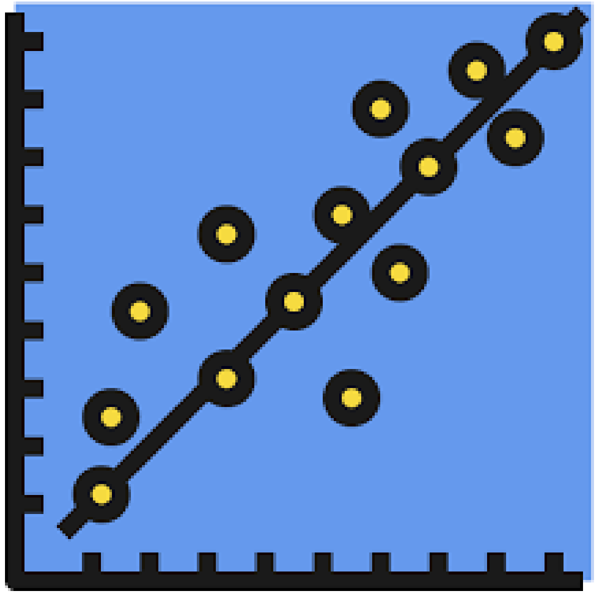
Predicting Prices of Used Cars for Potential Buyer in Singapore

Prepared by Anita

Objective

- To help potential buyer in Singapore to predict the prices of used cars as accurate as possible to be used as a benchmark before buying a used car.

Methodology



- Linear Regression Model
- Ridge Regression Model
- Lasso Regression Model
- Polynomial Regression Model

