 0.96	1.00 0.95 0.91 0.89 1.00 0.98 0.93	0.99 0.95 0.94 0.93 1.00 0.99 0.94	40 43 43 38 42 46 43
Toyota 4Runner S Toyota Camry Sed Toyota Corolla Sed Toyota Sequoia S Volkswagen Beetle Hatchba Volkswagen Golf Hatchba Volkswagen Golf Hatchba Volvo 240 Sed Volvo C30 Hatchba	dan 2012 SUV 2012 dan 2012 dan 2012 SUV 2012 dek 2012 dek 1991 dek 2012 dan 1993	0.98 0.95 0.97 0.97 1.00 1.00 0.95 0.96 1.00	1.00 0.95 0.91 0.89 1.00 0.98 0.93 0.96	0.99 0.95 0.94 0.93 1.00 0.99 0.94 0.96	40 43 43 38 42 46 43 45
Toyota 4Runner S Toyota Camry Seé Toyota Corolla Sec Toyota Sequoia S Volkswagen Beetle Hatchbe Volkswagen Golf Hatchbe Volvo 240 Sec Volvo C30 Hatchbe Volvo C30 Usto XC90 S	dan 2012 SUV 2012 dan 2012 dan 2012 SUV 2012 sek 2012 sek 2012 dek 2012 dan 1993 dek 2012	0.98 0.95 0.97 0.97 1.00 1.00 0.95 0.96 1.00 0.95	1.00 0.95 0.91 0.89 1.00 0.98 0.93 0.96 0.95	0.99 0.95 0.94 0.93 1.00 0.99 0.94 0.96 0.97	40 43 43 38 42 46 43 45 41
Toyota 4Runner S Toyota Camry Sed Toyota Corolla Sed Toyota Sequoia S Volkswagen Beetle Hatchba Volkswagen Golf Hatchba Volkswagen Golf Hatchba Volvo 240 Sed Volvo C30 Hatchba	dan 2012 SUV 2012 dan 2012 dan 2012 SUV 2012 sek 2012 sek 2012 dek 2012 dan 1993 dek 2012	0.98 0.95 0.97 0.97 1.00 1.00 0.95 0.96 1.00	1.00 0.95 0.91 0.89 1.00 0.98 0.93 0.96	0.99 0.95 0.94 0.93 1.00 0.99 0.94 0.96	40 43 43 38 42 46 43 45
Toyota 4Runner S Toyota Camry Sed Toyota Corolla Sed Toyota Sequoia S Volkswagen Beetle Hatchba Volkswagen Golf Hatchba Volvo 240 Sed Volvo C30 Hatchba Volvo XC90 S smart fortwo Convertib	dan 2012 SUV 2012 dan 2012 dan 2012 SUV 2012 sek 2012 sek 2012 dek 2012 dan 1993 dek 2012	0.98 0.95 0.97 0.97 1.00 1.00 0.95 0.96 1.00 0.95	1.00 0.95 0.91 0.89 1.00 0.98 0.93 0.96 0.95	0.99 0.95 0.94 0.93 1.00 0.99 0.94 0.96 0.97 0.97	40 43 43 38 42 46 43 45 41
Toyota 4Runner S Toyota Camry Seé Toyota Corolla Sec Toyota Sequoia S Volkswagen Beetle Hatchbe Volkswagen Golf Hatchbe Volvo 240 Sec Volvo C30 Hatchbe Volvo C30 Hatchbe Security Secu	dan 2012 SUV 2012 dan 2012 dan 2012 SUV 2012 dek 2012 dek 2012 dan 1993 dek 2012 dan 2007 sole 2012	0.98 0.95 0.97 0.97 1.00 1.00 0.95 0.96 1.00 0.95	1.00 0.95 0.91 0.89 1.00 0.98 0.93 0.96 0.95	0.99 0.95 0.94 0.93 1.00 0.99 0.94 0.96 0.97 0.97	40 43 43 38 42 46 43 45 41 43 40
Toyota 4Runner S Toyota Camry Seé Toyota Corolla Seé Toyota Sequoia S Volkswagen Beetle Hatchbe Volkswagen Golf Hatchbe Volvo C30 Hatchbe Volvo C30 Hatchbe Volvo C30 Seé Volvo C30 Hatchbe Smart fortwo Convertib	Ian 2012 SUV 2012 Ian 2012 Ian 2012 SUV 2012 SUV 2012 ICK 2012 ICK 2012 ICK 2012 ICK 2012 ICK 2012 SUV 2007 SUV 2007	0.98 0.95 0.97 0.97 1.00 1.00 0.95 0.96 1.00 0.95	1.00 0.95 0.91 0.89 1.00 0.98 0.93 0.96 0.95 0.98	0.99 0.95 0.94 0.93 1.00 0.99 0.94 0.96 0.97 0.98	40 43 43 38 42 46 43 45 41 43 40
Toyota 4Runner S Toyota Camry Seé Toyota Corolla Seé Toyota Sequoia S Volkswagen Beetle Hatchbe Volkswagen Golf Hatchbe Volvo C30 Hatchbe Volvo C30 Hatchbe Volvo C30 Seé Volvo C30 Hatchbe Smart fortwo Convertib	ian 2012 SUV 2012 Ian 2012 SUV 2012 SUV 2012 SUV 2012 Ick 2012 Ick 2012 Ian 1993 Ick 2012 SUV 2007 Ole 2012	0.98 0.95 0.97 0.97 1.00 1.00 0.95 0.96 1.00 0.95	1.00 0.95 0.91 0.89 1.00 0.98 0.93 0.96 0.95 0.98 1.00	0.99 0.95 0.94 0.93 1.00 0.99 0.94 0.96 0.97 0.98	40 43 43 38 42 46 43 45 41 43 40

