A complete guide on Linear Regression(Using Car price prediction)

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1.What is Linear Regression?

Linear Regression is a parametric algorithm of machine learning.It is a linear approach to model the relationship between a dependent variable and one or more independent variables.It is used to predict the values for regression type problem,which means that the dependent variable should be of continuous datatype.

The main objective of the linear regression model is to reduce the error between the predicted and the actual values i.e. to reduce the cost function.It is done by updating the weights using gradient descent.Gradient is the partial derivative of the cost function with respect to old weight.

Formula for updating the weights is:

$W_n = W_o + \frac{\partial L}{\partial W_o}$

The hypothesis function of linear regression is $y = W_0 + W_1 * X_1 + W_2 * X_2 + ... + W_n X_n$

Where Ws are the weights or parameters

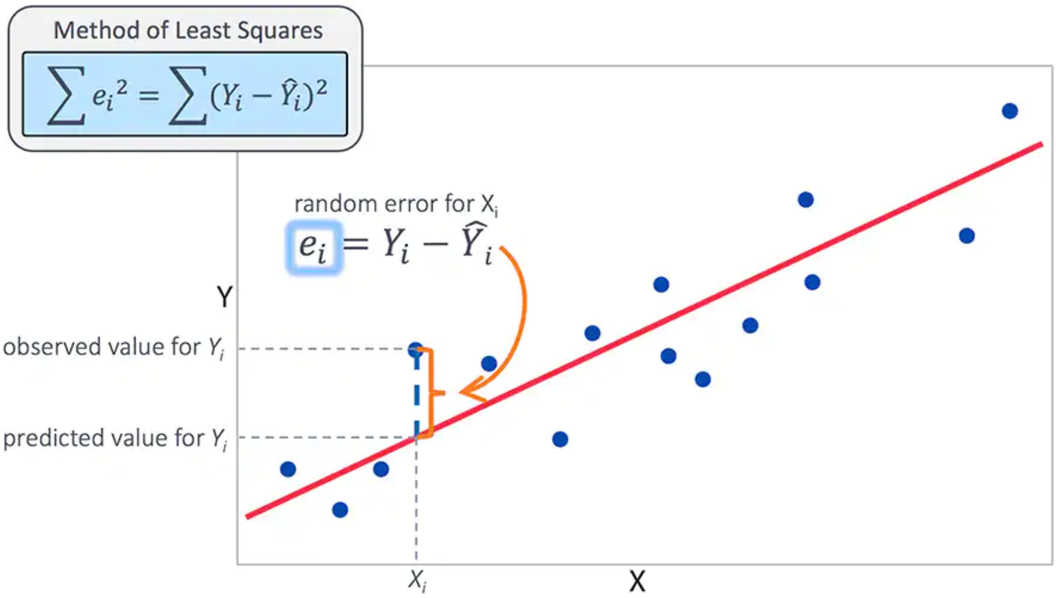
cost function=$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$

To learn more about Linear Regression click here

2.Assumptions of Linear Regression

The assumptions are:

1. **Linearity** :The independent and the dependent variables should be linearly related to each other.
2. **No endogeniety**: The indepednent features should not have any relation with the error term.
3. **Normality and homoscedasticity**: The error term should be normally distributed.It should not show variable variance, which means that the error term should be same across all the values of independent variables.
4. **No autocorrelation**: There should not be any autocorrelation between the residuals which means that the error term should not be related to the lag of itself.
5. **No multicollinearity**: The independent variables should not be having high correlation between themselves.



As the above image shows we need to minimise the loss. Which is the difference between the actual and predicted value.

The predicted line which makes the loss least is known as the best fit line.

3.Problem Statement

With the rise in the variety of cars with differentiated capabilities and features such as model, production year, category, brand, fuel type, engine volume, mileage, cylinders, colour, airbags and many more, we all aspire to own a car within budget with the best features available. The objective of the problem is to build a model with the dataset that can predict the price of the car with the features given.Regression analysis(Linear regression) has been used to predict the price of the cars.

Data Definitions:

1.ID: This is the unique identity if each car

2.Levy: The road tax on each car

3.Manufacturer: Manufacturer of each car

4.Model: Model of each car

5.Prod. year: Year of production of the car

6.Category: Category of the car such as sedan,hatchback,jeep etc.

7.Leather interior: Whether the interior is of leather or not

8.Fuel type: Is it a petrol,diesel or hybrid

9.Engine volume: Volume of engine

10.Mileage: Mileage of the car

11.Gear box type: Type of gear box

12.Drive wheels: Is it a front or rear drive vehicle

13.Doors: Number of doors in the car

14.Wheel: Is it left wheel or right wheel drive

15.Color: Color of the car

16.Airbags: Number of airbags in the car

4.Importing Libraries

In [337…

```
# suppress display of warnings
import warnings
warnings.filterwarnings("ignore")

# 'Pandas' is used for data manipulation and analysis
import pandas as pd

# 'Numpy' is used for mathematical operations on large, multi-dimensional arrays and
import numpy as np

# 'Matplotlib' is a data visualization library for 2D plots built on numpy arrays
import matplotlib.pyplot as plt

# 'Seaborn' is a Python data-visualisation library based on Matplotlib that provides
#for drawing statistical graphics
import seaborn as sns

# 'datetime' library is used to perform datetime operations
import datetime as dt

# 'GridSearchCV' is used to search for the best parameters to train the model
from sklearn.model_selection import GridSearchCV

#'train_test_split' function is used to split the data for training and testing the
from sklearn.model_selection import train_test_split

#importing metrics for tabulating the result
from sklearn.metrics import mean_squared_log_error
from sklearn.metrics import mean_squared_error
from statsmodels.tools.eval_measures import rmse
from sklearn.metrics import r2_score,mean_absolute_error

#Algorithm used for feature selection
from sklearn.ensemble import RandomForestRegressor

#Importing function to perform regression
from sklearn.linear_model import LinearRegression, Ridge,Lasso
import statsmodels.api as sm
```

```
# 'SciPy' is used to perform scientific computations
from scipy.stats import shapiro

# set the plot size using 'rcParams'
# once the plot size is set using 'rcParams', it sets the size of all the forthcomin
# pass width and height in inches to 'figure.figsize'
plt.rcParams['figure.figsize'] = [15,8]
```

5.Importing data

In [266…

```
#Importing the data using "read_csv" and storing it into the variable df
#This method is used by pandas to import data directly from the local 'C' drive
df = pd.read_csv('train.csv')
```

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6.Understanding the Dataset

In [267…

```
#Displaying the first five records of the dataset
df.head()
```

Out[267…

	ID	Price	Levy	Manufacturer	Model	Prod. year	Category	Leather interior	Fuel type	Engine volume	Mile
0	45654403	13328	1399	LEXUS	RX 450	2010	Jeep	Yes	Hybrid	3.5	186
1	44731507	16621	1018	CHEVROLET	Equinox	2011	Jeep	No	Petrol	3	192
2	45774419	8467	-	HONDA	FIT	2006	Hatchback	No	Petrol	1.3	200
3	45769185	3607	862	FORD	Escape	2011	Jeep	Yes	Hybrid	2.5	168
4	45809263	11726	446	HONDA	FIT	2014	Hatchback	Yes	Petrol	1.3	91

Interpretation from the data displayed above:

1)The 'Levy' column contains '-' symbol.We need to look into this column and understand the meaning of the symbol '-'.

2)In the 'Doors' column there are month names present.We need to remove them, as the doors column should be an interger.

3)In the 'Mileage' column there is 'km' written, we need to remove this 'km' from the 'Mileage' column. It is because the algorithms only understand numbers and not characters.

In [268…

```
#Understanding the shape of the data
#The function 'shape' returns a tuple with the first element representing rows
#the second element represents the number of columns
df.shape
```

Out[268...

```
(19237, 18)
```

We can see that there are 19237 rows and 18 columns

In [269...

```python
#assigning the column 'Price' to the variable 'y'
#This is our dependent feature and hence we are seperating it out from the dataset
#before performing any preprocessing on the dataset
y=df['Price']
```

In [270...

```python
#Dropping the dependent feature from the dataset
#'drop' function is used for dropping a row or a column
#We use axis=1 of we want to drop a column and axis=0 if we want to drop a row
df = df.drop(['Price'],axis=1)
```

Data Type:

The main data types in Pandas dataframes are the object, float64, int64, bool, and datetime64. To understand each attribute of our data, it is always good for us to know the data type of each column.

In our dataset, we have numerical and categorical variables. The numeric variables should have data type 'int'/'float' while categorical variables should have data type 'object'.

> 1. Check for the data type
> 2. For any incorrect data type, change the data type with the appropriate type

In [271...

```python
#creating an empty dataframe 'info'
info = pd.DataFrame()

#checking the datatypes and Unique values of each column
#checking unique values in a column helps us to understand whether a column
#should be of categorical type or numerical type
#creating two columns named 'DataTypes' and 'Unique_values' in the dataframe info
#These columns will store the original datatype of the columns in the dataset and th
#unique values of the corresponding columns
info['DataTypes'] = df.dtypes
info['Unique_values'] = df.nunique()
info
```

Out[271...

	DataTypes	Unique_values
ID	int64	18924
Levy	object	559
Manufacturer	object	65
Model	object	1590
Prod. year	int64	54
Category	object	11
Leather interior	object	2
Fuel type	object	7
Engine volume	object	107

	DataTypes	Unique_values
Mileage	object	7687
Cylinders	float64	13
Gear box type	object	4
Drive wheels	object	3
Doors	object	3
Wheel	object	2
Color	object	16
Airbags	int64	17

From the above table we can see that the column 'Mileage' is mentioned to be of object datatype, whereas it should be either float/integer type.We will change the datatype of this column.

Importance of converting a column into right datatype:

1)The model doesn't understands string type data such as name,grades,place etc.Hence, before training a model we need to convert all the data into numerical form.

2)For converting a string type data into numerical datatype we use either "Label encoding" or "one hot encoding".

3)Label encoding is used when the data is of object type and has some order for example rating given by customers(A,B,C,D,E,F) or grades of students(A+,A,B+,B).Here in the examples cited, there is an order in the data. In such a scenario we use label encoding to convert a string type data into numerical data.

4)When the data is of object type but there is no order in the data, then we use 'one hot encoding' to convert the object type data into numerical data type for example name of places,name of persons etc.

5)'get_dummies' from pandas is used to convert the object datatype into numerical datatype.

Summary Statistics:

Here we take a look at the summary of each attribute. This includes the count, mean, the minimum and maximum values as well as some percentiles for numeric variables and count, unique, top, frequency for categorical variables.

In our dataset we have both numerical and categorical variables. Now we check for summary statistics of all the variables

1. For numerical variables, use the describe()
2. For categorical variables, use the describe(include=object)

In [272...

```
#Using the describe function to find:
#count,unique values,frequency of the most occuring element and the most occuring
#element in a column
df.describe(include='object')
```

Out[272...

	Levy	Manufacturer	Model	Category	Leather interior	Fuel type	Engine volume	Mileage	Gear box type	Dri whe
count	19237	19237	19237	19237	19237	19237	19237	19237	19237	192
unique	559	65	1590	11	2	7	107	7687	4	
top	-	HYUNDAI	Prius	Sedan	Yes	Petrol	2	0 km	Automatic	Frc
freq	5819	3769	1083	8736	13954	10150	3916	721	13514	128

In [273...

```
# the describe() returns the statistical summary of the variables
# by default, it returns the summary of numerical variables
df.describe()
```

Out[273...

	ID	Prod. year	Cylinders	Airbags
count	1.923700e+04	19237.000000	19237.000000	19237.000000
mean	4.557654e+07	2010.912824	4.582991	6.582627
std	9.365914e+05	5.668673	1.199933	4.320168
min	2.074688e+07	1939.000000	1.000000	0.000000
25%	4.569837e+07	2009.000000	4.000000	4.000000
50%	4.577231e+07	2012.000000	4.000000	6.000000
75%	4.580204e+07	2015.000000	4.000000	12.000000
max	4.581665e+07	2020.000000	16.000000	16.000000

Deductions from statistical summary:

1.The highest car manufacturer is 'Hyundai' and its count is 3769 out of 19237 records.
2.There are 16 different color of cars and the most used color is 'black'.
3.The gear box type in maximum cars is 'automatic'. 4.It can also be noticed that there are no missing values in any column as the count of all the columns are 19237.

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7.Preprocessing the data

Why is preprocessing of data required?

It is said a model is as good as its data. This is the reason we need to prepare the data before training the model. Data preparation is the process of cleaning and transforming raw data before building predictive models.In data preprocessing following steps are followed as and when required.

Here, we analyze and prepare data to perform regression analysis:

```
                      1. Check data types. Ensure your data types are
    correct. Refer data definitions to validate
                      2. If data types are not as per business
    definition, change the data types as per requirement
```

```
                    3. Study summary statistics
                    4. Distribution of variables
                    5. Study correlation
                    6. Detect outliers
                    7. Check for missing values
                    8. Do feature engineering to add meaning features
    to train the model
```

Note: It is an art to explore data, and one needs more and more practice to gain expertise in this area

In [274…

```
#removing the 'km' from the mileage column
#'split' function can only be used in string type of data.Hence we always convert a
#column to string type before splitting it.
#(" ",n=1,expand=True) the arguments does splits the column by the first space
#it encounters

df['Mileage'] =df['Mileage'].str.split(" ",n=1,expand=True)
```

In [275…

```
#Converting the column into float datatype
#before converting a column into integer or float its important to remove string
#literals from the column
#Hence, it was important to seperate out 'km' from the column

df['Mileage']=df['Mileage'].astype('float')
```

In [276…

```
#replacing all the '0' values with the mean values of the 'Mileage' column
df['Mileage'] = np.where(df['Mileage'] == 0.0,df['Mileage'].mean(),df['Mileage'])
```

In [277…

```
#checking the unique values of 'Doors' column
df['Doors'].unique()
```

Out[277…

```
array(['04-May', '02-Mar', '>5'], dtype=object)
```

In [278…

```
#Removing the string literals from 'Doors' column
#Using 'np.where' function of numpy to find the specific values
#syntax of "np.where" is (condition,if true value,if false value)
# '|' is the symbol of the or operand

df['Doors'] = np.where((df['Doors'] == '04-May') | (df['Doors'] == '02-Mar'), df['Do
```

In [279…

```
#checking the unique values of 'Doors' column after removing the string literals
df['Doors'].unique()
```

Out[279…

```
array(['04', '02', '>5'], dtype=object)
```

In [280…

```
#checking the unique values of 'Levy' column
df['Levy'].unique()
```

Out[280…

```
array(['1399', '1018', '-', '862', '446', '891', '761', '751', '394',
       '1053', '1055', '1079', '810', '2386', '1850', '531', '586',
       '1249', '2455', '583', '1537', '1288', '915', '1750', '707',
       '1077', '1486', '1091', '650', '382', '1436', '1194', '503',
       '1017', '1104', '639', '629', '919', '781', '530', '640', '765',
```

```
'777', '779', '934', '769', '645', '1185', '1324', '830', '1187',
'1111', '760', '642', '1604', '1095', '966', '473', '1138', '1811',
'988', '917', '1156', '687', '11714', '836', '1347', '2866',
'1646', '259', '609', '697', '585', '475', '690', '308', '1823',
'1361', '1273', '924', '584', '2078', '831', '1172', '893', '1872',
'1885', '1266', '447', '2148', '1730', '730', '289', '502', '333',
'1325', '247', '879', '1342', '1327', '1598', '1514', '1058',
'738', '1935', '481', '1522', '1282', '456', '880', '900', '798',
'1277', '442', '1051', '790', '1292', '1047', '528', '1211',
'1493', '1793', '574', '930', '1998', '271', '706', '1481', '1677',
'1661', '1286', '1408', '1090', '595', '1451', '1267', '993',
'1714', '878', '641', '749', '1511', '603', '353', '877', '1236',
'1141', '397', '784', '1024', '1357', '1301', '770', '922', '1438',
'753', '607', '1363', '638', '490', '431', '565', '517', '833',
'489', '1760', '986', '1841', '1620', '1360', '474', '1099', '978',
'1624', '1946', '1268', '1307', '696', '649', '666', '2151', '551',
'800', '971', '1323', '2377', '1845', '1083', '694', '463', '419',
'345', '1515', '1505', '2056', '1203', '729', '460', '1356', '876',
'911', '1190', '780', '448', '2410', '1848', '1148', '834', '1275',
'1028', '1197', '724', '890', '1705', '505', '789', '2959', '518',
'461', '1719', '2858', '3156', '2225', '2177', '1968', '1888',
'1308', '2736', '1103', '557', '2195', '843', '1664', '723',
'4508', '562', '501', '2018', '1076', '1202', '3301', '691',
'1440', '1869', '1178', '418', '1820', '1413', '488', '1304',
'363', '2108', '521', '1659', '87', '1411', '1528', '3292', '7058',
'1578', '627', '874', '1996', '1488', '5679', '1234', '5603',
'400', '889', '3268', '875', '949', '2265', '441', '742', '425',
'2476', '2971', '614', '1816', '1375', '1405', '2297', '1062',
'1113', '420', '2469', '658', '1951', '2670', '2578', '1995',
'1032', '994', '1011', '2421', '1296', '155', '494', '426', '1086',
'961', '2236', '1829', '764', '1834', '1054', '617', '1529',
'2266', '637', '626', '1832', '1016', '2002', '1756', '746',
'1285', '2690', '1118', '5332', '980', '1807', '970', '1228',
'1195', '1132', '1768', '1384', '1080', '7063', '1817', '1452',
'1975', '1368', '702', '1974', '1781', '1036', '944', '663', '364',
'1539', '1345', '1680', '2209', '741', '1575', '695', '1317',
'294', '1525', '424', '997', '1473', '1552', '2819', '2188',
'1668', '3057', '799', '1502', '2606', '552', '1694', '1759',
'1110', '399', '1470', '1174', '5877', '1474', '1688', '526',
'686', '5908', '1107', '2070', '1468', '1246', '1685', '556',
'1533', '1917', '1346', '732', '692', '579', '421', '362', '3505',
'1855', '2711', '1586', '3739', '681', '1708', '2278', '1701',
'722', '1482', '928', '827', '832', '527', '604', '173', '1341',
'3329', '1553', '859', '167', '916', '828', '2082', '1176', '1108',
'975', '3008', '1516', '2269', '1699', '2073', '1031', '1503',
'2364', '1030', '1442', '5666', '2715', '1437', '2067', '1426',
'2908', '1279', '866', '4283', '279', '2658', '3015', '2004',
'1391', '4736', '748', '1466', '644', '683', '2705', '1297', '731',
'1252', '2216', '3141', '3273', '1518', '1723', '1588', '972',
'682', '1094', '668', '175', '967', '402', '3894', '1960', '1599',
'2000', '2084', '1621', '714', '1109', '3989', '873', '1572',
'1163', '1991', '1716', '1673', '2562', '2874', '965', '462',
'605', '1948', '1736', '3518', '2054', '2467', '1681', '1272',
'1205', '750', '2156', '2566', '115', '524', '3184', '676', '1678',
'612', '328', '955', '1441', '1675', '3965', '2909', '623', '822',
'867', '3025', '1993', '792', '636', '4057', '3743', '2337',
'2570', '2418', '2472', '3910', '1662', '2123', '2628', '3208',
'2080', '3699', '2913', '864', '2505', '870', '7536', '1924',
'1671', '1064', '1836', '1866', '4741', '841', '1369', '5681',
'3112', '1366', '2223', '1198', '1039', '3811', '3571', '1387',
'1171', '1365', '1531', '1590', '11706', '2308', '4860', '1641',
'1045', '1901'], dtype=object)
```

We see that all the values are of interger type except one which is '-'.