Tools Used

pandas

NumPy

SM StatsModels
Statistics in Python

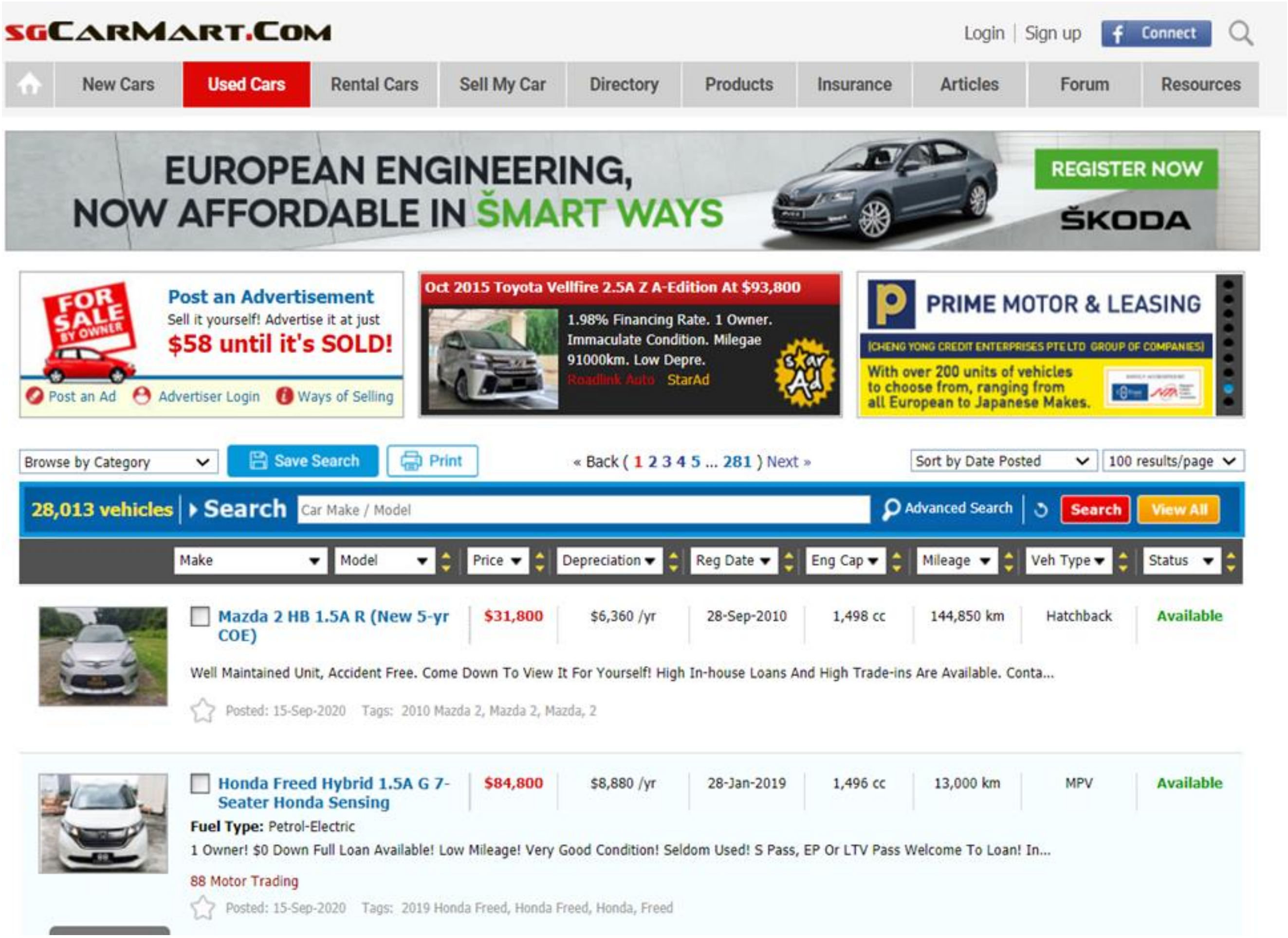
scikits learn

matplotlib

Seaborn

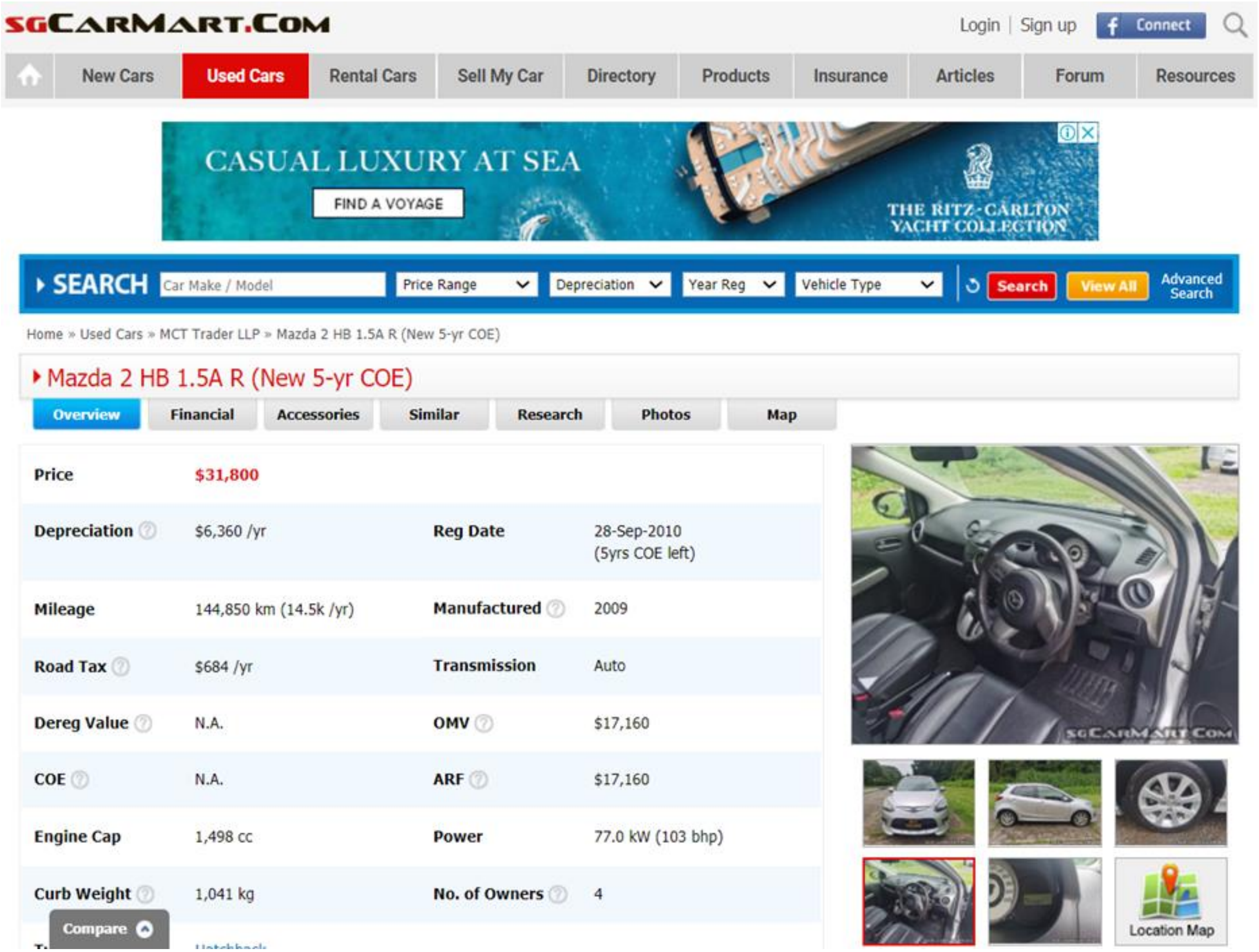
Data Collection

- Webscrapping from SgCarMart website using Beautiful Soup.



Data Collection (cont…)

- Webscrapping from SgCarMart website using Beautiful Soup.