# Visualizing class activation maps

#### **Front View**





## **Diagonal View**





#### Side View





#### **Back View**





# Limitations and Future Considerations

Limitations



Insufficient computing power

**Future Work** 



Add more data and add more classes, split models up by classes



Realistically, number of brand, model and make is very high



Resolution of input images need to be high



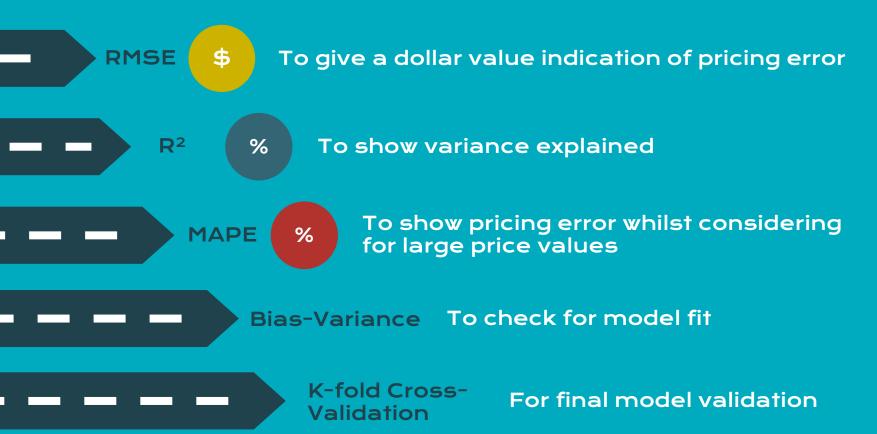
Try more transfer-learning backbone



Optimizing NN hyperparameters further (batch-size, epochs, optimizers,)

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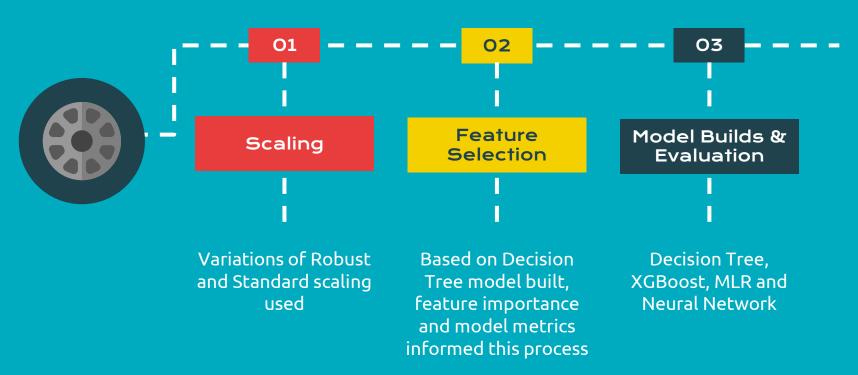
# Our model evaluation metrics