[**Whenever we encounter such situations following steps can be taken:**]()

1)We can drop all the rows with such special characters

2)We can replace those special characters with the mean,median or mode values of the specific column

3)We can replace it with any other value of ones choice

<u>Note</u>: We need to try out different ways of replacing such special characters and find out which will give us better accuracy.

In [281…

```
# Replacing the '-' character with 0
# converting the Levy column to float as it is the Tax
# "to_numeric" is a function of pandas which is used to convert an
#object datatype into numeric datatype
# downcast='float' changes the datatype into float

df['Levy'] = pd.to_numeric(df['Levy'].replace('-', '0'), downcast='float')
```

In [282…

```
# Replacing the 0 in the 'Levy' column with mean of that column
# First the special character '-' needs to be replaced with 0 because
#for finding the mean of the column
# all the values of a column should be of numeric type in order to
#find the mean of the column

df['Levy'] = np.where(df['Levy'] == 0.0,df['Levy'].mean(),df['Levy'])
```

In [283…

```
# checking the unique values in the 'Engine volume' column

df['Engine volume'].unique()
```

Out[283…

```
array(['3.5', '3', '1.3', '2.5', '2', '1.8', '2.4', '4', '1.6', '3.3',
       '2.0 Turbo', '2.2 Turbo', '4.7', '1.5', '4.4', '3.0 Turbo',
       '1.4 Turbo', '3.6', '2.3', '1.5 Turbo', '1.6 Turbo', '2.2',
       '2.3 Turbo', '1.4', '5.5', '2.8 Turbo', '3.2', '3.8', '4.6', '1.2',
       '5', '1.7', '2.9', '0.5', '1.8 Turbo', '2.4 Turbo', '3.5 Turbo',
       '1.9', '2.7', '4.8', '5.3', '0.4', '2.8', '3.2 Turbo', '1.1',
       '2.1', '0.7', '5.4', '1.3 Turbo', '3.7', '1', '2.5 Turbo', '2.6',
       '1.9 Turbo', '4.4 Turbo', '4.7 Turbo', '0.8', '0.2 Turbo', '5.7',
       '4.8 Turbo', '4.6 Turbo', '6.7', '6.2', '1.2 Turbo', '3.4',
       '1.7 Turbo', '6.3 Turbo', '2.7 Turbo', '4.3', '4.2', '2.9 Turbo',
       '0', '4.0 Turbo', '20', '3.6 Turbo', '0.3', '3.7 Turbo', '5.9',
       '5.5 Turbo', '0.2', '2.1 Turbo', '5.6', '6', '0.7 Turbo',
       '0.6 Turbo', '6.8', '4.5', '0.6', '7.3', '0.1', '1.0 Turbo', '6.3',
       '4.5 Turbo', '0.8 Turbo', '4.2 Turbo', '3.1', '5.0 Turbo', '6.4',
       '3.9', '5.7 Turbo', '0.9', '0.4 Turbo', '5.4 Turbo', '0.3 Turbo',
       '5.2', '5.8', '1.1 Turbo'], dtype=object)
```

In [284…

```
# We will remove all the string literals from the column so that it can be
#converted into numeric data type
# function "to_numeric" of pandas is used to convert the column to numeric datatype

df['Engine volume'] = pd.to_numeric(df['Engine volume'].str.split(' ').str[0], downc
```

In [285…

```
# Replacing the '0' in the 'Engine volume' column with the mean value of that column
# We can see from the unique values of 'Engine Volume' that there is '0'
# since the 'Engine volume' of no vehicle can be '0', so we replace it with the mean

df['Engine volume']=np.where(df['Engine volume'] == 0.0,df['Engine volume'].mean(),d
```

Feature engineering is the process of deriving new features(indepedent variable) from the

existing features(independent variable), that will help in training the model and in turn would improve the accuracy of the model or reduce the loss of the model.

In [286…

```
# Feature engineering using the "production year" column
# "datetime.now()" gives the current date and time as in the system

curr_time = dt.datetime.now()
df['Prod. year'] = curr_time.year - df['Prod. year']
```

In [287…

```
# checking the missing values in the dataset
# "isnull" function gives the missing values in a column
df.isnull().sum()
```

Out[287…

```
ID                  0
Levy                0
Manufacturer        0
Model               0
Prod. year          0
Category            0
Leather interior    0
Fuel type           0
Engine volume       0
Mileage             0
Cylinders           0
Gear box type       0
Drive wheels        0
Doors               0
Wheel               0
Color               0
Airbags             0
dtype: int64
```

We can see that there are no missing values in the dataset. Incase there would have been missing values in the dataset,we would had replaced them by the mean,meadian or mode of that column depending upon the datatype of the column.

In [288…

```
#Checking the dataset after all the pre-processing steps
df.head()
```

Out[288…

	ID	Levy	Manufacturer	Model	Prod. year	Category	Leather interior	Fuel type	Engine volume	Mile
0	45654403	1399.000000	LEXUS	RX 450	11	Jeep	Yes	Hybrid	3.5	1860(
1	44731507	1018.000000	CHEVROLET	Equinox	10	Jeep	No	Petrol	3.0	1920(
2	45774419	632.528687	HONDA	FIT	15	Hatchback	No	Petrol	1.3	2000(
3	45769185	862.000000	FORD	Escape	10	Jeep	Yes	Hybrid	2.5	1689(
4	45809263	446.000000	HONDA	FIT	7	Hatchback	Yes	Petrol	1.3	919(

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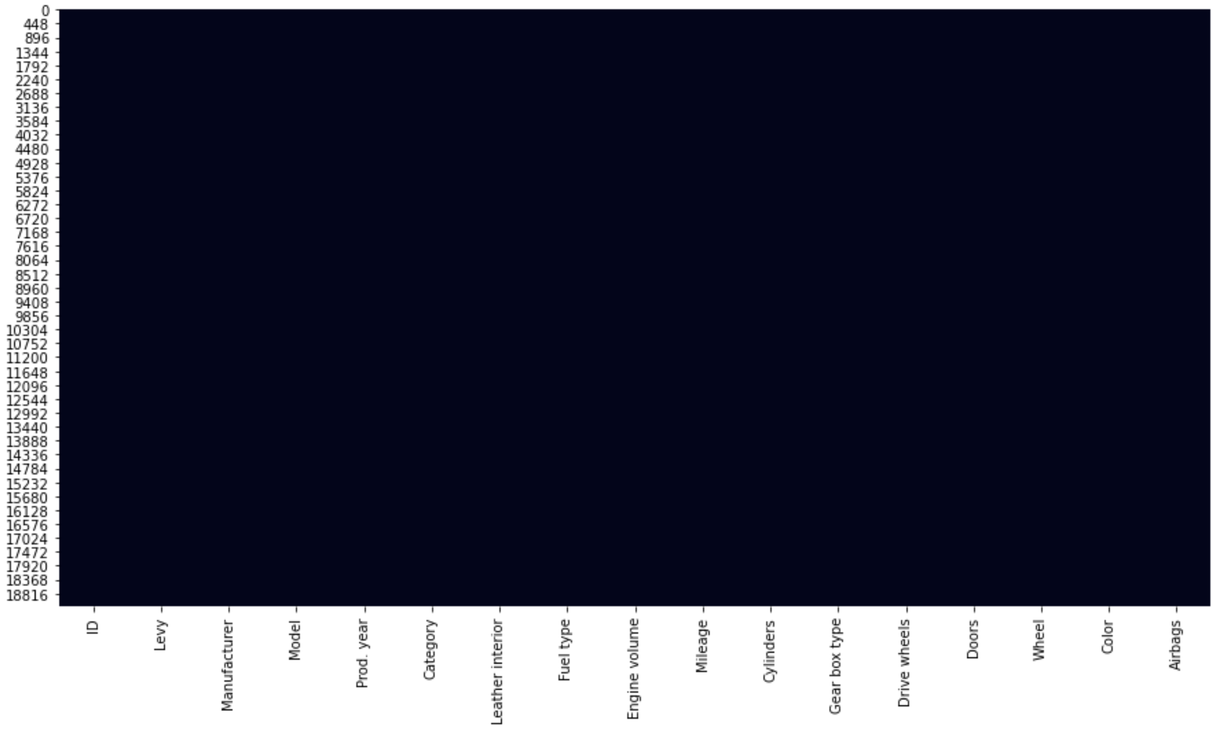
8.Extrapolatory data analysis

Why do we need extrapolatory data analysis?

It is required to do extrapolatory data analysis on the data to discover patterns,to spot anomalies,to test hypothesis and to check assumptions with the help of summary statistics and graphical representations. It can be univariate or bivariate analysis where we analyze a single feature or analyze two features together respectively.

In [289…

```
# plotting the missing values in the dataset using heatmap function of seaborn
# A heatmap represents the data in 2-dimensional format
sns.heatmap(df.isnull(),cbar=False)
plt.show()
```



We can see that there are no missing values

Correlation:

1) The function 'corr' tells us about the correlation between two features.

2) The value of correlation lies between -1 to 1.

3) The value between -0.5 to 0.5 means low correlation.

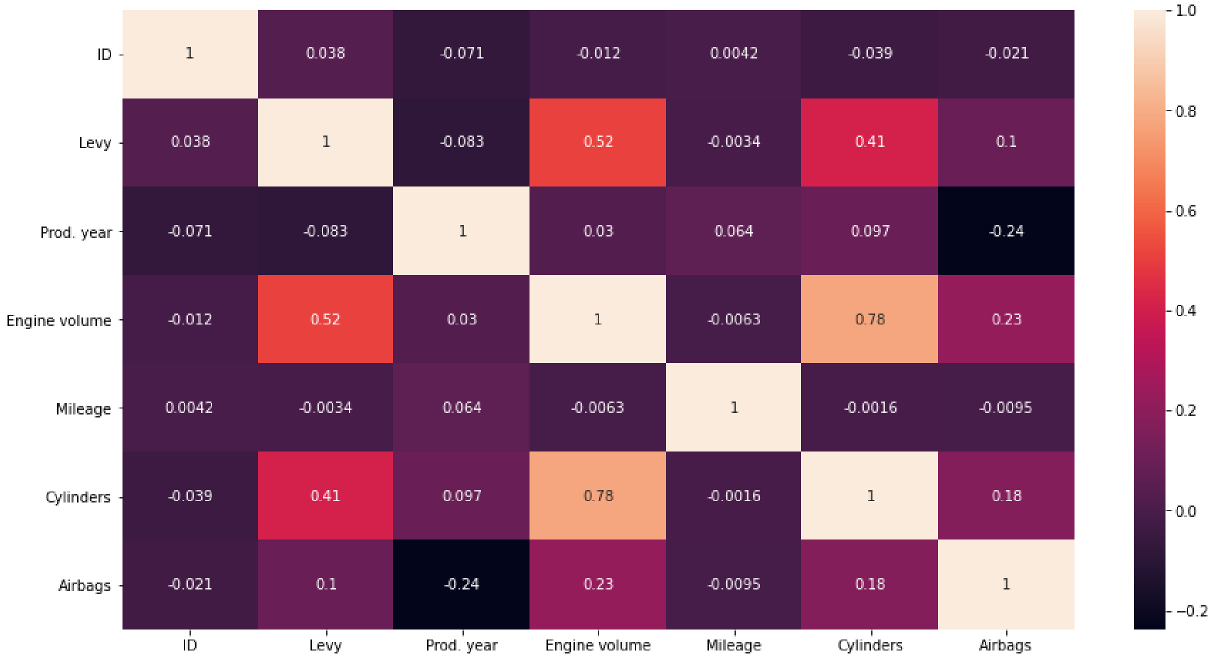
4) The value >0.5 and <-0.5 means high correlation.

5) We drop the features with high correation to avoid multicollinearity, since it is one of the assumption of linear regression that the dataset should have no multicollinearity.

In [290…

```
# Checking for correlation among the independent variables
# Uisng heatmap function of seaborn, we plot the correlations between all independen
# The argument "cbar=True" gives the bar at the side, showing the color
# transition from high to low correlation
# The argument "annot=True" prints the values of correlation between features in the
# The diagonal of a correlation matrix is always 1, as its a correlation of a featur
```

```
sns.heatmap(df.corr(), cbar=True, annot=True)
plt.show()
```



We can see that 'Engine volume' is having high correlation with 'Cylinders' column. We will drop the 'Cylinders' column to avoid multicollinearity.

In [291…

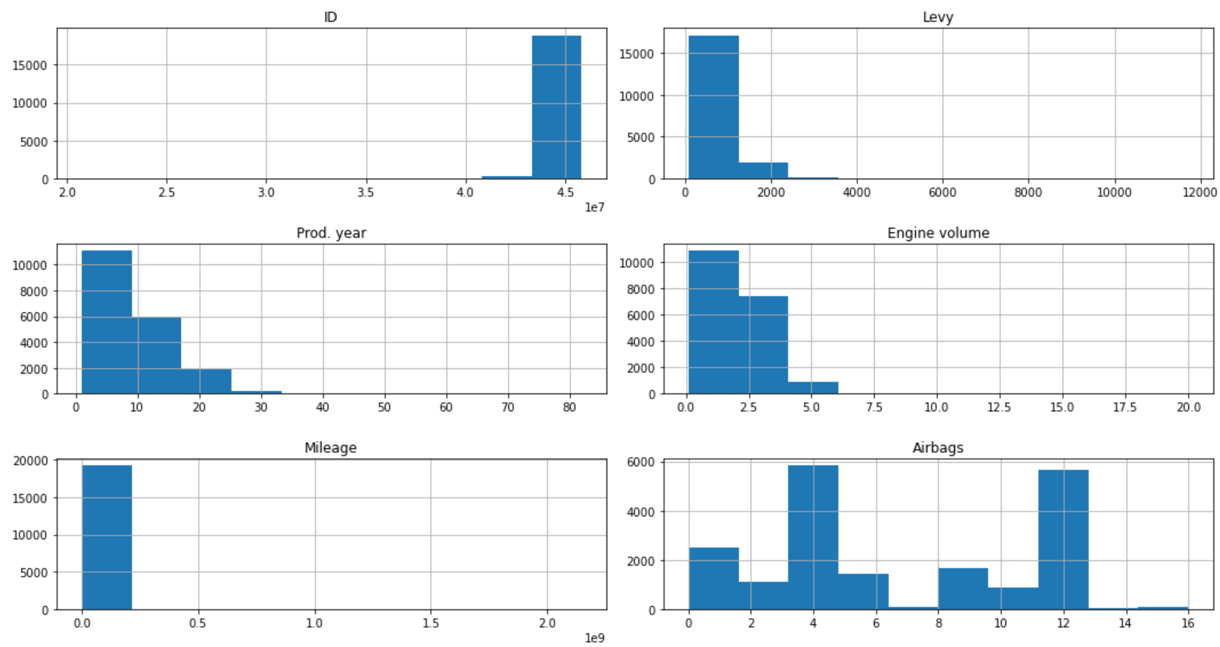
```
# dropping the 'Cylinders' column from the dataset using the 'drop' function
# argument 'axis=1' drops the data columwise
# argument 'inplace=True' reflects the modified data in the original dataset

df.drop(['Cylinders'],axis=1,inplace=True)
```

In [292…

```
# Plotting the histogram of all numeric variables
# Plotting the histogram help to identify the distribution and skewness of a column
# the function "tight_layout" helps to plot all the columns together

df.hist()
plt.tight_layout()
plt.show()
```



We can see that 'Prod. year','Levy' and 'Engine volume' columns are right skewed.

Skewness:

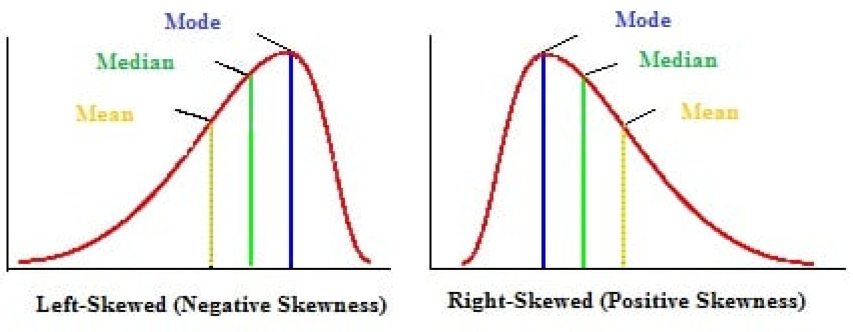
Skewness is the measure of asymmetry in the data distribution.It is of three types:

1)Positively skewed or right skewed

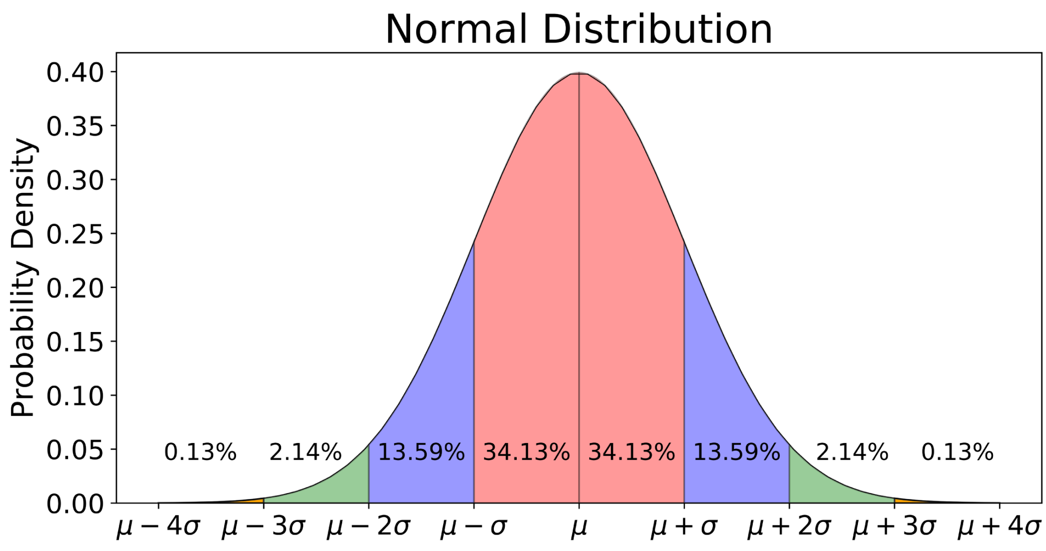
2)Negatively skewed or left skewed

3)No skewed

The following diagrams elaborates how the right skewed or the left skewed distribution looks and how mean,median and mode varies in those distribution.



For getting the best accuracy we need that our dependent variable also known as target variable is normally distributed.In normal distribution the mean,median and the mode lies at the center.If the independent variable is right or left skewed it does not reduce the accuracy, but the dependent variable should always be normally distributed.The normal distribution can be understood from the following diagram:



If the dependent variable is not normally distributed then we use the following two methods to make it normally distributed:

1)Log transformation

2)Box-cox transformation

Some information on normal distribution:

1) In normal distribution mean,median and mode lies at the center of the distribution.