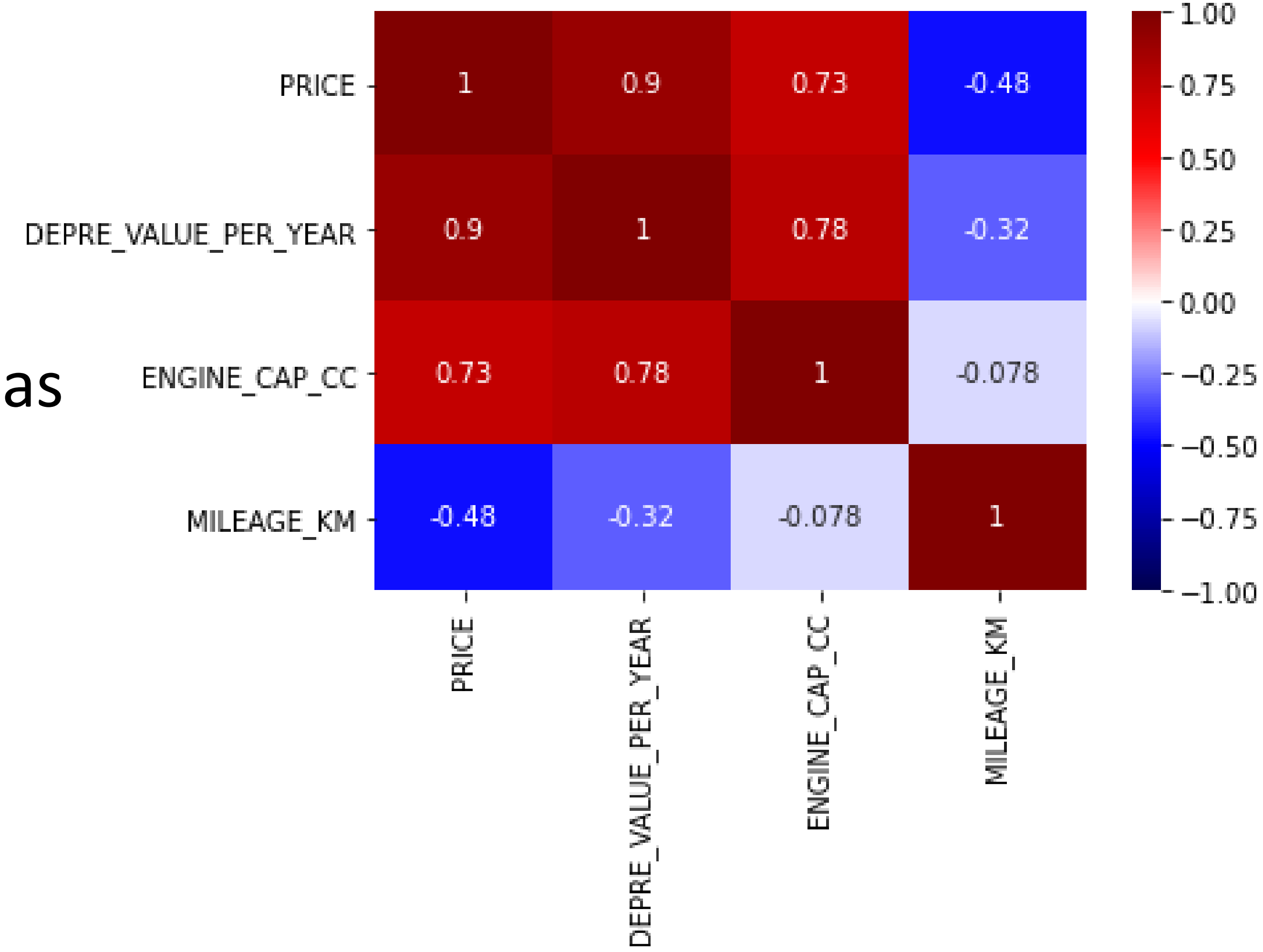


Data Cleaning

- 322 rows
- 6 columns:
  - Price (target)
  - Make (categorical feature)
  - Depreciation value per year (numerical feature)
  - Engine Cap cc (numerical feature)
  - Mileage km (numerical feature)
  - Vehicle Type (categorical feature)