# In any price negotiation...



# Overview of our process for price prediction



# Models were built on scaled data after each feature was omitted in feature selection

Train-Test-Val Split: 60-20-20

Low feature importance

#### Scaling

By Sci-kit Learn



#### Robust

Addresses outliers



#### **Standard**

Centers data around the mean

#### Feature selection - variables omitted Based on Decision Tree model 01 02 SAVINGS AMOUNT TRANSMISSION TYPE Definition unclear Low feature importance 04 **FUEL TYPE** MAX. SEATING Low feature importance for some values Low feature importance 06 **ENGINE TYPE BODY TYPE** Low feature importance Low feature importance 08 LISTING COLOUR STATE

Low feature importance

# Feature Selection Justification

#### Models

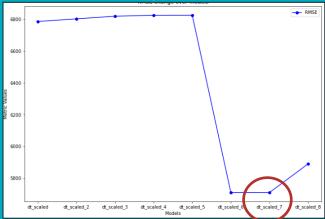
MAX. SEATING



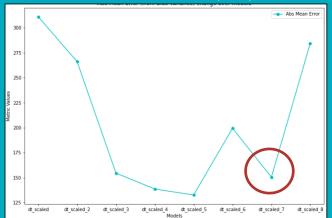
#### Model 7 Analysis

- Among the Lowest RMSE
- R<sup>2</sup> goes up to ~0.86
- Abs. Mean Error drops to ~150
- Variance increases quite significantly to ~2.1
- Bias-Variance tradeoff prioritize lower bias since test data shows model is less overfit

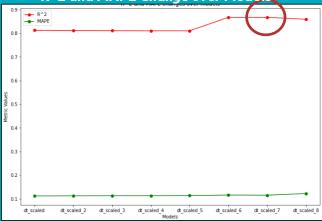
#### RMSE Change over Models



#### Absolute Mean Error (Bias)



#### R^2 and MAPE Change over Models



#### Mean Variance Error (Variance)



# Final Model Variables











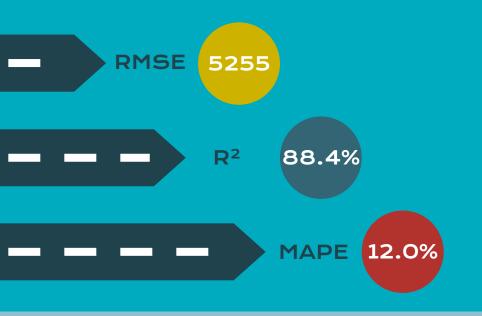


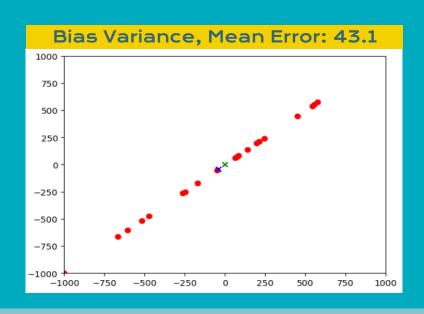






### Final Decision Tree – Results on Test data



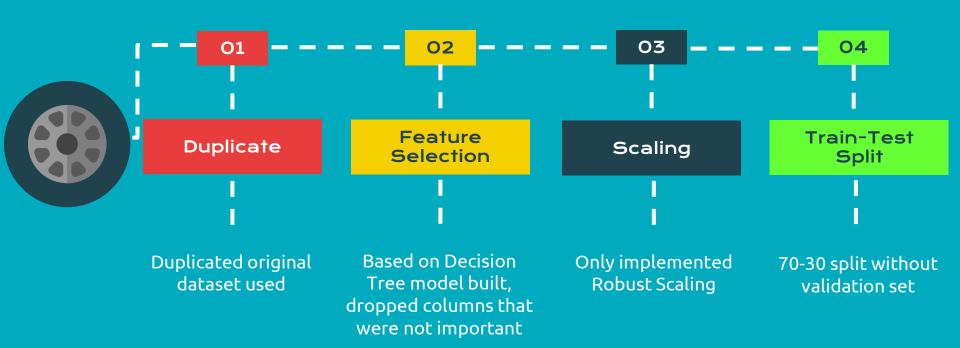


K-fold Cross-Validation (10 splits)