2) In normal distribution 68% of the data lies within the first standard distribution of the mean.

3) 95% of the data lies within the second standard deviation of the mean.

4) 99.7% data lies within the third standard deviation of the mean.

In [293…

```
#We can check the skewness values using the function "skew()"
#Using "f-string" to print the values along with the statement

print(f"The skewness values of the production year is:{df['Prod. year'].skew()}")
print(f"The skewness values of the production year is:{df['Levy'].skew()}")
print(f"The skewness values of the production year is:{df['Engine volume'].skew()}")
```

```
The skewness values of the production year is:2.0822607659292403
The skewness values of the production year is:6.133322715759277
The skewness values of the production year is:2.2034800052642822
```

In order to check for normality of the target variable

1. Plot a histogram and also perform the Shapiro-Wilk test

2. If the data is not normally distributed, use log transformation to get near normally distributed data

3. Recheck for normality by plotting histogram and performing Shapiro-Wilk test

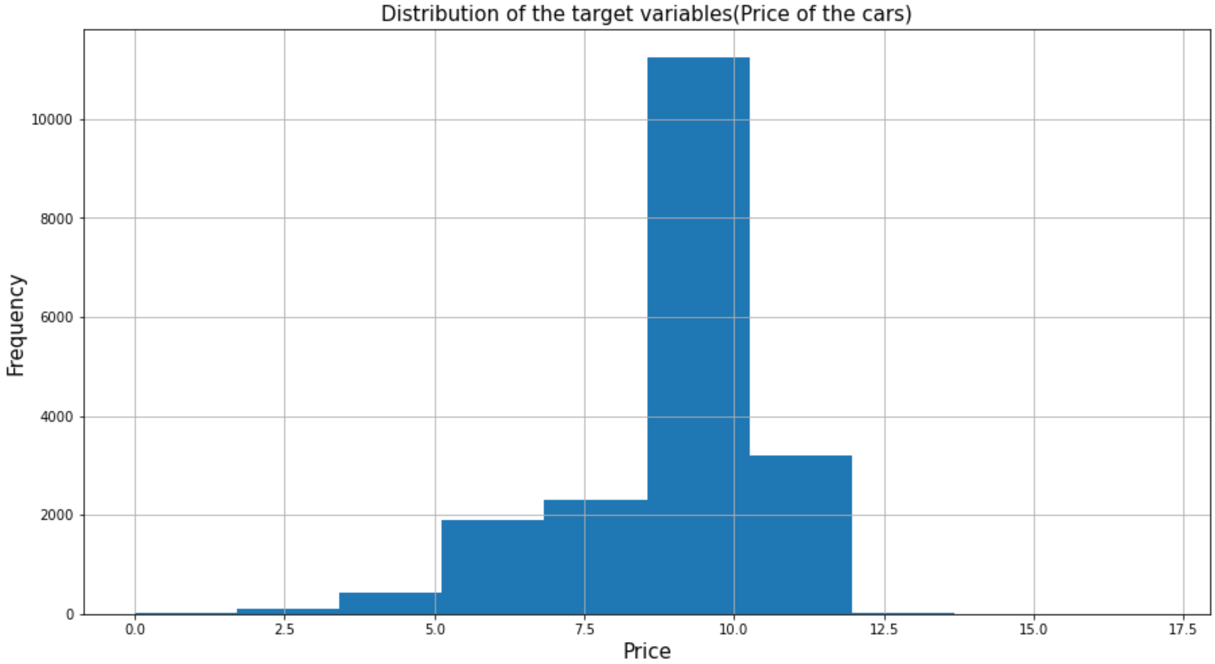
The Shapiro-Wilk test is a statistical test that evaluates the normality of a population. It was developed by Samuel Sanford Shapiro and Martin Wilk in 1965.

In [338…

```
# check the distribution of target variable
y.hist()

# add plot and axes labels
# set text size using 'fontsize'
plt.title('Distribution of the target variables(Price of the cars)', fontsize = 15)
plt.xlabel('Price', fontsize = 15)
plt.ylabel('Frequency', fontsize = 15)

# display the plot
plt.show()
```



The dependent variable column is left skewed

The null and alternate hypothesis of Shapiro-Wilk test is as follows:

H_0: The data is normally distributed

H_1: The data is not normally distributed

In [295...

```
# normality test using shapiro()
# the test returns the the test statistics and the p-value of the test
stat, p = shapiro(y)

# to print the numeric outputs of the Shapiro-Wilk test upto 3 decimal places
# %.3f: returns the a floating point with 3 decimal digit accuracy
# the '%' holds the place where the number is to be printed
print('Statistics=%.3f, p-value=%.3f' % (stat, p))

# display the conclusion
# set the level of significance to 0.05
alpha = 0.05

# if the p-value is greater than alpha print we accept alpha
# if the p-value is less than alpha print we reject alpha
if p > alpha:
    print('The data is normally distributed (fail to reject H0)')
else:
    print('The data is not normally distributed (reject H0)')
```

```
Statistics=0.013, p-value=0.000
The data is not normally distributed (reject H0)
```

In [296...

```
# Checking the skewness value

print("The skewness value of the target variable is:",y.skew())
```

```
The skewness value of the target variable is: 136.47042654268714
```

In [297...

```
# As from the shapiro test and the skewness value we can see that 'Price'
# column is highly positively skewed
```

```
# Hence,we normalize the column using log transformation

y = np.log(y)
```

In [298…

```
# rechecking the skeweness after log transformation
print(f"The skewness of the dependent variable after log transformation is:{y.skew()
```

```
The skewness of the dependent variable after log transformation is:-1.39155733953427
1
```

Hence, we can see that the skewness of the dependent variable has considerably got reduced.

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9.Preparing the data for model building

We need to perform dummy encoding on our categorical variables before we proceed; since the model can understand only the numeric data.

In order to dummy encode, we do the following:

```
                    1. Filter numerical and categorical variables<br>
                    2. Dummy encode the catergorical variables<br>
                    3. Concatenate numerical and dummy encoded categorical
    variables
```

In [299…

```
# seperating the categorical and numerical data
# This is being done to apply "one hot encoding" on the columns which
# are having object datatype
# "select_dtypes" function selects the particular datatypes given as argument

categorical = df.select_dtypes(include='object')
numerical = df.select_dtypes(include = np.number)
```

Understanding how 'get_dummies' function work:

Suppose there is a feature named gender and it has got three categories,namely:

1)Male

2)Female

3)Transgender

When we apply "get_dummies" on this feature it gives the following output:

```
        gender_Male          0 1 0
        gender_Female        1 0 0
        gender_Transgender   0 0 1
```

Points to be noted:

1)The categorical variables are dummy encoded creating n-1 variables for each categorical variables, where n is the number of classes in each categorical variable.

2)The row having gender as 'Male', will have value 1 in the 'gender_Male' column for that particular row, while other columns of the feature gender will have value 0.

3)We drop the first or the last column to reduce model complexity and even it is obvious, that if the gender is not 'Male' or 'Female' then it is going to be 'Transgender'

In [300…

```
# getting dummies for the categorical variables
# This is being done as the model cannot understand string data
# "get_dummies" function of pandas is used for one hot encoding

dummies = pd.get_dummies(categorical,drop_first=True)
```

In [301…

```
# creating the final dataset
# the function 'concat' of pandas do concatenate two or more dataframes together
# 'axis=1' means that all the data are being concatenated column wise

df_final = pd.concat([numerical,dummies], axis=1)
```

In [302…

```
# checking the shape of the final dataset

df_final.shape
```

Out[302…

```
(19237, 1699)
```

Phases of model building:

1)Training phase: In this phase we use training data to train the model using an algorithm

2)Validation phase: In this phase the model is checked with the validation data.This is used to fine tune the model.

3)Testing phase: In this phase the model is exposed to new data and the accuracy of the model is checked.

Model building and testing steps:

1. Split the data into training and test set using train_test_split
2. Build model using sklearn.linear_model
3. Predict the values using test set
4. Compute accuracy measures
5. Tabulate the results

In [303…

```
# splitting the data into test and train
# Assigning all the independent variables in the variable X
# Assigning the dependent variable in the variable y
X =df_final
Y=y
```

```
# Splitting the data before building the model in order to train the model
# and later check its accuracy
# The argument "test_size" tells about the ratio of data, that needs to
# be kept for testing the model

X_train, X_test, y_train, y_test = train_test_split(X,Y, test_size=0.3, random_state
```

In [304…

```
# Displaying the shape of the train and test data

print(f"The shape of the X_train data is:{X_train.shape}")
print(f"The shape of the X_test data is:{X_test.shape}")
print(f"The shape of the y_train data is:{y_train.shape}")
print(f"The shape of the y_test data is:{y_test.shape}")
```

```
The shape of the X_train data is:(13465, 1699)
The shape of the X_test data is:(5772, 1699)
The shape of the y_train data is:(13465,)
The shape of the y_test data is:(5772,)
```

10.Model 1(Linear Regression)

In [305…

```
# Instantiating the Linear Regression model

LR=LinearRegression()

#fitting the model on the training data

model1=LR.fit(X_train,y_train)
```

In [306…

```
# predicting the output on the test data

predicted=model1.predict(X_test)
```

In [307…

```
# calculating the metrics root mean squared log error
RMSLE=np.sqrt(mean_squared_log_error(predicted,y_test))
```

In [308…

```
# calculating the metrics root mean squared error
RMSE=rmse(predicted,y_test)
```

In [309…

```
mae=mean_absolute_error(y_test,predicted)
```

In [310…

```
# create the result table for all accuracy scores
# accuracy measures considered for model comparision are RMSE, R-squared value
# and Adjusted R-squared value
# create a list of column names
cols = ['Model', 'RMSE', 'RMSLE','Mean Absolute Error']

# create a empty dataframe of the colums
# columns: specifies the columns to be selected
result_tabulation = pd.DataFrame(columns = cols)

# compile the required information
linreg_full_model_withlog_metrics = pd.Series({'Model': "Linear Regression",
                     'RMSE':RMSE,
                     'RMSLE': RMSLE,
```

```
                        'Mean Absolute Error': mae
                      })

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_full_model_withlog_metrics, igno

# print the result table
result_tabulation
```

Out[310…

	Model	RMSE	RMSLE	Mean Absolute Error
0	Linear Regression	1.327445	0.164084	0.929873

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Feature Selection Techniques:

We need to select significant features to train the model.If there are lot of features it results in increasing the model complexity.

Different feature selection techniques:

1.For small datasets:

> i) Forward Selection: This method considers the null model (model with no predictors) in the first step. In the next steps start adding one variable at each step until we run out of the independent variables or the stopping rule is achieved. The variable is added based on its correlation with the target variable.
>
> ii) Backward elimination: This method considers the full model (model with all the predictors) in the first step. In the next steps start removing one variable at each step until we run out of the independent variables or the stopping rule is achieved. The least significant variable (with the highest p-value) is removed at each step.
>
> iii)Recursive feature elimination: It is the process that returns the significant features in the dataset by recursively removing the less significant feature subsets.

2.For big datasets:

We train a model such as random forest,extra trees or decision tree with the available dataset and use a property of the model known as ***featureimportances*** to find out the most significant features.

3.Features can be selected using the correlation plot, where the features with high correlation with the dependent variable gets selected.

11.Model 2(Ridge regressor using feature selection and hyperparameter tuning technique)

Steps used for model building:

1. In this model, linear regression from statsmodels has been used to find the probability values of all the features.All the significant features have been selected i.e. features having p-value less than 0.05.

2. Ridge regressor has been used to find the best parameters.These parameters have been used in the ridge regressor to predict the price of cars.

Ridge Regressor:

Ridge regressor addresses the overfitting issue of linear regression.The main objective of linear regression is to reduce the error between the actual and predicted value i.e it tries to reduce the cost function.In doing so sometimes the model gets overfittied.We should always aim at creating a generalised model so that, the model works well even with the test data.

Overfitting: It is a situation of low bias and high variance. In another words the model gives good accuracy with the training data but gives low accuracy with the test data.

In ridge regressor and lasso regressor we add a parameter to the cost function.This parameter is square of weight(slope) in ridge regressor and the weight(slope) in lasso regressor.This whole term i.e. the cost function and the parameter added needs to get reduced in ridge and lasso regressor. This reduces the overfitting issue.In short ridge and lasso regressor penalizes the features having high slope.

To know more about ridge and lasso regressor click here

In [311…

```
#instantiating the ordinary least square model
model2=sm.OLS(y_train, X_train).fit()
```

In [312…

```
#displaying all the statistical summary of the model
model2.summary()
```

Out[312…

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.354
Model:	OLS	**Adj. R-squared:**	0.282
Method:	Least Squares	**F-statistic:**	4.924
Date:	Sat, 02 Oct 2021	**Prob (F-statistic):**	0.00
Time:	03:30:49	**Log-Likelihood:**	-22474.
No. Observations:	13465	**AIC:**	4.765e+04
Df Residuals:	12114	**BIC:**	5.779e+04
Df Model:	1350		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
ID	1.565e-07	1.53e-08	10.223	0.000	1.26e-07	1.86e-07
Levy	-0.0002	4.32e-05	-5.199	0.000	-0.000	-0.000
Prod. year	-0.0800	0.004	-19.722	0.000	-0.088	-0.072
Engine volume	-0.0724	0.043	-1.697	0.090	-0.156	0.011

Mileage	-4.957e-10	2.33e-10	-2.132	0.033	-9.51e-10	-3.99e-11
Airbags	-0.0482	0.004	-12.176	0.000	-0.056	-0.040
Manufacturer_ALFA ROMEO	3.1715	0.849	3.736	0.000	1.507	4.836
Manufacturer_ASTON MARTIN	-1.624e-06	1.61e-06	-1.008	0.313	-4.78e-06	1.53e-06
Manufacturer_AUDI	4.5215	0.815	5.546	0.000	2.923	6.120
Manufacturer_BENTLEY	4.2673	0.804	5.307	0.000	2.691	5.843
Manufacturer_BMW	4.9721	0.971	5.122	0.000	3.069	6.875
Manufacturer_BUICK	7.6179	1.729	4.405	0.000	4.228	11.008
Manufacturer_CADILLAC	4.4724	0.826	5.414	0.000	2.853	6.092
Manufacturer_CHEVROLET	4.2579	0.793	5.372	0.000	2.704	5.811
Manufacturer_CHRYSLER	5.0024	1.135	4.408	0.000	2.778	7.227
Manufacturer_CITROEN	4.0971	0.834	4.912	0.000	2.462	5.732
Manufacturer_DAEWOO	3.8349	0.841	4.562	0.000	2.187	5.483
Manufacturer_DAIHATSU	3.0254	0.825	3.667	0.000	1.408	4.643
Manufacturer_DODGE	4.1600	0.818	5.084	0.000	2.556	5.764
Manufacturer_FERRARI	3.3162	0.802	4.135	0.000	1.744	4.888
Manufacturer_FIAT	4.1286	0.795	5.190	0.000	2.569	5.688
Manufacturer_FORD	4.5563	0.807	5.648	0.000	2.975	6.138
Manufacturer_GAZ	4.5657	0.852	5.357	0.000	2.895	6.236
Manufacturer_GMC	2.8769	0.754	3.815	0.000	1.399	4.355
Manufacturer_GREATWALL	1.7854	0.787	2.268	0.023	0.242	3.329
Manufacturer_HAVAL	-1.367e-06	1.36e-06	-1.002	0.317	-4.04e-06	1.31e-06
Manufacturer_HONDA	4.5748	0.817	5.603	0.000	2.974	6.175
Manufacturer_HUMMER	4.6805	0.851	5.500	0.000	3.012	6.349
Manufacturer_HYUNDAI	4.5554	0.811	5.619	0.000	2.966	6.145
Manufacturer_INFINITI	4.9202	0.826	5.956	0.000	3.301	6.539
Manufacturer_ISUZU	3.8520	0.845	4.558	0.000	2.196	5.508
Manufacturer_JAGUAR	4.1133	0.794	5.183	0.000	2.558	5.669
Manufacturer_JEEP	4.4321	0.769	5.764	0.000	2.925	5.939
Manufacturer_KIA	4.4273	0.810	5.465	0.000	2.839	6.015
Manufacturer_LAMBORGHINI	-1.556e-07	4.88e-07	-0.319	0.750	-1.11e-06	8.01e-07
Manufacturer_LANCIA	2.2515	0.793	2.838	0.005	0.696	3.807
Manufacturer_LAND ROVER	5.2019	0.808	6.438	0.000	3.618	6.786
Manufacturer_LEXUS	5.3344	0.813	6.561	0.000	3.741	6.928
Manufacturer_LINCOLN	3.5005	0.796	4.399	0.000	1.941	5.060
Manufacturer_MASERATI	2.3000	0.568	4.048	0.000	1.186	3.414
Manufacturer_MAZDA	4.1024	0.815	5.033	0.000	2.505	5.700

Manufacturer_MERCEDES-BENZ	5.2260	0.860	6.080	0.000	3.541	6.911
Manufacturer_MERCURY	3.9611	2.004	1.976	0.048	0.032	7.890
Manufacturer_MINI	4.2919	0.810	5.296	0.000	2.703	5.880
Manufacturer_MITSUBISHI	4.5173	0.809	5.586	0.000	2.932	6.102
Manufacturer_MOSKVICH	4.4243	0.867	5.102	0.000	2.724	6.124
Manufacturer_NISSAN	4.4823	0.816	5.490	0.000	2.882	6.083
Manufacturer_OPEL	3.9515	0.817	4.834	0.000	2.349	5.554
Manufacturer_PEUGEOT	4.2077	0.819	5.139	0.000	2.603	5.813
Manufacturer_PONTIAC	2.0928	0.792	2.642	0.008	0.540	3.645
Manufacturer_PORSCHE	5.5415	0.785	7.062	0.000	4.003	7.080
Manufacturer_RENAULT	3.6352	0.814	4.468	0.000	2.041	5.230
Manufacturer_ROLLS-ROYCE	3.4811	0.627	5.555	0.000	2.253	4.709
Manufacturer_ROVER	5.0227	1.674	3.001	0.003	1.742	8.304
Manufacturer_SAAB	3.6693	1.587	2.312	0.021	0.558	6.780
Manufacturer_SATURN	2.6196	0.794	3.299	0.001	1.063	4.176
Manufacturer_SCION	3.1218	0.708	4.410	0.000	1.734	4.509
Manufacturer_SEAT	2.3182	0.842	2.754	0.006	0.668	3.968
Manufacturer_SKODA	3.4682	0.801	4.328	0.000	1.897	5.039
Manufacturer_SSANGYONG	4.3498	0.733	5.938	0.000	2.914	5.786
Manufacturer_SUBARU	4.4027	0.815	5.405	0.000	2.806	5.999
Manufacturer_SUZUKI	4.5754	0.809	5.653	0.000	2.989	6.162
Manufacturer_TESLA	3.1330	0.791	3.960	0.000	1.582	4.684
Manufacturer_TOYOTA	4.7632	0.811	5.873	0.000	3.173	6.353
Manufacturer_UAZ	6.2619	1.253	4.999	0.000	3.807	8.717
Manufacturer_VAZ	3.7969	0.820	4.630	0.000	2.189	5.405
Manufacturer_VOLKSWAGEN	4.2092	0.815	5.163	0.000	2.611	5.807
Manufacturer_VOLVO	4.2697	0.830	5.147	0.000	2.644	5.896
Manufacturer_ZAZ	2.9478	0.841	3.504	0.000	1.299	4.597
Manufacturer_სხვა	3.5481	0.830	4.274	0.000	1.921	5.175
Model_100	-0.3710	0.950	-0.390	0.696	-2.234	1.492
Model_100 NX	-0.2531	1.342	-0.189	0.850	-2.883	2.377
Model_1000	-1.0997	0.440	-2.501	0.012	-1.961	-0.238
Model_1111	1.5684	1.267	1.238	0.216	-0.915	4.052
Model_114	-0.4622	1.101	-0.420	0.675	-2.620	1.695
Model_116	-1.378e-07	3.91e-07	-0.353	0.724	-9.04e-07	6.28e-07
Model_118	-0.4766	1.459	-0.327	0.744	-3.337	2.384
Model_118 2,0	-2.92e-08	6.07e-07	-0.048	0.962	-1.22e-06	1.16e-06