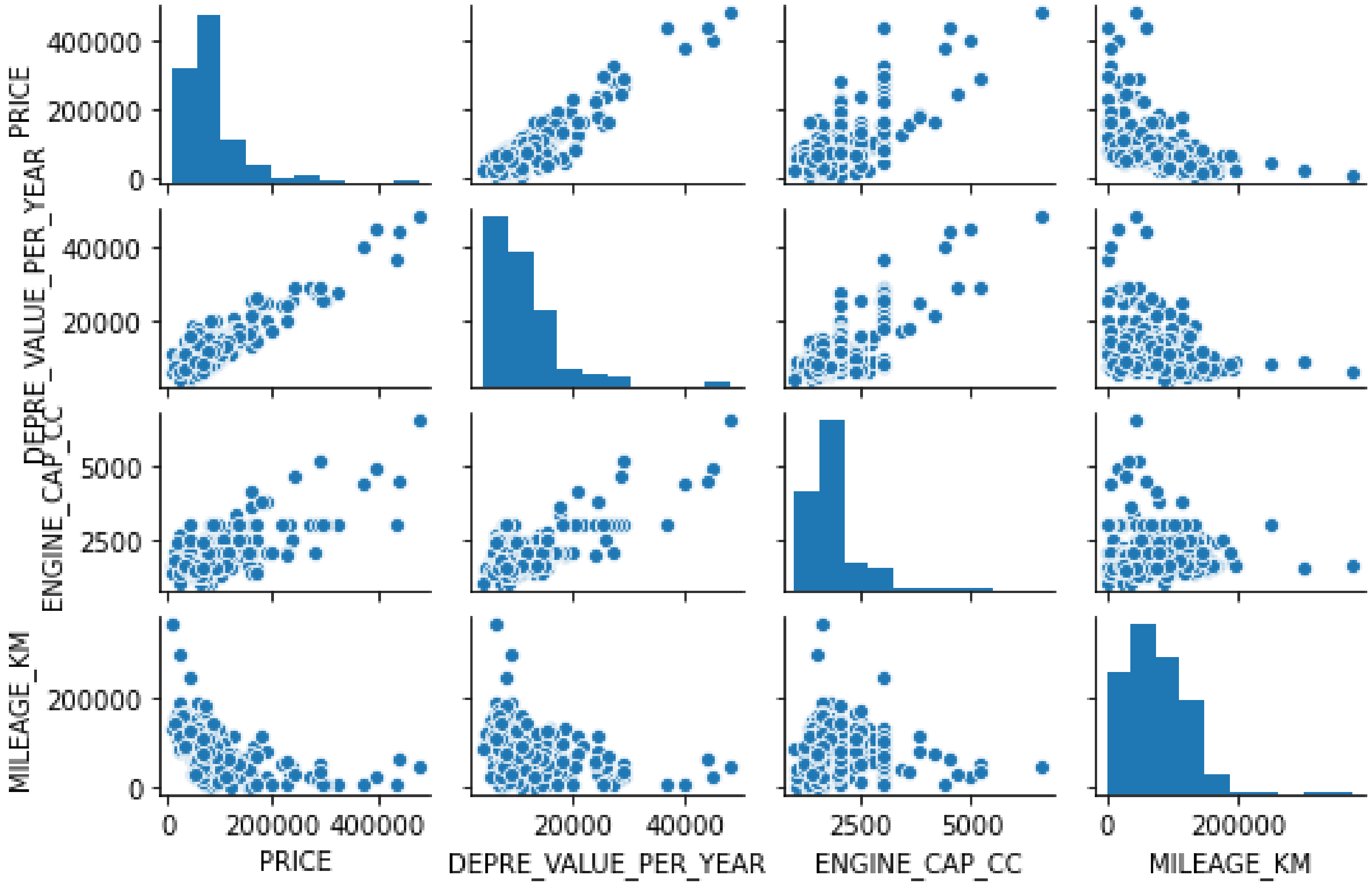
Data Analysis

- To view the correlation between feature to feature and feature to target.
- No feature is removed as there is no high correlation between features.



Data Analysis (cont…)

- To view the distribution plot of features and target.



Data Analysis (cont…)

- Fit in statsmodels
- Based from the p-value, all features are significant.
- Adj. R-squared = 0.859

OLS Regression Results

Dep. Variable:	PRICE	**R-squared:**	0.861
Model:	OLS	**Adj. R-squared:**	0.859
Method:	Least Squares	**F-statistic:**	654.4
Date:	Tue, 15 Sep 2020	**Prob (F-statistic):**	1.14e-135
Time:	16:48:58	**Log-Likelihood:**	-3723.9
No. Observations:	322	**AIC:**	7456.
Df Residuals:	318	**BIC:**	7471.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-7642.9409	4923.592	-1.552	0.122	-1.73e+04	2043.990
DEPRE_VALUE_PER_YEAR	7.4692	0.396	18.854	0.000	6.690	8.249
ENGINE_CAP_CC	17.0354	3.367	5.060	0.000	10.412	23.659
MILEAGE_KM	-0.3456	0.033	-10.516	0.000	-0.410	-0.281

Omnibus:	23.665	**Durbin-Watson:**	2.065
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	86.289
Skew:	0.035	**Prob(JB):**	1.83e-19
Kurtosis:	5.535	**Cond. No.**	3.11e+05

Data Analysis (cont…)

- Log transform the mileage
- Fit in statsmodels
- Based from the p-value, all features are significant.
- Adj. R-squared = 0.875

OLS Regression Results

Dep. Variable:	PRICE	**R-squared:**	0.876
Model:	OLS	**Adj. R-squared:**	0.875
Method:	Least Squares	**F-statistic:**	751.3
Date:	Tue, 15 Sep 2020	**Prob (F-statistic):**	6.09e-144
Time:	16:49:02	**Log-Likelihood:**	-3704.6
No. Observations:	322	**AIC:**	7417.
Df Residuals:	318	**BIC:**	7432.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.636e+05	1.59e+04	10.262	0.000	1.32e+05	1.95e+05
DEPRE_VALUE_PER_YEAR	7.3177	0.370	19.792	0.000	6.590	8.045
ENGINE_CAP_CC	18.9153	3.179	5.951	0.000	12.661	25.169
np.log(MILEAGE_KM)	-1.821e+04	1417.194	-12.852	0.000	-2.1e+04	-1.54e+04

Omnibus:	46.742	**Durbin-Watson:**	2.079
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	116.250
Skew:	-0.696	**Prob(JB):**	5.71e-26
Kurtosis:	5.593	**Cond. No.**	1.61e+05

Data Analysis (cont…)

- Create dummy variables into dataset.

Target:
Price

+

Features:
Depreciation value
Engine Cap
Log Mileage

+

Dummy variables:
Make
Vehicle Type

Data Analysis (cont…)

- After fit in statsmodels again, based from the p-value, only following features are significant:
  - Depreciation value
  - Engine cap
  - Log mileage
  - Make Ferrari
  - Make Mini
  - Make Rolls Royce
  - Vehicle type SUV
- Adj. R-squared = 0.882