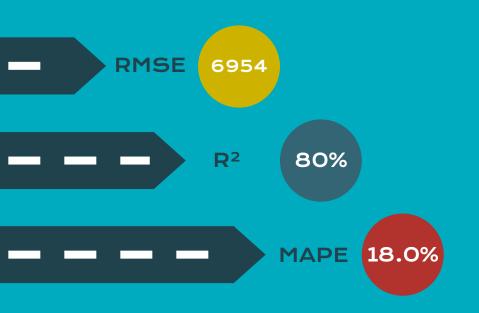
Average R<sup>2</sup> 84.5%

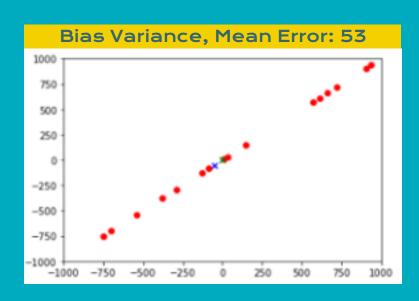
Average MAPE 10.0%

# Preprocessing for multilinear regression



# Final Multilinear Regression – Results on Test data



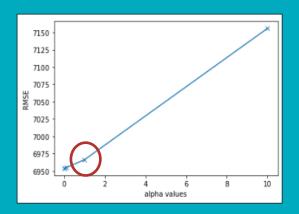


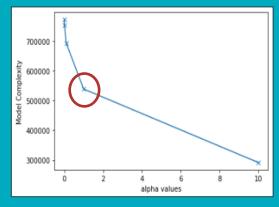
Optimal Alpha = 1

# Regularization

Lasso Metrics by Alpha

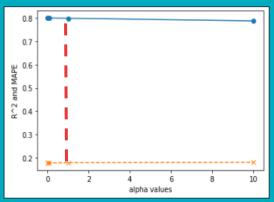
RMSE

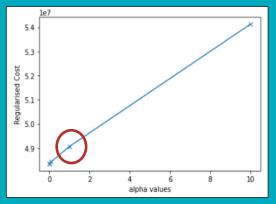




Model Complexity

R2 and MAPE



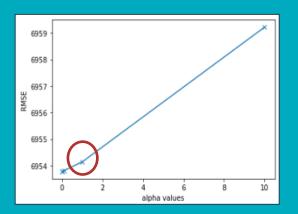


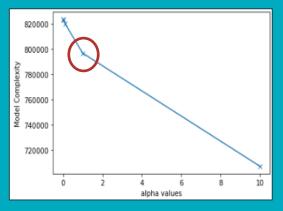
Regularized Cost Optimal Alpha = 1

# Regularization

Ridge Metrics by Alpha

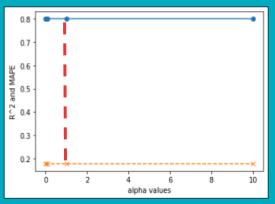
**RMSE** 

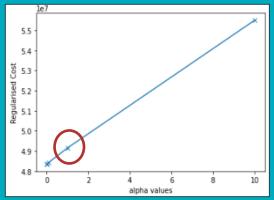




Model Complexity

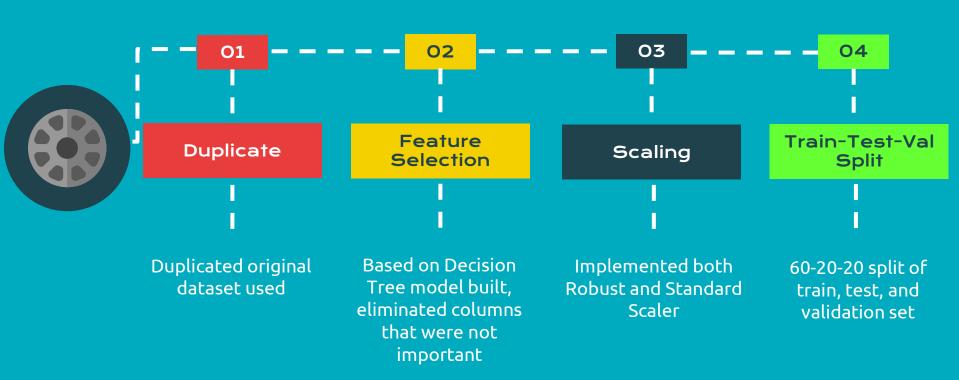
R2 and MAPE



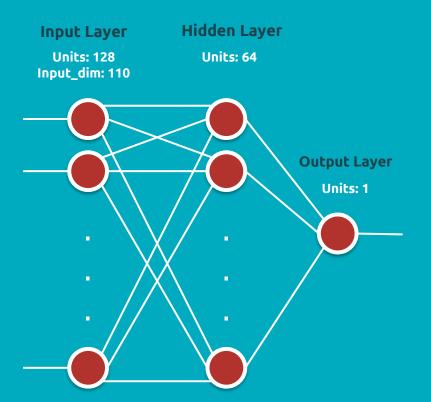


Regularized Cost

# Preprocessing for neural network



# Model of the neural network



#### **Parameters**

• Sample size: 750k