Model_118 M-sport LCI	-7.192e-07	4.04e-07	-1.781	0.075	-1.51e-06	7.22e-08
Model_120	-0.4429	1.459	-0.304	0.761	-3.303	2.417
Model_128	-0.0514	1.463	-0.035	0.972	-2.919	2.816
Model_128 M tech	-0.3759	1.510	-0.249	0.803	-3.337	2.585
Model_130	0.3608	1.462	0.247	0.805	-2.505	3.227
Model_1300	-1.0182	0.617	-1.650	0.099	-2.228	0.191
Model_135	-0.7476	1.463	-0.511	0.609	-3.616	2.121
Model_147	0.7407	1.144	0.647	0.517	-1.503	2.984
Model_1500	-1.6060	0.782	-2.055	0.040	-3.138	-0.074
Model_1500,1600 Schtufenheck	0.9244	1.342	0.689	0.491	-1.706	3.555
Model_159	1.7833	1.141	1.562	0.118	-0.454	4.020
Model_166	0.6475	1.144	0.566	0.571	-1.594	2.890
Model_190	-0.4541	1.006	-0.451	0.652	-2.427	1.519
Model_20	4.0150	0.956	4.200	0.000	2.141	5.889
Model_200	-1.6293	0.585	-2.786	0.005	-2.775	-0.483
Model_206	-0.4010	0.948	-0.423	0.672	-2.259	1.457
Model_206 CC	-0.0462	1.262	-0.037	0.971	-2.521	2.428
Model_207	-0.1218	1.292	-0.094	0.925	-2.654	2.411
Model_208	-0.7214	1.014	-0.711	0.477	-2.709	1.266
Model_21	2.3530	1.280	1.839	0.066	-0.155	4.861
Model_21 3.0	3.641e-08	2.12e-07	0.172	0.864	-3.79e-07	4.52e-07
Model_2101 01	0.6211	1.274	0.488	0.626	-1.876	3.118
Model_2103 03	1.4249	1.270	1.122	0.262	-1.064	3.914
Model_2105	-9.262e-07	4.97e-07	-1.862	0.063	-1.9e-06	4.88e-08
Model_2106	0.2013	0.523	0.385	0.700	-0.824	1.227
Model_2107	-0.4351	0.787	-0.553	0.580	-1.978	1.107
Model_2107 07	-2.012e-07	3.12e-07	-0.646	0.518	-8.12e-07	4.09e-07
Model_2109	0.1490	1.265	0.118	0.906	-2.331	2.629
Model_2111	0.2646	1.265	0.209	0.834	-2.215	2.744
Model_2121 (Niva)	0.4725	0.511	0.924	0.355	-0.529	1.474
Model_2140	0.1656	1.155	0.143	0.886	-2.098	2.429
Model_216	-1.9071	2.004	-0.951	0.341	-5.836	2.022
Model_220	-0.3097	1.394	-0.222	0.824	-3.042	2.422
Model_225	-3.216e-07	4.78e-07	-0.673	0.501	-1.26e-06	6.15e-07
Model_230	-0.3046	0.839	-0.363	0.717	-1.949	1.340
Model_230 W153	9.5638	1.420	6.733	0.000	6.779	12.348
Model_24	0.5398	1.284	0.420	0.674	-1.977	3.056

Model_24 10	-1.1627	1.268	-0.917	0.359	-3.648	1.323
Model_240	5.178e-08	4.7e-07	0.110	0.912	-8.69e-07	9.73e-07
Model_250	0.3972	1.003	0.396	0.692	-1.569	2.363
Model_270	-1.1688	1.012	-1.155	0.248	-3.153	0.815
Model_280	-0.5086	1.001	-0.508	0.611	-2.471	1.454
Model_290	-0.5887	1.406	-0.419	0.676	-3.346	2.168
Model_3.18E+38	-0.5670	1.462	-0.388	0.698	-3.433	2.299
Model_3.20E+38	1.37e-07	5.25e-07	0.261	0.794	-8.92e-07	1.17e-06
Model_3.25E+48	-0.4036	1.458	-0.277	0.782	-3.261	2.453
Model_300	0.2275	1.144	0.199	0.842	-2.015	2.470
Model_300 LIMITED	-0.2577	1.569	-0.164	0.870	-3.333	2.818
Model_3008	1.4919	1.260	1.184	0.237	-0.979	3.963
Model_3008 2.0	2.1911	1.261	1.738	0.082	-0.280	4.663
Model_307	2.608e-08	5.36e-07	0.049	0.961	-1.02e-06	1.08e-06
Model_311	0.0392	1.399	0.028	0.978	-2.703	2.782
Model_3110	-2.4490	0.949	-2.581	0.010	-4.309	-0.589
Model_31105	-0.3122	1.304	-0.239	0.811	-2.868	2.244
Model_31514	-0.3278	1.151	-0.285	0.776	-2.583	1.928
Model_31514 UAZ	-5.905e-09	5.29e-07	-0.011	0.991	-1.04e-06	1.03e-06
Model_316	-0.2698	0.955	-0.283	0.778	-2.141	1.602
Model_316 1995	-0.4649	1.459	-0.319	0.750	-3.325	2.395
Model_316 i	2.18e-07	5.55e-07	0.393	0.694	-8.69e-07	1.31e-06
Model_318	-0.6228	0.607	-1.025	0.305	-1.813	0.568
Model_318 318	-0.4782	1.458	-0.328	0.743	-3.335	2.379
Model_318 m	-6e-07	4.88e-07	-1.229	0.219	-1.56e-06	3.57e-07
Model_318 რესტაილინგი	-0.3602	1.458	-0.247	0.805	-3.219	2.498
Model_318 სასწრაფოდ	-0.1604	1.462	-0.110	0.913	-3.026	2.705
Model_320	-0.4452	0.525	-0.848	0.396	-1.474	0.584
Model_320 2.0	-0.1455	1.457	-0.100	0.920	-3.002	2.711
Model_320 2.2	-3.194e-08	4.45e-07	-0.072	0.943	-9.04e-07	8.41e-07
Model_320 320	0.0040	1.462	0.003	0.998	-2.862	2.870
Model_320 DIESEL	-0.4493	1.458	-0.308	0.758	-3.307	2.408
Model_320 Diesel	-0.2673	1.458	-0.183	0.855	-3.126	2.591
Model_320 Gran Turismo	-0.1120	1.458	-0.077	0.939	-2.969	2.745
Model_320 I	0.3955	1.461	0.271	0.787	-2.468	3.259
Model_320 M	1.596e-07	2.33e-07	0.685	0.493	-2.97e-07	6.16e-07
Model_320 i	-7.447e-08	5.37e-07	-0.139	0.890	-1.13e-06	9.78e-07

Model_32214	0.5915	1.432	0.413	0.680	-2.216	3.399
Model_322173	-1.1e-07	4.96e-07	-0.222	0.825	-1.08e-06	8.63e-07
Model_323	-0.6908	0.785	-0.880	0.379	-2.229	0.847
Model_323 F	0.5444	1.331	0.409	0.683	-2.064	3.153
Model_325	0.1252	0.637	0.197	0.844	-1.124	1.374
Model_325 CI	-0.9684	1.508	-0.642	0.521	-3.924	1.988
Model_325 XI	-0.1494	1.458	-0.102	0.918	-3.008	2.709
Model_325 i	7.69e-08	3.3e-07	0.233	0.816	-5.7e-07	7.24e-07
Model_328	-0.4458	0.579	-0.770	0.441	-1.581	0.689
Model_328 DIZEL	-0.4671	1.458	-0.320	0.749	-3.325	2.391
Model_328 DRIFT CAR	-0.0839	1.464	-0.057	0.954	-2.953	2.785
Model_328 Xdrive	-4.261e-07	4.56e-07	-0.934	0.350	-1.32e-06	4.68e-07
Model_328 i	-0.7873	1.467	-0.537	0.592	-3.663	2.088
Model_328 sulev	1.3568	1.457	0.931	0.352	-1.500	4.213
Model_330	-0.9024	0.660	-1.368	0.171	-2.195	0.390
Model_335	-0.4108	0.645	-0.637	0.524	-1.675	0.854
Model_335 335i	0.4361	1.457	0.299	0.765	-2.421	3.293
Model_335 D	-1.361e-07	3.77e-07	-0.361	0.718	-8.75e-07	6.02e-07
Model_335 M paket	-0.0051	1.462	-0.003	0.997	-2.872	2.861
Model_335 ტურბო	0.1135	1.458	0.078	0.938	-2.745	2.972
Model_340	2.731e-07	5.46e-07	0.500	0.617	-7.98e-07	1.34e-06
Model_370Z	0.7924	1.349	0.587	0.557	-1.852	3.437
Model_3796	0.9902	1.286	0.770	0.441	-1.531	3.511
Model_400	4.1478	1.151	3.605	0.000	1.893	6.403
Model_400X	-2.367e-07	5.55e-07	-0.426	0.670	-1.32e-06	8.52e-07
Model_401	0.1109	1.156	0.096	0.924	-2.155	2.377
Model_406	4.082e-07	3.84e-07	1.063	0.288	-3.45e-07	1.16e-06
Model_407	-1.341e-08	4.78e-07	-0.028	0.978	-9.5e-07	9.23e-07
Model_416	0.0469	1.410	0.033	0.973	-2.717	2.811
Model_420	0.1882	1.462	0.129	0.898	-2.678	3.054
Model_428	0.2622	0.755	0.347	0.728	-1.218	1.743
Model_428 Sport Line	1.2328	1.462	0.843	0.399	-1.633	4.099
Model_428 i	0.1477	1.462	0.101	0.920	-2.718	3.014
Model_435	-0.0870	1.108	-0.079	0.937	-2.258	2.084
Model_435 CUPE	0.7540	1.463	0.516	0.606	-2.113	3.621
Model_456	-9.188e-08	5.13e-07	-0.179	0.858	-1.1e-06	9.14e-07
Model_4Runner	-0.0659	0.366	-0.180	0.857	-0.783	0.651

Model_4Runner LIMITED	1.1095	1.353	0.820	0.412	-1.544	3.762
Model_5.30E+62	4.06e-07	5.09e-07	0.798	0.425	-5.91e-07	1.4e-06
Model_50	5.909e-07	5.16e-07	1.145	0.252	-4.21e-07	1.6e-06
Model_500	-0.5935	0.361	-1.645	0.100	-1.301	0.114
Model_500 46 ml	-9.542e-08	5.49e-07	-0.174	0.862	-1.17e-06	9.8e-07
Model_500 Abarth	0.5414	0.636	0.851	0.395	-0.705	1.788
Model_500 Abarth ტურბო	-3.381e-07	4.44e-07	-0.762	0.446	-1.21e-06	5.32e-07
Model_500 Lounge	-0.0396	1.304	-0.030	0.976	-2.596	2.517
Model_500 SPORT	4.958e-08	5.13e-07	0.097	0.923	-9.56e-07	1.06e-06
Model_500 Sport	0.4818	0.789	0.610	0.542	-1.065	2.029
Model_500 s	0.4847	1.302	0.372	0.710	-2.067	3.036
Model_500 sport	0.9136	0.942	0.970	0.332	-0.932	2.759
Model_500 sport panorama	0.8527	1.302	0.655	0.512	-1.698	3.404
Model_500 turbo	6.422e-08	5.35e-07	0.120	0.904	-9.84e-07	1.11e-06
Model_500C	0.8565	1.303	0.657	0.511	-1.697	3.410
Model_500C Lounge	0.1584	1.344	0.118	0.906	-2.477	2.793
Model_500L	0.1847	0.944	0.196	0.845	-1.666	2.035
Model_500L LONG	2.827e-08	5.31e-07	0.053	0.958	-1.01e-06	1.07e-06
Model_500X	0.6519	1.307	0.499	0.618	-1.910	3.214
Model_500X Lounge	0.8268	1.303	0.634	0.526	-1.728	3.381
Model_508	1.0482	1.258	0.833	0.405	-1.418	3.515
Model_520	-0.2646	0.695	-0.381	0.703	-1.626	1.097
Model_520 I	-4.245e-07	5.37e-07	-0.790	0.430	-1.48e-06	6.29e-07
Model_520 Vanos	-0.5980	1.458	-0.410	0.682	-3.456	2.260
Model_520 d xDrive Luxury	-0.1004	1.478	-0.068	0.946	-2.997	2.797
Model_523	0.0185	1.458	0.013	0.990	-2.838	2.876
Model_525	-0.6615	0.630	-1.050	0.294	-1.896	0.573
Model_525 ///M	3.397e-07	5.46e-07	0.622	0.534	-7.31e-07	1.41e-06
Model_525 525	0.6904	1.459	0.473	0.636	-2.170	3.551
Model_525 TDI	-2.606e-07	5.02e-07	-0.519	0.604	-1.25e-06	7.24e-07
Model_525 Vanos	-0.0660	1.461	-0.045	0.964	-2.929	2.797
Model_525 i	-0.4962	1.458	-0.340	0.734	-3.353	2.361
Model_528	-0.1406	0.589	-0.239	0.811	-1.295	1.014
Model_528 3.0	0.0861	1.457	0.059	0.953	-2.771	2.943
Model_528 i	3.119e-07	5.58e-07	0.559	0.576	-7.82e-07	1.41e-06
Model_530	-0.1245	0.612	-0.203	0.839	-1.325	1.076
Model_530 525i	1.3669	1.458	0.938	0.348	-1.490	4.224

Model_530 G30	1.1876	1.457	0.815	0.415	-1.669	4.044
Model_530 GT	1.8773	1.104	1.701	0.089	-0.287	4.041
Model_530 I	-0.1070	1.458	-0.073	0.941	-2.964	2.750
Model_530 M	-1.801e-07	5.32e-07	-0.339	0.735	-1.22e-06	8.62e-07
Model_530 i	-0.4152	1.458	-0.285	0.776	-3.273	2.443
Model_535	-0.1209	0.587	-0.206	0.837	-1.271	1.030
Model_535 535	0.3169	1.457	0.217	0.828	-2.540	3.173
Model_535 Diesel	1.6109	1.458	1.105	0.269	-1.248	4.469
Model_535 I	0.2203	1.458	0.151	0.880	-2.637	3.077
Model_535 M	-3.7474	1.458	-2.570	0.010	-6.605	-0.889
Model_535 M PAKET	-1.912e-07	5.93e-07	-0.322	0.747	-1.35e-06	9.71e-07
Model_535 Twinturbo	0.7373	1.457	0.506	0.613	-2.119	3.594
Model_535 XI	2.143e-07	4.94e-07	0.434	0.665	-7.54e-07	1.18e-06
Model_535 comfort-sport	0.0539	1.458	0.037	0.971	-2.804	2.912
Model_535 i	0.0384	1.457	0.026	0.979	-2.818	2.895
Model_535 i xDrive	0.2165	1.458	0.148	0.882	-2.642	3.075
Model_540 I	3.4033	1.462	2.327	0.020	0.537	6.270
Model_545	0.5858	1.105	0.530	0.596	-1.580	2.752
Model_550	0.4367	0.700	0.624	0.533	-0.935	1.808
Model_550 F10	0.4143	1.460	0.284	0.777	-2.447	3.275
Model_550 GT	1.888e-09	5.49e-07	0.003	0.997	-1.07e-06	1.08e-06
Model_550 M Packet	1.26e-07	5.41e-07	0.233	0.816	-9.35e-07	1.19e-06
Model_607	7.538e-07	5.69e-07	1.326	0.185	-3.61e-07	1.87e-06
Model_616	-0.6513	0.685	-0.951	0.342	-1.994	0.691
Model_626	0.1431	1.331	0.108	0.914	-2.465	2.751
Model_630	0.5212	1.458	0.358	0.721	-2.336	3.379
Model_635	0.9675	1.457	0.664	0.507	-1.889	3.824
Model_640	1.2130	1.458	0.832	0.405	-1.644	4.070
Model_640 GRAN-COUPE	1.3772	1.457	0.945	0.345	-1.480	4.234
Model_640 M	2.1031	1.459	1.441	0.149	-0.757	4.963
Model_645	-0.3208	1.518	-0.211	0.833	-3.296	2.654
Model_645 CI	-0.0284	1.465	-0.019	0.985	-2.901	2.844
Model_650	-0.4342	0.758	-0.573	0.567	-1.921	1.052
Model_650 450 HP	1.3399	1.460	0.918	0.359	-1.522	4.202
Model_7.30E+34	0.5285	1.459	0.362	0.717	-2.332	3.389
Model_730	0.0473	1.457	0.032	0.974	-2.809	2.904
Model_730 3.0	0.6894	1.459	0.473	0.637	-2.171	3.549