OLS Regression Results

Dep. Variable:	PRICE	**R-squared:**	0.885
Model:	OLS	**Adj. R-squared:**	0.882
Method:	Least Squares	**F-statistic:**	345.3
Date:	Tue, 15 Sep 2020	**Prob (F-statistic):**	2.26e-143
Time:	16:50:49	**Log-Likelihood:**	-3692.8
No. Observations:	322	**AIC:**	7402.
Df Residuals:	314	**BIC:**	7432.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.676e+05	1.59e+04	10.523	0.000	1.36e+05	1.99e+05
DEPRE_VALUE_PER_YEAR	7.0185	0.372	18.864	0.000	6.286	7.751
ENGINE_CAP_CC	17.8814	3.157	5.664	0.000	11.670	24.093
LOG_MILEAGE_KM	-1.822e+04	1395.843	-13.054	0.000	-2.1e+04	-1.55e+04
MAKE_Ferrari	8.341e+04	2.48e+04	3.364	0.001	3.46e+04	1.32e+05
MAKE_MINI	-5.858e+04	2.36e+04	-2.484	0.014	-1.05e+05	-1.22e+04
MAKE_Rolls_Royce	5.241e+04	2.55e+04	2.055	0.041	2240.757	1.03e+05
VEHICLE_TYPE_SUV	6301.6449	3284.534	1.919	0.056	-160.833	1.28e+04

Omnibus:	49.299	**Durbin-Watson:**	2.055
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	157.598
Skew:	-0.647	**Prob(JB):**	6.00e-35
Kurtosis:	6.173	**Cond. No.**	2.77e+05

Cross Validation

```
Linear Regression Cross Val Score: [0.93333532 0.52448046 0.87522598 0.8712238  0.88953408]
Mean cv r^2: 0.819 +- 0.149

Ridge Cross Val Score: [0.92969153 0.54775207 0.86333013 0.86641585 0.89195441]
Mean cv r^2: 0.82 +- 0.138

Lasso Cross Val Score: [0.93296689 0.52822619 0.87501454 0.87075869 0.88946554]
Mean cv r^2: 0.819 +- 0.147

Degree 3 Poly Regression Cross Val Score: [-0.22285902  0.12113914  0.86517433  0.91012124  0.90049184]
Mean cv r^2: 0.515 +- 0.475
```

- It seems like Ridge Regression provides the highest R^2 as compared to others. Therefore, will choose to use Ridge regression.

Results
Prediction

```
Ridge Regression RMSE - train: 24160.46597176425
Ridge Regression R2 Score - train: 0.8874145159737489

Ridge Regression RMSE - test: 18951.41407514264
Ridge Regression R2 Score - test: 0.8436070187572133
```

- From the train dataset, 89% of data variation explained by model and root mean squared error is $24,160.
- From the test dataset, 84% of data variation explained by model and root mean squared error is $18,951.

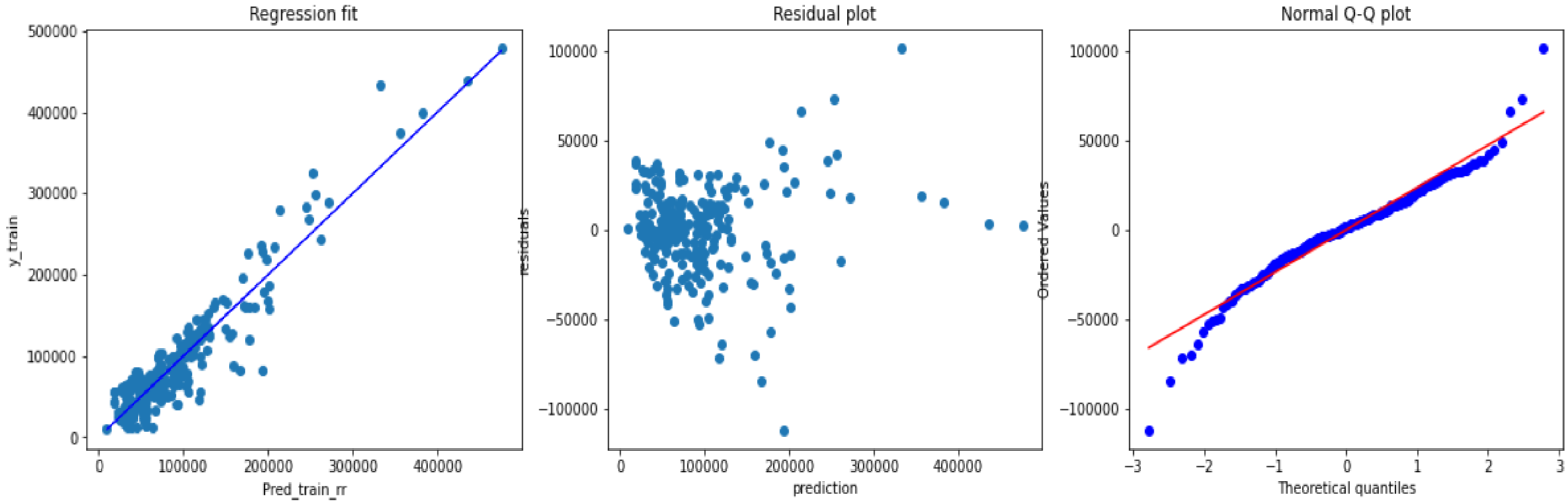
Results
Coefficients

```
[('DEPRE_VALUE_PER_YEAR', 44577.66498575446),
 ('ENGINE_CAP_CC', 13419.433108206378),
 ('LOG_MILEAGE_KM', -19028.67403481724),
 ('MAKE_Ferrari', 5508.863705839609),
 ('MAKE_MINI', -3433.150015257121),
 ('MAKE_Rolls_Royce', 3655.35391418426),
 ('VEHICLE_TYPE_SUV', 3408.6844210868144)]
```