• Package used: Tensorflow, Keras

Learning rates: 0.001, 0.01, 0.025, 0.05, 0.1

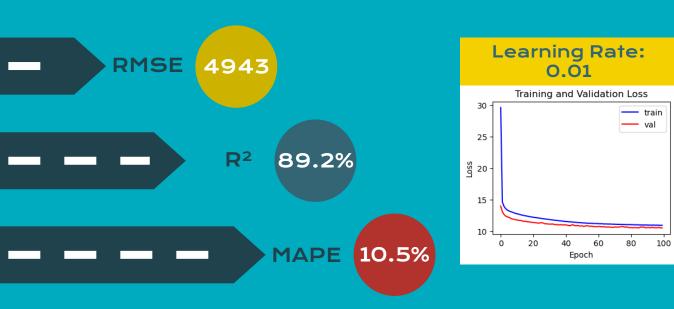
Activation function: Leaky ReLU

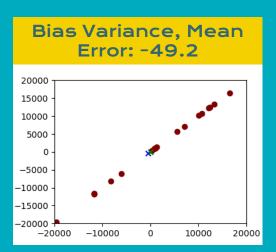
• **Epochs:** 100

• Batch\_size: 1024

• Evaluation metrics: MAPE, R^2, RMSE

### Final Neural Network - Results on Test data





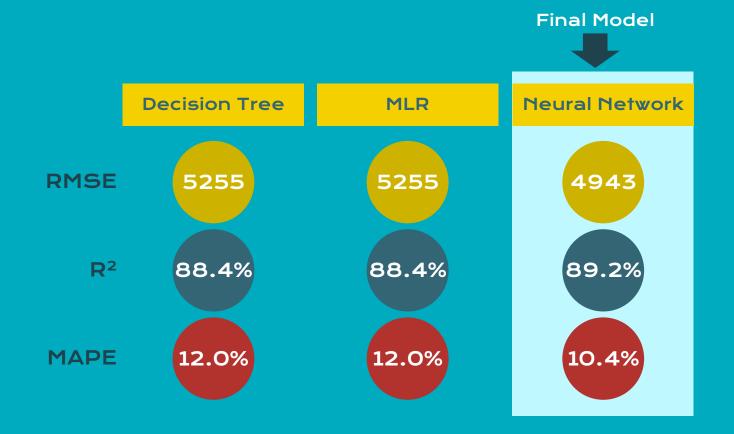
K-fold Cross-Validation (10 splits)

Average R<sup>2</sup> 85.7%

Average MAPE 10.4%

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# Overall results



# Limitations and Future Considerations

Limitations



Insufficient computing power



Transferability of model limited for SG, etc



Additional variables that are difficult to quantify (e.g. condition of car, market conditions)

**Future Work** 



Performing Polynomial Regression



Regularization for Decision Tree



Optimizing NN (pruning, batch-size, epochs, optimizers)

# Be Car-eful now Thank you



# **APPENDIX**

# XGBoost with GridSearchCV and K-fold