Model_735	-0.0855	1.462	-0.058	0.953	-2.952	2.781
Model_740	0.2654	0.816	0.325	0.745	-1.333	1.864
Model_740 i	-9.682e-08	5.32e-07	-0.182	0.856	-1.14e-06	9.47e-07
Model_745	0.2586	0.956	0.270	0.787	-1.616	2.133
Model_745 i	0.6651	1.462	0.455	0.649	-2.201	3.531
Model_750	0.2540	0.820	0.310	0.757	-1.354	1.862
Model_750 4.8	0.2677	1.465	0.183	0.855	-2.603	3.138
Model_807	0.0454	1.268	0.036	0.971	-2.440	2.531
Model_911	0.7922	0.638	1.242	0.214	-0.459	2.043
Model_911 meqanika	1.9510	1.243	1.569	0.117	-0.486	4.388
Model_940	-0.7032	1.294	-0.543	0.587	-3.241	1.834
Model_960	-3.208e-07	5.18e-07	-0.619	0.536	-1.34e-06	6.94e-07
Model_969 968m	0.6120	1.050	0.583	0.560	-1.446	2.670
Model_969 luaz	2.3357	1.051	2.222	0.026	0.276	4.396
Model_A 140	-1.2676	0.840	-1.510	0.131	-2.913	0.378
Model_A 140 140	-0.5369	1.412	-0.380	0.704	-3.304	2.231
Model_A 160	-1.6888	0.745	-2.268	0.023	-3.148	-0.229
Model_A 170	-1.0407	0.841	-1.237	0.216	-2.690	0.609
Model_A 170 Avangard	4.597e-07	5.2e-07	0.884	0.376	-5.59e-07	1.48e-06
Model_A 170 CDI	3.748e-07	5.28e-07	0.709	0.478	-6.61e-07	1.41e-06
Model_A 190	-1.6237	0.634	-2.560	0.010	-2.867	-0.381
Model_A 200	1.159e-07	5.94e-07	0.195	0.845	-1.05e-06	1.28e-06
Model_A3	-0.0993	0.788	-0.126	0.900	-1.643	1.445
Model_A3 4X4	0.9345	1.325	0.705	0.481	-1.663	3.532
Model_A3 PREMIUM	0.5512	1.326	0.416	0.678	-2.048	3.150
Model_A4	-0.8825	0.286	-3.081	0.002	-1.444	-0.321
Model_A4 B5	-0.4592	1.327	-0.346	0.729	-3.060	2.141
Model_A4 B6	-1.99e-07	5.87e-07	-0.339	0.734	-1.35e-06	9.51e-07
Model_A4 B7	-0.2967	1.325	-0.224	0.823	-2.894	2.301
Model_A4 S line	0.4501	1.325	0.340	0.734	-2.146	3.047
Model_A4 S4	-0.2975	1.325	-0.225	0.822	-2.895	2.300
Model_A4 Sline	-0.2363	1.327	-0.178	0.859	-2.837	2.364
Model_A4 premium	1.4558	1.325	1.099	0.272	-1.142	4.053
Model_A4 premium plius	-2.819e-08	5.7e-07	-0.049	0.961	-1.14e-06	1.09e-06
Model_A5	-0.7333	0.695	-1.055	0.291	-2.095	0.629
Model_A5 Sportback	7.383e-07	5.52e-07	1.337	0.181	-3.44e-07	1.82e-06
Model_A6	-1.2855	0.348	-3.697	0.000	-1.967	-0.604

Model_A6 C7	0.6350	1.332	0.477	0.634	-1.976	3.246
Model_A6 QUATTRO	1.49e-07	5.43e-07	0.274	0.784	-9.15e-07	1.21e-06
Model_A6 UNIVERSAL	-3.88e-08	5.35e-07	-0.072	0.942	-1.09e-06	1.01e-06
Model_A6 evropuli	-0.5549	1.327	-0.418	0.676	-3.155	2.046
Model_A6 premium plus	0.7862	1.325	0.593	0.553	-1.811	3.383
Model_A6 C6	1.2334	1.327	0.929	0.353	-1.368	3.835
Model_A7	-0.8197	0.339	-2.416	0.016	-1.485	-0.155
Model_A7 Prestige	2.6827	1.325	2.025	0.043	0.085	5.280
Model_A8	0.9409	0.688	1.367	0.172	-0.408	2.290
Model_AMG GT S	2.3034	1.387	1.661	0.097	-0.414	5.021
Model_ATS	2.0229	1.229	1.647	0.100	-0.385	4.431
Model_Acadia	1.5708	0.638	2.464	0.014	0.321	2.821
Model_Accent	-0.6199	0.252	-2.464	0.014	-1.113	-0.127
Model_Accent GS	-0.1683	1.340	-0.126	0.900	-2.796	2.459
Model_Accent SE	-0.1901	1.341	-0.142	0.887	-2.818	2.438
Model_Accord	-0.9018	0.423	-2.132	0.033	-1.731	-0.073
Model_Accord CL9 type S	-4.645e-07	5.08e-07	-0.914	0.361	-1.46e-06	5.31e-07
Model_Actyon	1.0497	0.305	3.444	0.001	0.452	1.647
Model_Aerio SX	-2.64e-07	5.91e-07	-0.447	0.655	-1.42e-06	8.94e-07
Model_Agila	-0.3289	0.953	-0.345	0.730	-2.196	1.539
Model_Airtrek	-0.3559	0.396	-0.898	0.369	-1.133	0.421
Model_Airtrek turbo	0.1230	1.332	0.092	0.926	-2.489	2.735
Model_Allante	1.1681	1.225	0.953	0.340	-1.234	3.570
Model_Allroad	0.0651	0.579	0.112	0.911	-1.070	1.200
Model_Allroad Allroad	-5.695e-08	5.9e-07	-0.096	0.923	-1.21e-06	1.1e-06
Model_Almera	-0.7708	1.348	-0.572	0.568	-3.413	1.872
Model_Almera dci	-0.4941	1.345	-0.367	0.713	-3.130	2.141
Model_Alphard	1.3690	0.982	1.394	0.163	-0.556	3.294
Model_Altezza	0.5358	0.689	0.777	0.437	-0.815	1.887
Model_Altima	-0.5366	0.310	-1.730	0.084	-1.145	0.072
Model_Alto Lapin	7.542e-07	5.94e-07	1.271	0.204	-4.09e-07	1.92e-06
Model_Aqua	0.2784	0.147	1.893	0.058	-0.010	0.567
Model_Aqua G	-0.0656	1.384	-0.047	0.962	-2.779	2.648
Model_Aqua G klas	0.9561	1.360	0.703	0.482	-1.710	3.622
Model_Aqua HIBRID	0.9695	1.351	0.717	0.473	-1.679	3.618
Model_Aqua L paketi	8.951e-08	5.53e-07	0.162	0.871	-9.95e-07	1.17e-06
Model_Aqua S	-0.7449	0.616	-1.209	0.227	-1.953	0.463

Model_Aqua g soft leather sele	7.531e-07	5.67e-07	1.328	0.184	-3.58e-07	1.86e-06
Model_Aqua s	1.4627	1.351	1.083	0.279	-1.186	4.111
Model_Aqua sport	0.9829	1.351	0.727	0.467	-1.666	3.631
Model_Aqua სასწრაფოდ	-0.1993	1.350	-0.148	0.883	-2.846	2.448
Model_Armada	-0.8760	1.351	-0.649	0.517	-3.524	1.772
Model_Astra	-0.0224	0.228	-0.098	0.922	-0.470	0.425
Model_Astra 1600	0.2808	1.333	0.211	0.833	-2.332	2.894
Model_Astra A.H	-2.59e-08	5.38e-07	-0.048	0.962	-1.08e-06	1.03e-06
Model_Astra BERTONE	0.8331	1.337	0.623	0.533	-1.787	3.454
Model_Astra CNG	-0.6664	1.339	-0.498	0.619	-3.291	1.958
Model_Astra G	0.3167	0.533	0.595	0.552	-0.727	1.361
Model_Astra GE	0.4226	1.336	0.316	0.752	-2.196	3.041
Model_Astra GTC 1.9 turbo dies	0.6739	1.346	0.501	0.617	-1.964	3.311
Model_Astra H	0.1991	0.502	0.397	0.692	-0.785	1.183
Model_Astra astra	4.527e-08	5.58e-07	0.081	0.935	-1.05e-06	1.14e-06
Model_Astra g	0.1653	0.956	0.173	0.863	-1.709	2.039
Model_Astra gi	2.287e-07	5.16e-07	0.443	0.657	-7.82e-07	1.24e-06
Model_Astra j	2.95e-07	4.9e-07	0.602	0.547	-6.66e-07	1.26e-06
Model_Astra suzuki mr wagon	0.4139	1.336	0.310	0.757	-2.205	3.033
Model_Astra td	-1.4093	1.336	-1.054	0.292	-4.029	1.210
Model_Atenza	0.8748	1.329	0.658	0.510	-1.731	3.480
Model_Auris	3.227e-07	5.34e-07	0.605	0.545	-7.24e-07	1.37e-06
Model_Avalanche	0.6527	0.960	0.680	0.497	-1.229	2.534
Model_Avalon	0.7036	0.348	2.019	0.044	0.021	1.387
Model_Avalon LIMITED	0.9550	0.789	1.210	0.226	-0.592	2.502
Model_Avalon Limited	0.2458	1.352	0.182	0.856	-2.404	2.895
Model_Avalon limited	-9.779e-10	5.75e-07	-0.002	0.999	-1.13e-06	1.13e-06
Model_Avella	-1.2212	0.458	-2.664	0.008	-2.120	-0.323
Model_Avenger	-1.0118	0.499	-2.028	0.043	-1.990	-0.034
Model_Avensis	0.7754	1.351	0.574	0.566	-1.872	3.423
Model_Aveo	0.4633	0.316	1.468	0.142	-0.155	1.082
Model_Axela	1.5580	0.953	1.635	0.102	-0.310	3.426
Model_Azera	4.705e-07	5.75e-07	0.818	0.413	-6.57e-07	1.6e-06
Model_B 170	-0.8089	0.633	-1.277	0.201	-2.050	0.432
Model_B 170 B Class	-1.1120	1.386	-0.802	0.422	-3.828	1.604
Model_B 170 Edition One	-1.418e-07	5.49e-07	-0.258	0.796	-1.22e-06	9.35e-07
Model_B 180	-0.6656	1.393	-0.478	0.633	-3.396	2.065

Model_B 200	-0.1908	1.390	-0.137	0.891	-2.916	2.534
Model_B 200 Turbo	-6.039e-07	5.74e-07	-1.052	0.293	-1.73e-06	5.22e-07
Model_B 220	-1.1170	1.387	-0.805	0.421	-3.837	1.603
Model_B-MAX	-1.7326	0.963	-1.799	0.072	-3.621	0.156
Model_B9 Tribeca	-1.328e-07	5.46e-07	-0.243	0.808	-1.2e-06	9.38e-07
Model_BB	0.4535	1.358	0.334	0.738	-2.208	3.115
Model_BRZ	0.9619	1.323	0.727	0.467	-1.632	3.556
Model_Belta	-0.2729	1.350	-0.202	0.840	-2.920	2.374
Model_Berlingo	0.1276	1.250	0.102	0.919	-2.322	2.577
Model_Bluebird	-0.8699	1.348	-0.645	0.519	-3.513	1.773
Model_Bora	-0.3931	1.341	-0.293	0.769	-3.022	2.236
Model_C 180	-0.5224	0.378	-1.382	0.167	-1.263	0.219
Model_C 180 2.0	-0.7735	1.388	-0.557	0.577	-3.493	1.946
Model_C 180 komp	-1.2104	1.394	-0.868	0.385	-3.942	1.521
Model_C 200	-0.5294	0.424	-1.248	0.212	-1.361	0.302
Model_C 200 2.0	-2.5656	1.393	-1.842	0.066	-5.296	0.165
Model_C 200 7G-TRONIC	-1.327e-07	5.33e-07	-0.249	0.804	-1.18e-06	9.13e-07
Model_C 200 KOMPRESSOR	-1.2274	1.391	-0.883	0.377	-3.953	1.499
Model_C 200 Kompressor	1.393e-07	5.47e-07	0.254	0.799	-9.34e-07	1.21e-06
Model_C 220	-1.0690	0.447	-2.389	0.017	-1.946	-0.192
Model_C 220 CDI	-0.8053	1.386	-0.581	0.561	-3.522	1.911
Model_C 230	-0.2746	0.452	-0.607	0.544	-1.161	0.612
Model_C 230 2.0 kompresor	-0.5552	1.390	-0.399	0.690	-3.280	2.169
Model_C 230 2.5	2.449e-07	5.67e-07	0.432	0.666	-8.67e-07	1.36e-06
Model_C 230 kompresor	0.1024	1.387	0.074	0.941	-2.616	2.821
Model_C 240	-0.7110	0.480	-1.480	0.139	-1.653	0.231
Model_C 240 W 203	-1.0853	1.385	-0.783	0.433	-3.801	1.630
Model_C 240 w203	0.4068	1.391	0.292	0.770	-2.320	3.133
Model_C 250	-0.2869	0.401	-0.715	0.475	-1.074	0.500
Model_C 250 1,8 turbo	0.0350	1.385	0.025	0.980	-2.681	2.751
Model_C 250 1.8	-0.3485	1.385	-0.252	0.801	-3.064	2.367
Model_C 250 1.8 ტურბო	-3.193e-07	5.96e-07	-0.535	0.592	-1.49e-06	8.5e-07
Model_C 250 A.M.G	-1.5308	1.385	-1.105	0.269	-4.246	1.184
Model_C 250 AMG	-1.4391	1.006	-1.430	0.153	-3.412	0.534
Model_C 250 AMG-PAKET-1,8	-0.2068	1.385	-0.149	0.881	-2.921	2.508
Model_C 250 luxury	-0.7186	1.385	-0.519	0.604	-3.433	1.996
Model_C 270	-0.6485	1.384	-0.469	0.639	-3.361	2.064

Model_C 280	-0.3305	1.003	-0.329	0.742	-2.297	1.636
Model_C 300	-1.3497	0.377	-3.583	0.000	-2.088	-0.611
Model_C 300 4matic	-0.1598	1.384	-0.115	0.908	-2.872	2.552
Model_C 300 6.3 AMG Package	1.6609	1.385	1.199	0.230	-1.054	4.375
Model_C 300 sport	-0.2087	1.384	-0.151	0.880	-2.921	2.504
Model_C 32 AMG	-0.5616	1.383	-0.406	0.685	-3.273	2.150
Model_C 320	-0.5747	0.835	-0.688	0.492	-2.212	1.063
Model_C 320 AMG	-2.451e-07	5.49e-07	-0.447	0.655	-1.32e-06	8.3e-07
Model_C 320 CDI	-0.2593	1.390	-0.187	0.852	-2.983	2.465
Model_C 350	-2.2558	0.834	-2.704	0.007	-3.891	-0.620
Model_C 36 AMG	1.9980	1.387	1.441	0.150	-0.720	4.717
Model_C 400	-0.7929	1.384	-0.573	0.567	-3.506	1.920
Model_C 43 AMG	2.7867	1.388	2.008	0.045	0.067	5.507
Model_C 63 AMG	1.8964	1.392	1.363	0.173	-0.831	4.624
Model_C-MAX	0.1747	0.279	0.627	0.531	-0.372	0.721
Model_C-MAX C-MAX	1.3023	1.356	0.960	0.337	-1.356	3.961
Model_C-MAX HYBRID	0.9796	1.349	0.726	0.468	-1.664	3.623
Model_C-MAX PREMIUM	1.7623	1.350	1.306	0.192	-0.884	4.408
Model_C-MAX SE	1.1867	0.963	1.232	0.218	-0.701	3.074
Model_C-MAX SEL	0.9630	0.961	1.002	0.317	-0.922	2.848
Model_C1	0.1500	1.239	0.121	0.904	-2.278	2.578
Model_C1 C	-0.2183	1.239	-0.176	0.860	-2.647	2.210
Model_C30	1.7854	0.787	2.268	0.023	0.242	3.329
Model_C30 2010	0.4898	1.291	0.379	0.704	-2.042	3.021
Model_C4	-0.1994	0.938	-0.213	0.832	-2.037	1.639
Model_C5	1.878e-08	5.42e-07	0.035	0.972	-1.04e-06	1.08e-06
Model_C70	0.5648	1.294	0.437	0.662	-1.971	3.100
Model_C8	2.0389	1.242	1.641	0.101	-0.396	4.474
Model_CC	0.8047	0.387	2.080	0.038	0.046	1.563
Model_CC 2.0 T	3.732e-07	5.59e-07	0.668	0.504	-7.22e-07	1.47e-06
Model_CC R line	0.7281	0.953	0.764	0.445	-1.141	2.597
Model_CC sport	0.7593	1.340	0.567	0.571	-1.868	3.387
Model_CERVO	-0.6457	1.313	-0.492	0.623	-3.219	1.927
Model_CHR	-1.0795	0.227	-4.745	0.000	-1.525	-0.634
Model_CHR Limited	-0.0183	1.353	-0.014	0.989	-2.670	2.633
Model_CL 500	0.0909	1.010	0.090	0.928	-1.890	2.071
Model_CL 55 AMG KOMPRESSOR	3.392e-07	5.68e-07	0.597	0.550	-7.74e-07	1.45e-06

Model_CL 550	-3.843e-07	5.44e-07	-0.707	0.480	-1.45e-06	6.81e-07
Model_CL 600	6.262e-07	5.54e-07	1.130	0.258	-4.6e-07	1.71e-06
Model_CL550 AMG	1.15e-07	5.35e-07	0.215	0.830	-9.34e-07	1.16e-06
Model_CLA 250	-0.7449	0.465	-1.603	0.109	-1.656	0.166
Model_CLA 250 AMG	-0.0962	1.006	-0.096	0.924	-2.068	1.876
Model_CLA 45 AMG	1.0468	1.385	0.756	0.450	-1.668	3.762
Model_CLK 200	-0.5725	0.636	-0.900	0.368	-1.819	0.674
Model_CLK 200 200	0.6338	1.388	0.457	0.648	-2.088	3.355
Model_CLK 200 208	-0.0413	1.389	-0.030	0.976	-2.763	2.681
Model_CLK 200 Kompressor	-0.1779	1.388	-0.128	0.898	-2.899	2.543
Model_CLK 200 kompresor	-0.2449	1.386	-0.177	0.860	-2.962	2.472
Model_CLK 230	-3.1786	0.841	-3.779	0.000	-4.827	-1.530
Model_CLK 230 .	-1.3859	1.388	-0.999	0.318	-4.106	1.334
Model_CLK 240	0.3672	1.006	0.365	0.715	-1.604	2.339
Model_CLK 270	-1.0826	1.005	-1.077	0.282	-3.053	0.888
Model_CLK 280	-0.5352	1.388	-0.386	0.700	-3.255	2.185
Model_CLK 320	-0.0647	0.573	-0.113	0.910	-1.188	1.058
Model_CLK 320 AMG	-0.3252	1.386	-0.235	0.814	-3.041	2.391
Model_CLK 320 avangarde	-0.4845	1.388	-0.349	0.727	-3.205	2.236
Model_CLK 350	4.171e-07	5.88e-07	0.709	0.478	-7.35e-07	1.57e-06
Model_CLK 430	0.7578	1.456	0.520	0.603	-2.096	3.612
Model_CLK 55 AMG	0.5251	1.388	0.378	0.705	-2.197	3.247
Model_CLS 350	0.8897	0.835	1.066	0.286	-0.746	2.526
Model_CLS 350 AMG	-0.0210	1.002	-0.021	0.983	-1.984	1.942
Model_CLS 350 JAPAN	0.3936	1.388	0.284	0.777	-2.327	3.114
Model_CLS 450 CLS 400	-2.119e-07	5.87e-07	-0.361	0.718	-1.36e-06	9.38e-07
Model_CLS 500	0.4081	0.741	0.551	0.582	-1.044	1.860
Model_CLS 55 AMG	0.4607	0.523	0.880	0.379	-0.565	1.486
Model_CLS 550	-0.0105	0.592	-0.018	0.986	-1.172	1.151
Model_CLS 550 550	0.1548	1.386	0.112	0.911	-2.562	2.871
Model_CLS 63 AMG	1.0074	1.006	1.002	0.317	-0.964	2.979
Model_CR-Z	0.4145	0.790	0.524	0.600	-1.135	1.964
Model_CR-Z ჰიბრიდი	-0.0756	1.343	-0.056	0.955	-2.709	2.558
Model_CRX	-3.8771	1.381	-2.808	0.005	-6.583	-1.171
Model_CT 200h	-1.5421	0.226	-6.817	0.000	-1.985	-1.099
Model_CT 200h 1.8	-0.0394	1.333	-0.030	0.976	-2.653	2.574
Model_CT 200h F SPORT	0.0971	1.334	0.073	0.942	-2.517	2.712