- Depreciation value, engine cap, make Ferrari, make Rolls-Royce and vehicle type SUV have positive impact on the price of used cars.
- Log mileage and make Mini have negative impact on the price of used cars.

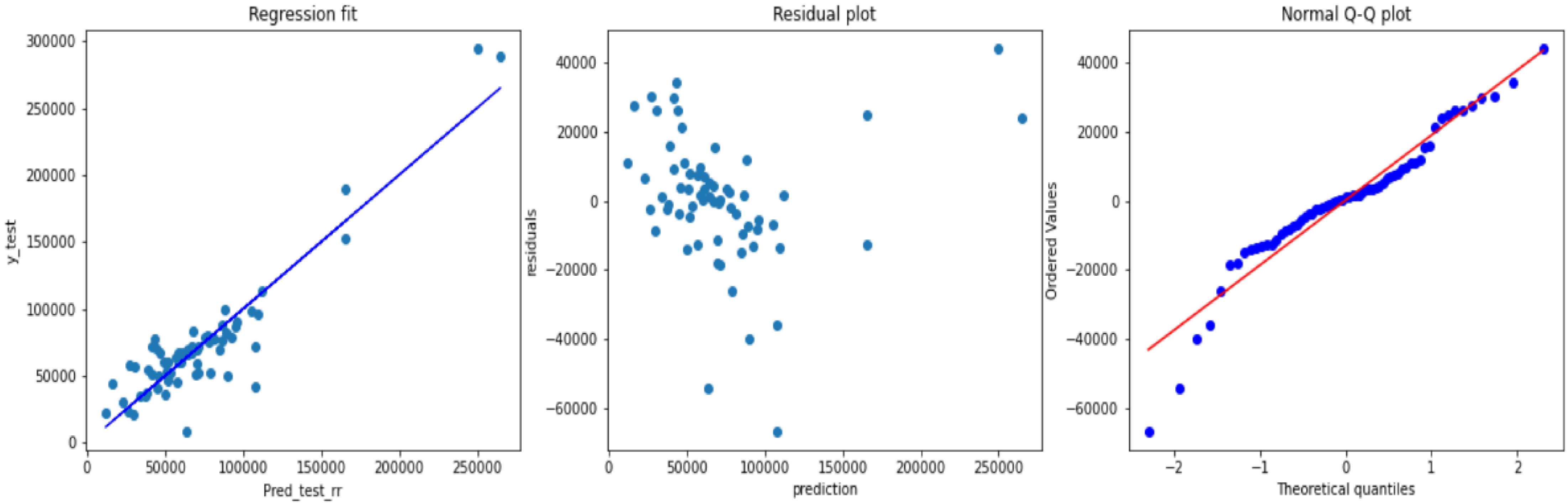
Linear Regression Assumption

- Train Dataset



Linear Regression Assumption

- Test Dataset



Conclusions

- This model still cannot do prediction accurate enough, with RMSE $18,951 from test dataset.
- This model can only explain 84% of data variation from test dataset.
- Other features that could affect the price of used cars are not captured.
- Observation data collected are not big enough.
- Outliers in dataset was not investigated and removed from dataset.


THANK
YOU