Model_CT 200h F sport	0.9417	1.333	0.706	0.480	-1.672	3.555
Model_CT 200h F-sport	-0.3896	1.335	-0.292	0.770	-3.006	2.227
Model_CTS	-0.8113	0.793	-1.023	0.306	-2.365	0.742
Model_CX-3	0.4033	1.329	0.303	0.762	-2.202	3.009
Model_CX-5	1.3247	0.572	2.314	0.021	0.203	2.447
Model_CX-5 Touring	0.8874	1.330	0.667	0.505	-1.720	3.495
Model_CX-7	-1.7169	0.478	-3.595	0.000	-2.653	-0.781
Model_CX-9	-1.1646	0.400	-2.908	0.004	-1.950	-0.380
Model_Caddy	-0.2922	0.545	-0.536	0.592	-1.361	0.777
Model_Caddy cadi	-2.594e-07	5.92e-07	-0.438	0.661	-1.42e-06	9.01e-07
Model_Cadenza	0.8374	0.618	1.356	0.175	-0.374	2.048
Model_Caldina	0.1407	0.961	0.146	0.884	-1.743	2.025
Model_Caliber	0.0137	0.425	0.032	0.974	-0.820	0.847
Model_Caliber journey	1.064e-07	5.46e-07	0.195	0.845	-9.63e-07	1.18e-06
Model_Caliber sxt	-0.3329	1.298	-0.257	0.798	-2.877	2.211
Model_Camaro	1.0362	0.493	2.101	0.036	0.070	2.003
Model_Camaro LS	1.7224	1.343	1.282	0.200	-0.911	4.356
Model_Camaro RS	1.1110	1.343	0.827	0.408	-1.521	3.743
Model_Cami	0.9221	1.354	0.681	0.496	-1.732	3.576
Model_Camry	-0.5493	0.129	-4.254	0.000	-0.802	-0.296
Model_Camry HYBRID	-0.0454	0.787	-0.058	0.954	-1.589	1.498
Model_Camry Hybrid	1.4215	0.965	1.473	0.141	-0.470	3.313
Model_Camry LE	0.5108	0.958	0.533	0.594	-1.367	2.389
Model_Camry Le	-0.5282	1.350	-0.391	0.696	-3.174	2.118
Model_Camry S	0.2275	1.351	0.168	0.866	-2.422	2.877
Model_Camry SE	0.6401	0.367	1.744	0.081	-0.079	1.360
Model_Camry SE HIBRYD	1.5705	1.350	1.163	0.245	-1.076	4.217
Model_Camry SPORT	-0.0037	0.959	-0.004	0.997	-1.884	1.877
Model_Camry SPORT PAKET	3.058e-07	5.48e-07	0.558	0.577	-7.68e-07	1.38e-06
Model_Camry Se	-0.5111	1.350	-0.379	0.705	-3.157	2.135
Model_Camry XLE	0.9934	0.443	2.244	0.025	0.126	1.861
Model_Camry XLEi	2.0610	1.352	1.524	0.127	-0.589	4.711
Model_Camry XSE	-0.9946	1.351	-0.736	0.461	-3.642	1.653
Model_Camry XV50	3.066e-07	6.28e-07	0.488	0.625	-9.24e-07	1.54e-06
Model_Camry se	0.2014	0.613	0.329	0.743	-1.000	1.403
Model_Camry sel	-2.412e-07	5.4e-07	-0.447	0.655	-1.3e-06	8.17e-07
Model_Camry sport	-1.1902	0.613	-1.940	0.052	-2.393	0.012

Model_Camry sport se	0.0950	1.350	0.070	0.944	-2.551	2.741
Model_Camry sporti	-0.1155	1.350	-0.086	0.932	-2.762	2.531
Model_Camry ჰიბრიდი	-0.0958	1.351	-0.071	0.943	-2.744	2.552
Model_Captiva	0.4389	0.220	1.997	0.046	0.008	0.870
Model_Captur QM3 Samsung	0.3885	1.287	0.302	0.763	-2.134	2.911
Model_Caravan	0.0561	0.796	0.070	0.944	-1.504	1.616
Model_Caravan tradesman	-0.5954	1.302	-0.457	0.647	-3.147	1.956
Model_Carens	0.2678	1.322	0.203	0.839	-2.323	2.859
Model_Carisma	-1.3725	0.952	-1.442	0.149	-3.238	0.494
Model_Carnival	0.0752	0.956	0.079	0.937	-1.798	1.948
Model_Carnival grand	0.5681	1.329	0.427	0.669	-2.038	3.174
Model_Catera	1.321e-07	5.66e-07	0.233	0.815	-9.77e-07	1.24e-06
Model_Cayenne	-0.2514	0.426	-0.589	0.556	-1.087	0.585
Model_Cayenne S	0.3838	0.910	0.422	0.673	-1.400	2.168
Model_Cayenne s	-3.883e-07	5.51e-07	-0.705	0.481	-1.47e-06	6.92e-07
Model_Cayman	-1.669e-07	5.43e-07	-0.307	0.758	-1.23e-06	8.97e-07
Model_Ceed	0.0003	0.685	0.000	1.000	-1.343	1.344
Model_Cefiro	-0.5514	1.344	-0.410	0.682	-3.187	2.084
Model_Celica	-3.915e-07	5.55e-07	-0.706	0.480	-1.48e-06	6.96e-07
Model_Century	-3.1761	1.321	-2.404	0.016	-5.766	-0.587
Model_Cerato	0.0543	0.502	0.108	0.914	-0.930	1.038
Model_Cerato K3	-0.4301	1.321	-0.326	0.745	-3.019	2.159
Model_Challenger	0.0705	0.530	0.133	0.894	-0.968	1.109
Model_Charger RT	2.0229	1.301	1.555	0.120	-0.527	4.573
Model_Chariot	4.534e-07	5.46e-07	0.830	0.407	-6.18e-07	1.52e-06
Model_Cherokee	0.0394	0.506	0.078	0.938	-0.953	1.032
Model_Cinquecento	4.124e-07	6.12e-07	0.674	0.501	-7.88e-07	1.61e-06
Model_Citan	-1.0664	1.402	-0.761	0.447	-3.815	1.682
Model_Civic	0.3568	0.211	1.691	0.091	-0.057	0.770
Model_Civic EX	3.842e-07	5.4e-07	0.712	0.476	-6.73e-07	1.44e-06
Model_Civic Ferio	-4.548e-07	5.47e-07	-0.832	0.405	-1.53e-06	6.17e-07
Model_Civic Hybrid	1.0525	1.339	0.786	0.432	-1.571	3.676
Model_Clio	0.1899	0.785	0.242	0.809	-1.349	1.728
Model_Colorado	2.7525	1.376	2.001	0.045	0.056	5.449
Model_Colt	-0.2131	0.346	-0.616	0.538	-0.891	0.465
Model_Colt Lancer	3.288e-07	4.96e-07	0.663	0.507	-6.43e-07	1.3e-06
Model_ColtPlus	0.3766	0.952	0.396	0.692	-1.489	2.242

Model_ColtPlus Plus	-0.4183	1.370	-0.305	0.760	-3.103	2.267
Model_Combo	0.3487	0.364	0.959	0.337	-0.364	1.061
Model_Combo 1700	-0.2448	1.341	-0.183	0.855	-2.874	2.384
Model_Combo 2001	-0.0733	1.344	-0.055	0.957	-2.708	2.561
Model_Combo TDI	0.2044	1.341	0.152	0.879	-2.425	2.834
Model_Compass	1.1354	0.378	3.001	0.003	0.394	1.877
Model_Continental	-1.7351	1.148	-1.511	0.131	-3.985	0.515
Model_Continental GT	4.535e-07	5.74e-07	0.790	0.430	-6.72e-07	1.58e-06
Model_Cooper	-0.2351	0.469	-0.502	0.616	-1.154	0.683
Model_Cooper CLUBMAN	0.5674	1.298	0.437	0.662	-1.978	3.112
Model_Cooper F-56	0.4381	1.296	0.338	0.735	-2.103	2.979
Model_Cooper S	1.4014	1.295	1.082	0.279	-1.137	3.940
Model_Cooper S Cabrio	-2.1850	0.703	-3.107	0.002	-3.563	-0.806
Model_Cooper S Cabrio R56	0.0166	1.296	0.013	0.990	-2.524	2.558
Model_Cooper r50	-1.811e-07	5.78e-07	-0.313	0.754	-1.31e-06	9.52e-07
Model_Corolla	-0.8229	0.221	-3.730	0.000	-1.255	-0.390
Model_Corolla 04	0.3749	1.350	0.278	0.781	-2.271	3.021
Model_Corolla 140	-4.9629	1.355	-3.663	0.000	-7.619	-2.307
Model_Corolla ECO	2.098e-07	5.6e-07	0.375	0.708	-8.88e-07	1.31e-06
Model_Corolla IM	-0.2985	1.352	-0.221	0.825	-2.948	2.351
Model_Corolla Im	-0.9010	1.350	-0.667	0.505	-3.548	1.746
Model_Corolla LE	0.4035	0.785	0.514	0.607	-1.135	1.942
Model_Corolla S	0.4205	0.785	0.535	0.592	-1.119	1.960
Model_Corolla se	-1.645e-08	5.72e-07	-0.029	0.977	-1.14e-06	1.1e-06
Model_Corolla spacio	-0.8295	1.352	-0.614	0.539	-3.479	1.820
Model_Corolla verso	-2.5663	1.359	-1.888	0.059	-5.230	0.098
Model_Corsa	-0.0845	0.350	-0.241	0.809	-0.771	0.602
Model_Corsa Corsa	0.0667	1.333	0.050	0.960	-2.546	2.680
Model_Corvette	5.889e-07	5.6e-07	1.052	0.293	-5.08e-07	1.69e-06
Model_Cougar	-0.8047	1.299	-0.619	0.536	-3.351	1.742
Model_Countryman	0.6452	0.507	1.272	0.203	-0.349	1.639
Model_Countryman S	0.7500	0.941	0.797	0.426	-1.095	2.595
Model_Countryman S turbo	1.3264	1.297	1.023	0.306	-1.216	3.868
Model_Countryman s	-0.2470	1.296	-0.191	0.849	-2.787	2.293
Model_Countryman sport	0.5576	1.295	0.431	0.667	-1.981	3.096
Model_Courier	-0.3188	1.354	-0.236	0.814	-2.972	2.334
Model_Cr-v	0.6174	0.266	2.324	0.020	0.097	1.138

Model_Cr-v Cr-v	0.2369	1.342	0.176	0.860	-2.394	2.868
Model_Cr-v LX	0.6603	1.345	0.491	0.624	-1.977	3.297
Model_Crafter	0.9439	0.814	1.159	0.246	-0.652	2.540
Model_Crafter 2,5TDI	-3.107e-07	5.89e-07	-0.527	0.598	-1.47e-06	8.45e-07
Model_Crafter 2.5 TDI	-4.066e-07	5.59e-07	-0.728	0.467	-1.5e-06	6.89e-07
Model_Crossfire	0.6578	1.618	0.407	0.684	-2.513	3.829
Model_Crossland X	-0.4055	1.341	-0.303	0.762	-3.033	2.222
Model_Crossroad	0.7524	1.342	0.561	0.575	-1.878	3.383
Model_Crosstour	1.4832	1.340	1.107	0.268	-1.144	4.110
Model_Crosstrek	0.0241	0.629	0.038	0.969	-1.208	1.257
Model_Cruze	-0.2335	0.183	-1.276	0.202	-0.592	0.125
Model_Cruze Cruze	-9.559e-08	5.45e-07	-0.175	0.861	-1.16e-06	9.73e-07
Model_Cruze L T	-0.5135	1.335	-0.385	0.700	-3.130	2.103
Model_Cruze LS	0.3320	1.334	0.249	0.803	-2.283	2.947
Model_Cruze LT	0.2801	0.431	0.651	0.515	-0.564	1.124
Model_Cruze LT RS	-0.3047	1.335	-0.228	0.820	-2.922	2.313
Model_Cruze LTZ	-0.3173	1.336	-0.238	0.812	-2.936	2.301
Model_Cruze PREMIER	5.692e-07	5.49e-07	1.037	0.300	-5.07e-07	1.65e-06
Model_Cruze Premier	0.5363	1.334	0.402	0.688	-2.078	3.151
Model_Cruze RS	-0.9322	0.953	-0.978	0.328	-2.800	0.936
Model_Cruze S	1.4943	1.338	1.117	0.264	-1.128	4.117
Model_Cruze ltz	0.8467	1.336	0.634	0.526	-1.772	3.466
Model_Cruze sonic	0.8976	1.339	0.670	0.503	-1.727	3.522
Model_Cruze strocna	-0.1884	1.340	-0.141	0.888	-2.815	2.438
Model_DS 4	2.1983	1.240	1.773	0.076	-0.232	4.628
Model_DTS	1.7788	1.227	1.449	0.147	-0.627	4.185
Model_Daimler	3.99e-07	5.77e-07	0.692	0.489	-7.32e-07	1.53e-06
Model_Dart	0.0294	1.296	0.023	0.982	-2.510	2.569
Model_Dart GT 2.4	0.9723	1.295	0.751	0.453	-1.566	3.510
Model_Dart Limited	3.427e-07	5.88e-07	0.583	0.560	-8.1e-07	1.5e-06
Model_Defender 90 Cabrio	-3.125e-07	5.35e-07	-0.584	0.559	-1.36e-06	7.37e-07
Model_Delica	1.6676	0.628	2.653	0.008	0.436	2.900
Model_Delica 5	2.1164	1.339	1.581	0.114	-0.508	4.741
Model_Demio	0.0944	0.441	0.214	0.831	-0.770	0.959
Model_Demio 12	-4.693e-07	5.87e-07	-0.799	0.424	-1.62e-06	6.82e-07
Model_Demio Sport	0.6437	1.331	0.484	0.629	-1.965	3.253
Model_Demio evropuli	-0.2191	0.691	-0.317	0.751	-1.574	1.136

Model_Demio mazda2	-0.2130	1.332	-0.160	0.873	-2.824	2.398
Model_Discovery	0.4764	0.694	0.686	0.493	-0.884	1.837
Model_Discovery IV	-0.4045	1.268	-0.319	0.750	-2.890	2.081
Model_Discovery LR3	-3.1e-07	5e-07	-0.620	0.535	-1.29e-06	6.7e-07
Model_Doblo	-0.0600	0.965	-0.062	0.950	-1.952	1.832
Model_Durango	1.1333	0.942	1.203	0.229	-0.714	2.981
Model_Duster	0.6078	1.288	0.472	0.637	-1.916	3.132
Model_E 200	-0.5356	0.413	-1.297	0.195	-1.345	0.274
Model_E 200 2000	2.156e-07	5.71e-07	0.378	0.706	-9.03e-07	1.33e-06
Model_E 200 CGI	0.4345	1.394	0.312	0.755	-2.298	3.167
Model_E 200 w210	-1.248e-07	5.78e-07	-0.216	0.829	-1.26e-06	1.01e-06
Model_E 220	-0.3050	0.414	-0.736	0.462	-1.117	0.507
Model_E 220 211	-3.518e-07	5.05e-07	-0.697	0.486	-1.34e-06	6.37e-07
Model_E 220 CDI	1.8918	1.400	1.351	0.177	-0.853	4.636
Model_E 220 ELEGANCE	-2.314e-07	5.55e-07	-0.417	0.677	-1.32e-06	8.57e-07
Model_E 220 W210...CDI	-0.4374	1.385	-0.316	0.752	-3.153	2.278
Model_E 220 cdi	-3.628e-07	5.95e-07	-0.609	0.542	-1.53e-06	8.04e-07
Model_E 230	-0.8786	0.643	-1.367	0.172	-2.139	0.382
Model_E 230 124	-0.7537	1.388	-0.543	0.587	-3.474	1.966
Model_E 240	-0.2055	0.524	-0.392	0.695	-1.232	0.821
Model_E 240 E 240	-8.015e-08	5.97e-07	-0.134	0.893	-1.25e-06	1.09e-06
Model_E 250	-0.2119	1.002	-0.212	0.832	-2.176	1.752
Model_E 260	-1.2633	1.395	-0.905	0.365	-3.999	1.472
Model_E 270	-0.6036	0.542	-1.113	0.266	-1.667	0.460
Model_E 270 4	-0.9048	1.384	-0.654	0.513	-3.618	1.809
Model_E 270 AVANGARDI	-0.2545	1.384	-0.184	0.854	-2.967	2.458
Model_E 270 CDI	-1.1346	1.384	-0.820	0.412	-3.848	1.579
Model_E 280	0.0584	0.676	0.086	0.931	-1.266	1.383
Model_E 280 3.0	-1.865e-07	5.51e-07	-0.339	0.735	-1.27e-06	8.93e-07
Model_E 280 CDI	-1.674e-08	6.06e-07	-0.028	0.978	-1.2e-06	1.17e-06
Model_E 290	-0.1475	1.386	-0.106	0.915	-2.863	2.568
Model_E 300	-2.1225	0.365	-5.817	0.000	-2.838	-1.407
Model_E 300 AVANTGARDE-LTD	1.0083	1.401	0.719	0.472	-1.739	3.755
Model_E 320	-0.1821	0.369	-0.493	0.622	-0.906	0.542
Model_E 320 4matic	-0.4188	1.385	-0.302	0.762	-3.134	2.296
Model_E 320 4×4	-2.027e-07	5.53e-07	-0.366	0.714	-1.29e-06	8.81e-07
Model_E 320 bluetec	-0.1906	1.384	-0.138	0.890	-2.903	2.522

Model_E 350	-1.2108	0.306	-3.955	0.000	-1.811	-0.611
Model_E 350 212	-0.1510	1.384	-0.109	0.913	-2.864	2.562
Model_E 350 4 MATIC	0.6572	1.384	0.475	0.635	-2.056	3.371
Model_E 350 4 Matic AMG Packag	-2.406e-07	6.21e-07	-0.388	0.698	-1.46e-06	9.76e-07
Model_E 350 4 matic	0.2815	1.383	0.204	0.839	-2.430	2.993
Model_E 350 AMG	0.3842	1.000	0.384	0.701	-1.576	2.345
Model_E 350 w211	-3.172e-08	5.87e-07	-0.054	0.957	-1.18e-06	1.12e-06
Model_E 350 ამგ	0.2923	1.383	0.211	0.833	-2.419	3.004
Model_E 36 AMG	-2.3796	1.386	-1.717	0.086	-5.097	0.338
Model_E 400	0.4573	1.003	0.456	0.649	-1.509	2.424
Model_E 420	1.4803	1.386	1.068	0.286	-1.237	4.198
Model_E 430	1.2156	1.416	0.858	0.391	-1.560	3.992
Model_E 50	-0.1052	1.385	-0.076	0.939	-2.820	2.609
Model_E 500	0.6770	0.632	1.071	0.284	-0.562	1.916
Model_E 500 AMG	1.318e-08	5.64e-07	0.023	0.981	-1.09e-06	1.12e-06
Model_E 500 AVG	3.1691	1.454	2.179	0.029	0.319	6.020
Model_E 55	-5.1115	1.389	-3.680	0.000	-7.834	-2.389
Model_E 550	0.3032	0.836	0.363	0.717	-1.336	1.942
Model_E-pace	-0.6873	0.934	-0.736	0.462	-2.519	1.144
Model_E-pace p200	1.1545	1.280	0.902	0.367	-1.355	3.664
Model_ES 300	0.0566	0.380	0.149	0.882	-0.689	0.802
Model_ES 300 hybrid	1.6076	1.332	1.207	0.227	-1.003	4.218
Model_ES 350	-1.3509	0.471	-2.866	0.004	-2.275	-0.427
Model_EX35	0.1234	1.288	0.096	0.924	-2.402	2.649
Model_EX37	1.0215	0.941	1.086	0.277	-0.822	2.865
Model_Eclipse	-0.2029	0.971	-0.209	0.834	-2.106	1.700
Model_Eclipse ES	0.6723	1.330	0.506	0.613	-1.935	3.279
Model_EcoSport	0.1537	1.352	0.114	0.909	-2.496	2.803
Model_EcoSport SE	0.9480	1.349	0.703	0.482	-1.697	3.593
Model_Edge	-0.4383	0.692	-0.634	0.526	-1.794	0.918
Model_Edix	-5.353e-07	5.89e-07	-0.909	0.363	-1.69e-06	6.19e-07
Model_Edix FR-v	3.49e-08	5.42e-07	0.064	0.949	-1.03e-06	1.1e-06
Model_Elantra	-0.1317	0.157	-0.840	0.401	-0.439	0.176
Model_Elantra 2014	3.736e-07	6.12e-07	0.610	0.542	-8.27e-07	1.57e-06
Model_Elantra 2016	-3.251e-08	5.54e-07	-0.059	0.953	-1.12e-06	1.05e-06
Model_Elantra GLS / LIMITED	-0.9750	1.340	-0.728	0.467	-3.602	1.652
Model_Elantra GS	2.263e-07	5.57e-07	0.406	0.684	-8.65e-07	1.32e-06

Model_Elantra GT	0.0187	0.615	0.030	0.976	-1.186	1.223
Model_Elantra Gt	4.44e-07	5.72e-07	0.777	0.437	-6.76e-07	1.56e-06
Model_Elantra LIMITED	0.2567	0.953	0.269	0.788	-1.611	2.124
Model_Elantra LIMITEDI	-1.0063	1.340	-0.751	0.453	-3.632	1.619
Model_Elantra Limited	0.4051	0.682	0.594	0.553	-0.932	1.742
Model_Elantra SE	-0.3711	0.683	-0.544	0.587	-1.709	0.967
Model_Elantra Se	0.2674	1.340	0.200	0.842	-2.358	2.893
Model_Elantra gt	0.5797	0.954	0.607	0.544	-1.291	2.450
Model_Elantra i30	-0.6679	1.341	-0.498	0.618	-3.297	1.961
Model_Elantra limited	0.2225	0.783	0.284	0.776	-1.312	1.757
Model_Elantra se	-0.9629	1.339	-0.719	0.472	-3.588	1.663
Model_Elantra sport limited	-0.1730	0.953	-0.181	0.856	-2.042	1.696
Model_Element	-1.3230	0.956	-1.384	0.167	-3.197	0.551
Model_Elgrand	-0.7303	0.701	-1.042	0.298	-2.104	0.644
Model_Elysion	0.2002	0.456	0.440	0.660	-0.693	1.093
Model_Elysion 3.0	2.785e-07	5.76e-07	0.483	0.629	-8.51e-07	1.41e-06
Model_Enclave	-3.445e-07	5.98e-07	-0.576	0.565	-1.52e-06	8.28e-07
Model_Encore	-2.5654	1.718	-1.494	0.135	-5.932	0.801
Model_Envoy	-6.317e-08	5.83e-07	-0.108	0.914	-1.21e-06	1.08e-06
Model_Eos	-1.0789	1.342	-0.804	0.421	-3.709	1.552
Model_Equinox	-0.6708	0.354	-1.895	0.058	-1.365	0.023
Model_Equinox LT	0.7204	1.336	0.539	0.590	-1.899	3.340
Model_Escalade	1.4299	1.235	1.158	0.247	-0.991	3.851
Model_Escape	-0.8708	0.221	-3.949	0.000	-1.303	-0.439
Model_Escape 3.0	0.7019	1.350	0.520	0.603	-1.943	3.347
Model_Escape HYBRID	1.3054	1.350	0.967	0.334	-1.341	3.952
Model_Escape Hybrid	0.5094	1.351	0.377	0.706	-2.139	3.158
Model_Escape SE	0.8006	0.962	0.832	0.405	-1.086	2.687
Model_Escape Titanium	6.86e-08	5.79e-07	0.118	0.906	-1.07e-06	1.2e-06
Model_Escape escape	2.0774	1.350	1.539	0.124	-0.568	4.723
Model_Escape მერკური მერინერი	-0.1070	1.360	-0.079	0.937	-2.772	2.558
Model_Escape სასწრაფოდ	1.1630	1.358	0.856	0.392	-1.499	3.825
Model_Escort	-1.6719	0.796	-2.099	0.036	-3.233	-0.111
Model_Escudo	1.1085	1.307	0.848	0.396	-1.453	3.670
Model_Estima	0.9303	0.803	1.159	0.246	-0.643	2.504
Model_Eunos 500	-2.0035	0.949	-2.111	0.035	-3.864	-0.143
Model_Every Landy NISSAN SEREN	-0.6235	1.315	-0.474	0.635	-3.202	1.955

Model_Expedition	-1.4886	1.357	-1.097	0.273	-4.149	1.172
Model_Explorer	1.4376	0.288	4.985	0.000	0.872	2.003
Model_Explorer Turbo japan	2.1559	1.348	1.599	0.110	-0.487	4.798
Model_Explorer XLT	2.3137	1.353	1.710	0.087	-0.338	4.966
Model_F-pace	0.3743	0.644	0.582	0.561	-0.887	1.636
Model_F-type	-1.7933	0.939	-1.910	0.056	-3.633	0.047
Model_F-type R	2.6970	1.289	2.092	0.036	0.170	5.223
Model_F150	1.3019	0.576	2.262	0.024	0.173	2.430
Model_F50	3.3162	0.802	4.135	0.000	1.744	4.888
Model_FIT	-0.8142	0.187	-4.361	0.000	-1.180	-0.448
Model_FIT "S"- PAKETI.	0.0589	1.338	0.044	0.965	-2.564	2.682
Model_FIT GP-5	1.1972	1.338	0.894	0.371	-1.426	3.821
Model_FIT GP-6	1.2023	1.339	0.898	0.369	-1.421	3.826
Model_FIT HIBRID	0.4328	1.338	0.323	0.746	-2.190	3.056
Model_FIT HYBRYD	0.8900	1.338	0.665	0.506	-1.732	3.513
Model_FIT Hbrid	0.8473	1.338	0.633	0.527	-1.775	3.470
Model_FIT Hybrid	-4.503e-07	5.72e-07	-0.787	0.431	-1.57e-06	6.7e-07
Model_FIT LX	-8.317e-07	6.09e-07	-1.366	0.172	-2.03e-06	3.62e-07
Model_FIT Modulo	-5.946e-08	5.57e-07	-0.107	0.915	-1.15e-06	1.03e-06
Model_FIT NAVI PREMIUM	2.469e-07	5.86e-07	0.421	0.673	-9.01e-07	1.4e-06
Model_FIT PREMIUM PAKETI	-7.52e-08	5.43e-07	-0.138	0.890	-1.14e-06	9.89e-07
Model_FIT PREMIUMI	-0.4964	1.339	-0.371	0.711	-3.120	2.127
Model_FIT Premiym	-0.4948	0.960	-0.516	0.606	-2.376	1.386
Model_FIT RS	2.705e-07	6e-07	0.451	0.652	-9.06e-07	1.45e-06
Model_FIT RS MODELI	-0.5205	1.338	-0.389	0.697	-3.143	2.102
Model_FIT RS MUGEN	0.2648	1.338	0.198	0.843	-2.359	2.888
Model_FIT S	2.758e-07	6.09e-07	0.453	0.651	-9.18e-07	1.47e-06
Model_FIT SPORT	-4.4e-07	5.63e-07	-0.781	0.435	-1.54e-06	6.64e-07
Model_FIT Sport	-4.513e-07	5.41e-07	-0.834	0.404	-1.51e-06	6.09e-07
Model_FIT ex	-0.9377	1.344	-0.698	0.485	-3.572	1.697
Model_FIT fit	0.1751	1.371	0.128	0.898	-2.513	2.863
Model_FJ Cruiser	1.5652	1.353	1.157	0.247	-1.088	4.218
Model_FX35	-0.5830	0.604	-0.966	0.334	-1.766	0.600
Model_FX45	-0.5334	0.940	-0.567	0.570	-2.376	1.309
Model_Fabia	0.3323	0.902	0.368	0.713	-1.436	2.100
Model_Feroza	0.6950	1.216	0.572	0.568	-1.688	3.078
Model_Fiesta	-0.6160	0.280	-2.203	0.028	-1.164	-0.068

Model_Fiesta 1.6	-0.4694	1.349	-0.348	0.728	-3.113	2.174
Model_Fiesta SE	-1.4923	1.350	-1.106	0.269	-4.138	1.153
Model_Fit Aria	1.1535	1.338	0.862	0.389	-1.470	3.777
Model_Focus	-0.4174	0.267	-1.564	0.118	-0.941	0.106
Model_Focus Flexfuel	-0.0697	1.348	-0.052	0.959	-2.711	2.572
Model_Focus Fokusi	-0.7778	1.349	-0.576	0.564	-3.422	1.867
Model_Focus SE	-0.3199	0.690	-0.463	0.643	-1.673	1.033
Model_Focus SEL	0.2592	1.349	0.192	0.848	-2.385	2.903
Model_Focus ST	0.4572	1.360	0.336	0.737	-2.208	3.122
Model_Focus TITANIUM	-0.1708	0.790	-0.216	0.829	-1.720	1.378
Model_Focus Titanium	-0.7824	0.793	-0.986	0.324	-2.337	0.773
Model_Focus se	-0.3195	1.349	-0.237	0.813	-2.963	2.324
Model_Forester	-0.5549	0.280	-1.983	0.047	-1.104	-0.006
Model_Forester 4x4	2.605e-07	6.09e-07	0.428	0.669	-9.33e-07	1.45e-06
Model_Forester CrossSport	4.179e-07	5.82e-07	0.719	0.472	-7.22e-07	1.56e-06
Model_Forester L.L.BEAN	1.0709	1.324	0.809	0.418	-1.524	3.665
Model_Forester SH	-1.5126	1.318	-1.147	0.251	-4.097	1.072
Model_Forester XT	1.3690	1.319	1.038	0.299	-1.216	3.954
Model_Forester cross sport	-6.102e-07	5.76e-07	-1.060	0.289	-1.74e-06	5.18e-07
Model_Forester stb	7.653e-08	5.66e-07	0.135	0.892	-1.03e-06	1.19e-06
Model_Forte	-0.3335	0.682	-0.489	0.625	-1.670	1.003
Model_Fortuner	1.0530	0.964	1.093	0.275	-0.836	2.942
Model_Fred	0.3745	0.488	0.767	0.443	-0.582	1.331
Model_Fred HIBRIDI	-0.1685	1.345	-0.125	0.900	-2.804	2.467
Model_Freelander	-0.5316	0.928	-0.573	0.567	-2.350	1.287
Model_Frontera	-0.5894	1.345	-0.438	0.661	-3.226	2.048
Model_Frontera A B	2.499e-07	5.88e-07	0.425	0.671	-9.03e-07	1.4e-06
Model_Frontier	-0.1806	0.569	-0.317	0.751	-1.296	0.935
Model_Fuga	0.4114	0.684	0.602	0.547	-0.929	1.752
Model_Fun Cargo	0.2059	0.792	0.260	0.795	-1.346	1.758
Model_Fusion	-0.8766	0.193	-4.533	0.000	-1.256	-0.498
Model_Fusion 1.6	-0.1977	1.348	-0.147	0.883	-2.840	2.445
Model_Fusion 2015	2.888e-07	5.43e-07	0.532	0.595	-7.76e-07	1.35e-06
Model_Fusion Bybrid	1.7446	1.348	1.294	0.196	-0.898	4.387
Model_Fusion HIBRID	1.4114	1.348	1.047	0.295	-1.231	4.054
Model_Fusion HYBRID	0.3846	1.350	0.285	0.776	-2.261	3.030
Model_Fusion HYBRID SE	0.5390	1.350	0.399	0.690	-2.106	3.184

Model_Fusion Hybrid	-1.279e-08	6.04e-07	-0.021	0.983	-1.2e-06	1.17e-06
Model_Fusion SE	0.6909	0.622	1.112	0.266	-0.528	1.909
Model_Fusion TITANIUM	0.2038	0.790	0.258	0.797	-1.345	1.753
Model_Fusion Titanium	0.6684	1.348	0.496	0.620	-1.973	3.310
Model_Fusion hybrid	-0.2221	1.350	-0.165	0.869	-2.868	2.423
Model_Fusion phev	-0.6697	1.366	-0.490	0.624	-3.348	2.008
Model_G 230 2.2cdi	5.545e-07	6.1e-07	0.909	0.364	-6.42e-07	1.75e-06
Model_G 300	-2.813e-07	5.94e-07	-0.473	0.636	-1.45e-06	8.83e-07
Model_G 320	2.4137	1.386	1.742	0.082	-0.303	5.130
Model_G 350	2.2325	1.003	2.226	0.026	0.267	4.198
Model_G 55 AMG	-3.1525	0.847	-3.723	0.000	-4.812	-1.493
Model_G 550	0.8229	0.840	0.979	0.327	-0.824	2.470
Model_G 63 AMG	2.1411	1.008	2.125	0.034	0.166	4.116
Model_G 65 AMG 63AMG	2.6485	1.391	1.904	0.057	-0.078	5.375
Model_G 65 AMG G63 AMG	2.4162	1.387	1.741	0.082	-0.303	5.136
Model_G20	-0.1495	1.290	-0.116	0.908	-2.679	2.380
Model_G35 x	-1.695e-07	5.7e-07	-0.297	0.766	-1.29e-06	9.48e-07
Model_G37	-0.5341	0.796	-0.671	0.502	-2.094	1.026
Model_G6	2.0928	0.792	2.642	0.008	0.540	3.645
Model_GL 320	0.5905	0.741	0.796	0.426	-0.863	2.044
Model_GL 320 bluetec	0.7788	1.394	0.559	0.576	-1.953	3.510
Model_GL 350	-0.1706	0.677	-0.252	0.801	-1.499	1.157
Model_GL 350 BLUETEC	0.9938	1.385	0.717	0.473	-1.722	3.709
Model_GL 350 BLUTEC	0.2558	1.385	0.185	0.853	-2.459	2.970
Model_GL 350 Bluetec	0.3182	1.385	0.230	0.818	-2.397	3.033
Model_GL 350 დიზელი	1.2057	1.385	0.870	0.384	-1.510	3.921
Model_GL 450	-0.1936	0.546	-0.354	0.723	-1.264	0.877
Model_GL 450 3.0	1.1823	1.387	0.852	0.394	-1.536	3.901
Model_GL 500	3.096e-07	5.4e-07	0.574	0.566	-7.48e-07	1.37e-06
Model_GL 550	1.1387	0.633	1.800	0.072	-0.102	2.379
Model_GL 63 AMG	4.091e-07	6.38e-07	0.641	0.521	-8.42e-07	1.66e-06
Model_GLA 200	6.408e-09	5.62e-07	0.011	0.991	-1.1e-06	1.11e-06
Model_GLA 250	-1.6153	0.380	-4.248	0.000	-2.361	-0.870
Model_GLC 250	1.0850	1.386	0.783	0.434	-1.632	3.802
Model_GLC 300	0.4719	1.003	0.470	0.638	-1.494	2.438
Model_GLC 300 GLC coupe	1.2528	1.005	1.246	0.213	-0.718	3.223
Model_GLE 350	-0.2224	0.367	-0.606	0.545	-0.942	0.497

Model_GLE 400	1.6558	1.004	1.650	0.099	-0.311	3.623
Model_GLE 400 A M G	2.0989	1.385	1.516	0.130	-0.616	4.814
Model_GLE 400 Coupe, AMG Kit	2.6697	1.386	1.927	0.054	-0.046	5.386
Model_GLE 43 AMG	2.4823	1.389	1.787	0.074	-0.240	5.204
Model_GLE 450	-2.9536	1.385	-2.132	0.033	-5.669	-0.238
Model_GLE 63 AMG	0.1623	0.843	0.192	0.847	-1.490	1.815
Model_GLK 250	-0.2389	1.387	-0.172	0.863	-2.957	2.479
Model_GLK 300	2.88e-08	5.45e-07	0.053	0.958	-1.04e-06	1.1e-06
Model_GLK 350	-1.1020	0.594	-1.856	0.064	-2.266	0.062
Model_GLS 450	1.2962	1.385	0.936	0.349	-1.419	4.012
Model_GLS 63 AMG	-2.8233	1.396	-2.022	0.043	-5.560	-0.087
Model_GONOW	2.2931	1.039	2.206	0.027	0.256	4.331
Model_GS 300	-0.5400	1.335	-0.405	0.686	-3.156	2.076
Model_GS 350	1.0164	0.782	1.300	0.194	-0.516	2.549
Model_GS 450	0.7319	1.333	0.549	0.583	-1.881	3.344
Model_GTI	-0.6125	0.955	-0.641	0.521	-2.484	1.259
Model_GX 460	-0.6906	0.215	-3.218	0.001	-1.111	-0.270
Model_GX 470	-0.9272	0.224	-4.138	0.000	-1.366	-0.488
Model_GX 470 470	-5.943e-07	5.89e-07	-1.009	0.313	-1.75e-06	5.61e-07
Model_GX 470 SUV 4D (4.7L V8 S	0.5948	1.344	0.443	0.658	-2.040	3.229
Model_Galant	-0.4616	0.952	-0.485	0.628	-2.327	1.404
Model_Galant GTS	-0.2047	1.333	-0.154	0.878	-2.817	2.407
Model_Galaxy	-0.6132	0.972	-0.631	0.528	-2.518	1.292
Model_Galloper	-0.3179	1.347	-0.236	0.813	-2.959	2.323
Model_Genesis	0.7239	0.233	3.102	0.002	0.266	1.181
Model_Gentra	0.1203	0.676	0.178	0.859	-1.204	1.445
Model_Getz	-0.5750	0.684	-0.840	0.401	-1.916	0.767
Model_Ghibli	2.3000	0.568	4.048	0.000	1.186	3.414
Model_Giulietta	1.327e-07	5.62e-07	0.236	0.813	-9.69e-07	1.23e-06
Model_Gloria	0.8592	0.958	0.897	0.370	-1.018	2.737
Model_Golf	-0.0936	0.259	-0.362	0.717	-0.600	0.413
Model_Golf 1.8	0.6508	1.342	0.485	0.628	-1.980	3.282
Model_Golf 2	0.2873	1.346	0.214	0.831	-2.350	2.925
Model_Golf 3	-0.4790	0.687	-0.698	0.485	-1.825	0.867
Model_Golf 4	-0.2292	0.616	-0.372	0.710	-1.437	0.978
Model_Golf 6	-0.0291	1.342	-0.022	0.983	-2.659	2.601
Model_Golf GOLF 5	2.413e-07	6.25e-07	0.386	0.699	-9.83e-07	1.47e-06

Model_Golf GTI	-2.8015	0.964	-2.905	0.004	-4.692	-0.911
Model_Golf Gti	0.1916	1.344	0.142	0.887	-2.444	2.827
Model_Golf TDI	0.1177	0.955	0.123	0.902	-1.754	1.989
Model_Grand Cherokee	0.9445	0.398	2.372	0.018	0.164	1.725
Model_Grand Cherokee LAREDO	2.349e-07	5.57e-07	0.422	0.673	-8.57e-07	1.33e-06
Model_Grand Cherokee Saiubileo	2.0533	1.305	1.573	0.116	-0.506	4.612
Model_Grand Cherokee special e	1.1472	1.301	0.882	0.378	-1.404	3.698
Model_Grand HIACE	-0.7389	0.973	-0.759	0.448	-2.647	1.169
Model_Grand Vitara	0.4566	0.444	1.029	0.303	-0.413	1.326
Model_Grandeur	0.4997	0.390	1.282	0.200	-0.264	1.264
Model_Grandis	-0.7739	0.796	-0.972	0.331	-2.334	0.786
Model_H1	0.4720	0.215	2.198	0.028	0.051	0.893
Model_H1 GRAND STAREX	-0.5356	1.352	-0.396	0.692	-3.185	2.114
Model_H1 grandstarex	3.033e-07	5.91e-07	0.513	0.608	-8.55e-07	1.46e-06
Model_H1 starixs	-3.681e-07	6.02e-07	-0.612	0.541	-1.55e-06	8.11e-07
Model_H2	2.9583	1.053	2.810	0.005	0.895	5.022
Model_H3	1.7222	1.045	1.647	0.100	-0.327	3.771
Model_H6	9.237e-09	5.78e-07	0.016	0.987	-1.12e-06	1.14e-06
Model_HHR	-2.1210	1.337	-1.586	0.113	-4.742	0.500
Model_HS 250h	-1.3815	0.451	-3.064	0.002	-2.265	-0.498
Model_HS 250h Hybrid	1.3877	1.333	1.041	0.298	-1.226	4.001
Model_HUSTLER	-0.0938	1.312	-0.071	0.943	-2.665	2.478
Model_Harrier	0.5528	1.353	0.409	0.683	-2.099	3.205
Model_Hiace	0.4832	1.376	0.351	0.725	-2.213	3.179
Model_Highlander	0.0864	0.173	0.501	0.616	-0.252	0.425
Model_Highlander 2,4	1.569e-07	5.8e-07	0.271	0.787	-9.8e-07	1.29e-06
Model_Highlander 2.4 lit	1.4050	1.352	1.040	0.299	-1.244	4.054
Model_Highlander LIMITED	1.7082	0.963	1.774	0.076	-0.180	3.596
Model_Highlander XLE	5.132e-07	6.23e-07	0.823	0.410	-7.08e-07	1.73e-06
Model_Highlander limited	1.7236	1.352	1.274	0.203	-0.927	4.375
Model_Highlander sport	2.586e-08	5.62e-07	0.046	0.963	-1.08e-06	1.13e-06
Model_Hilux	0.9860	0.517	1.906	0.057	-0.028	2.000
Model_Hilux Surf	1.2617	1.354	0.932	0.351	-1.393	3.916
Model_Hr-v	-1.2756	0.956	-1.334	0.182	-3.149	0.598
Model_Hr-v EX	0.6317	1.339	0.472	0.637	-1.993	3.256
Model_Hr-v EXL	0.8222	1.339	0.614	0.539	-1.802	3.446
Model_I	-1.645e-07	5.68e-07	-0.290	0.772	-1.28e-06	9.49e-07

Model_I30	0.1461	0.295	0.495	0.621	-0.433	0.725
Model_INSIGNIA	0.4008	1.334	0.300	0.764	-2.214	3.016
Model_IS 200	-1.4942	0.501	-2.982	0.003	-2.476	-0.512
Model_IS 250	-0.7197	0.404	-1.781	0.075	-1.512	0.072
Model_IS 250 TURBO	-1.2450	1.334	-0.933	0.351	-3.860	1.370
Model_IS 250 რესტაილინგი	-2.012e-07	6.05e-07	-0.333	0.739	-1.39e-06	9.84e-07
Model_IS 300	1.2786	1.332	0.960	0.337	-1.332	3.890
Model_IS 350	-1.2455	0.781	-1.595	0.111	-2.777	0.286
Model_IS 350 C	-0.6529	1.385	-0.471	0.637	-3.368	2.062
Model_IS-F	0.9497	1.335	0.711	0.477	-1.667	3.566
Model_ISIS	-0.9825	0.579	-1.696	0.090	-2.118	0.153
Model_IVECO DAYLY	1.2551	1.068	1.175	0.240	-0.839	3.349
Model_IX35	1.2436	0.619	2.010	0.044	0.031	2.457
Model_IX35 2.0	-3.3130	1.351	-2.452	0.014	-5.961	-0.665
Model_Ibiza	0.8816	1.047	0.842	0.400	-1.172	2.935
Model_Ignis	-0.5639	1.306	-0.432	0.666	-3.124	1.997
Model_Impala	0.6569	0.314	2.095	0.036	0.042	1.272
Model_Impreza	-0.5458	0.476	-1.148	0.251	-1.478	0.386
Model_Impreza G4	0.3806	1.319	0.289	0.773	-2.205	2.966
Model_Impreza Sport	0.8969	1.321	0.679	0.497	-1.692	3.486
Model_Impreza WRX/STI LIMITED	1.2265	1.319	0.930	0.353	-1.360	3.813
Model_Insight	-1.3983	0.238	-5.875	0.000	-1.865	-0.932
Model_Insight EX	-1.3351	1.339	-0.997	0.319	-3.959	1.289
Model_Insight LX	-0.3923	1.340	-0.293	0.770	-3.020	2.235
Model_Inspire	-0.6135	0.957	-0.641	0.521	-2.489	1.262
Model_Integra	0.1156	1.343	0.086	0.931	-2.517	2.749
Model_Intrepid	-2.099e-07	5.67e-07	-0.370	0.711	-1.32e-06	9.01e-07
Model_Ioniq	-0.6332	1.341	-0.472	0.637	-3.262	1.996
Model_Ipsum	0.0827	0.538	0.154	0.878	-0.972	1.137
Model_Ipsum S	3.219e-07	5.94e-07	0.541	0.588	-8.43e-07	1.49e-06
Model_Ist	-0.0315	0.350	-0.090	0.928	-0.717	0.654
Model_Ist 1.5	0.7479	1.351	0.553	0.580	-1.901	3.397
Model_JX35	0.8961	1.288	0.696	0.486	-1.628	3.420
Model_Jetta	-0.5765	0.184	-3.135	0.002	-0.937	-0.216
Model_Jetta 1.4 TURBO	-2.648e-07	6.1e-07	-0.434	0.664	-1.46e-06	9.32e-07
Model_Jetta 2	0.5514	1.341	0.411	0.681	-2.077	3.180
Model_Jetta 2.0	-8.645e-08	5.63e-07	-0.153	0.878	-1.19e-06	1.02e-06

Model_Jetta GLI	0.1269	0.953	0.133	0.894	-1.741	1.995
Model_Jetta Hybrid	1.5587	1.341	1.162	0.245	-1.070	4.187
Model_Jetta SE	0.2902	0.683	0.425	0.671	-1.048	1.628
Model_Jetta SEL	0.3711	1.341	0.277	0.782	-2.258	3.000
Model_Jetta SPORT	-1.667e-07	5.04e-07	-0.331	0.741	-1.16e-06	8.22e-07
Model_Jetta TDI	0.8034	1.343	0.598	0.550	-1.829	3.435
Model_Jetta s	-0.3984	1.340	-0.297	0.766	-3.026	2.229
Model_Jetta se	0.0358	0.953	0.038	0.970	-1.833	1.905
Model_Jetta sei	0.6082	1.340	0.454	0.650	-2.018	3.235
Model_Jetta sel	1.0630	0.953	1.115	0.265	-0.806	2.932
Model_Jetta sport	-0.5793	1.340	-0.432	0.666	-3.206	2.047
Model_Jetta სასწაფოდ	0.0446	1.340	0.033	0.973	-2.582	2.671
Model_Jetta სპორტ	-0.1751	1.340	-0.131	0.896	-2.802	2.451
Model_Jimny	0.4477	1.310	0.342	0.732	-2.120	3.015
Model_Jimny GLX	-6.599e-07	5.77e-07	-1.144	0.253	-1.79e-06	4.71e-07
Model_Journey	-0.8786	0.936	-0.939	0.348	-2.713	0.956
Model_Juke	-0.8641	0.207	-4.168	0.000	-1.271	-0.458
Model_Juke Juke	1.3291	1.342	0.990	0.322	-1.302	3.961
Model_Juke NISMO	-0.2287	1.343	-0.170	0.865	-2.862	2.404
Model_Juke Nismo	9.106e-08	6.04e-07	0.151	0.880	-1.09e-06	1.28e-06
Model_Juke Nismo RS	-3.599e-07	5.82e-07	-0.619	0.536	-1.5e-06	7.8e-07
Model_Juke Turbo	-0.3357	1.344	-0.250	0.803	-2.970	2.298
Model_Juke juke	-1.957e-07	6.2e-07	-0.315	0.752	-1.41e-06	1.02e-06
Model_Juke nismo	0.3412	1.344	0.254	0.800	-2.293	2.975
Model_KA	-0.9815	1.356	-0.724	0.469	-3.640	1.676
Model_Kalos	-3.353e-07	6.25e-07	-0.537	0.591	-1.56e-06	8.89e-07
Model_Kangoo	-1.216e-07	5.42e-07	-0.224	0.822	-1.18e-06	9.41e-07
Model_Kangoo Waggon	-1.075e-07	6.26e-07	-0.172	0.864	-1.33e-06	1.12e-06
Model_Kicks	-0.2056	0.957	-0.215	0.830	-2.082	1.671
Model_Kicks SR	-6.027e-08	6.35e-07	-0.095	0.924	-1.3e-06	1.18e-06
Model_Kizashi	0.0258	0.787	0.033	0.974	-1.516	1.567
Model_Kizashi sporti	-5.627e-07	5.54e-07	-1.016	0.310	-1.65e-06	5.23e-07
Model_Korando	0.8272	0.327	2.528	0.011	0.186	1.469
Model_Kyron	-0.2161	0.626	-0.345	0.730	-1.443	1.010
Model_L 200	0.8997	0.575	1.565	0.118	-0.227	2.026
Model_LAFESTA	-0.3927	1.352	-0.291	0.771	-3.042	2.257
Model_LATIO	2.463e-07	6.22e-07	0.396	0.692	-9.72e-07	1.46e-06

Model_LS 460	0.6735	0.396	1.700	0.089	-0.103	1.450
Model_LX 470	-4.899e-07	5.83e-07	-0.840	0.401	-1.63e-06	6.53e-07
Model_LX 570	0.3476	0.624	0.557	0.577	-0.875	1.571
Model_Lacetti	0.5928	0.279	2.127	0.033	0.047	1.139
Model_Laguna	-0.2165	0.641	-0.338	0.736	-1.473	1.040
Model_Lancer	-0.5930	0.619	-0.958	0.338	-1.807	0.621
Model_Lancer GT	-1.357e-07	5.65e-07	-0.240	0.810	-1.24e-06	9.72e-07
Model_Lancer GTS	2.203e-07	6.12e-07	0.360	0.719	-9.79e-07	1.42e-06
Model_Land Cruiser	2.2994	0.504	4.561	0.000	1.311	3.288
Model_Land Cruiser 100	1.1184	1.357	0.824	0.410	-1.542	3.778
Model_Land Cruiser 105	-5.214e-07	6.46e-07	-0.808	0.419	-1.79e-06	7.44e-07
Model_Land Cruiser 11	4.427e-08	5.93e-07	0.075	0.940	-1.12e-06	1.21e-06
Model_Land Cruiser 200	1.4913	1.357	1.099	0.272	-1.168	4.150
Model_Land Cruiser 80	-1.472e-07	5.55e-07	-0.265	0.791	-1.23e-06	9.4e-07
Model_Land Cruiser PRADO	0.6717	1.354	0.496	0.620	-1.983	3.327
Model_Land Cruiser Prado	-0.6537	0.316	-2.068	0.039	-1.273	-0.034
Model_Land Cruiser Prado RX	1.7680	1.360	1.300	0.194	-0.898	4.434
Model_Land Rover Sport	0.8232	0.597	1.380	0.168	-0.346	1.993
Model_Lantra	-4.66e-07	6.02e-07	-0.774	0.439	-1.65e-06	7.14e-07
Model_Lantra LIMITED	0.5587	1.340	0.417	0.677	-2.067	3.184
Model_Leaf	-5.157e-07	5.56e-07	-0.928	0.353	-1.61e-06	5.74e-07
Model_Legacy	-0.0206	0.370	-0.056	0.956	-0.746	0.704
Model_Legacy B4	-0.1180	1.318	-0.090	0.929	-2.701	2.465
Model_Legacy B4 twin turbo	1.012e-07	5.83e-07	0.173	0.862	-1.04e-06	1.24e-06
Model_Legacy Bl5	-1.382e-07	5.83e-07	-0.237	0.813	-1.28e-06	1e-06
Model_Legacy Outback	0.6730	1.331	0.506	0.613	-1.936	3.282
Model_Legacy b4	0.5044	1.318	0.383	0.702	-2.080	3.088
Model_Legacy bl5	-0.1273	1.318	-0.097	0.923	-2.711	2.456
Model_Legend FULL	1.5403	1.341	1.148	0.251	-1.089	4.169
Model_Leon	1.4366	1.047	1.372	0.170	-0.616	3.489
Model_Liana	5.299e-07	5.18e-07	1.023	0.306	-4.85e-07	1.54e-06
Model_Liberty	0.6440	0.525	1.227	0.220	-0.385	1.673
Model_Lupo	-0.1775	1.346	-0.132	0.895	-2.815	2.460
Model_Lupo iaponuri	-3.316e-07	5.8e-07	-0.572	0.567	-1.47e-06	8.05e-07
Model_M3	1.1517	0.871	1.322	0.186	-0.556	2.859
Model_M37	0.2199	1.288	0.171	0.864	-2.305	2.744
Model_M4	0.4059	1.108	0.366	0.714	-1.765	2.577

Model_M4 Competition	2.2559	1.469	1.535	0.125	-0.624	5.136
Model_M5	1.0600	0.873	1.214	0.225	-0.651	2.771
Model_M5 Japan	1.9033	1.462	1.302	0.193	-0.963	4.770
Model_M5 Машина в максимально	1.8859	1.462	1.290	0.197	-0.979	4.751
Model_M550	0.7283	1.461	0.499	0.618	-2.135	3.592
Model_M6	1.6198	0.879	1.844	0.065	-0.102	3.342
Model_M6 Gran cupe	2.7000	1.459	1.850	0.064	-0.160	5.560
Model_MDX	4.7921	1.589	3.016	0.003	1.678	7.906
Model_MKZ	0.4981	0.878	0.567	0.571	-1.224	2.220
Model_MKZ hybrid	1.827e-07	6.08e-07	0.301	0.764	-1.01e-06	1.37e-06
Model_ML 250	0.7450	1.004	0.742	0.458	-1.223	2.714
Model_ML 270	-0.6863	0.743	-0.924	0.356	-2.143	0.770
Model_ML 270 CDI	-0.1477	1.386	-0.107	0.915	-2.864	2.569
Model_ML 280	1.1539	1.386	0.833	0.405	-1.562	3.870
Model_ML 280 სასწრაფოდ	0.7807	1.385	0.564	0.573	-1.934	3.495
Model_ML 300	-0.0814	1.385	-0.059	0.953	-2.796	2.633
Model_ML 320	-0.2293	0.411	-0.559	0.576	-1.034	0.575
Model_ML 320 AMG	1.456e-07	5.79e-07	0.251	0.802	-9.9e-07	1.28e-06
Model_ML 320 cdi	-0.1138	1.401	-0.081	0.935	-2.859	2.632
Model_ML 350	-1.3061	0.325	-4.021	0.000	-1.943	-0.669
Model_ML 350 3.7	3.412e-07	6.33e-07	0.539	0.590	-9e-07	1.58e-06
Model_ML 350 370	0.0165	1.385	0.012	0.990	-2.698	2.731
Model_ML 350 4 MATIC	0.6030	1.003	0.601	0.548	-1.362	2.568
Model_ML 350 4matic	-0.2726	1.386	-0.197	0.844	-2.990	2.445
Model_ML 350 BLUETEC	0.2098	1.385	0.152	0.880	-2.505	2.925
Model_ML 350 ML350	-0.1181	1.003	-0.118	0.906	-2.085	1.849
Model_ML 350 SPECIAL EDITION	0.0521	1.386	0.038	0.970	-2.665	2.769
Model_ML 350 sport	1.1985	1.385	0.865	0.387	-1.517	3.914
Model_ML 500	0.4427	0.680	0.651	0.515	-0.891	1.776
Model_ML 500 AMG	-0.3212	1.394	-0.230	0.818	-3.054	2.412
Model_ML 55 AMG	0.9550	1.006	0.949	0.343	-1.018	2.928
Model_ML 550	-5.791e-07	5.92e-07	-0.979	0.328	-1.74e-06	5.8e-07
Model_ML 550 4.7	1.5046	1.386	1.086	0.278	-1.212	4.221
Model_ML 63 AMG	1.2109	1.390	0.871	0.384	-1.514	3.936
Model_MPV	0.4237	0.478	0.887	0.375	-0.513	1.360
Model_MPV LX	0.6196	1.339	0.463	0.644	-2.006	3.245
Model_Malibu	0.3688	0.238	1.549	0.121	-0.098	0.835

Model_Malibu Hybrid	1.1092	1.335	0.831	0.406	-1.508	3.726
Model_Malibu LT	0.2542	0.682	0.373	0.709	-1.082	1.591
Model_Malibu eco	0.2536	1.374	0.185	0.854	-2.439	2.947
Model_March	-0.2537	0.297	-0.854	0.393	-0.836	0.328
Model_March 231212	0.6025	1.375	0.438	0.661	-2.093	3.298
Model_March Rafeet	-0.1363	1.343	-0.101	0.919	-2.770	2.497
Model_Mariner	1.9674	2.070	0.950	0.342	-2.090	6.025
Model_Mariner Hybrid	2.4568	2.275	1.080	0.280	-2.004	6.917
Model_Mark X	-0.3081	1.353	-0.228	0.820	-2.960	2.343
Model_Mark X Zio	-3.728e-07	5.92e-07	-0.630	0.529	-1.53e-06	7.87e-07
Model_Matiz	-0.5389	0.569	-0.947	0.344	-1.654	0.576
Model_Matrix XR	0.0180	1.352	0.013	0.989	-2.632	2.668
Model_Maverick	-0.1766	1.358	-0.130	0.897	-2.838	2.485
Model_Maxima	-1.2081	0.959	-1.260	0.208	-3.088	0.672
Model_Mazda 2	-0.3611	1.335	-0.271	0.787	-2.977	2.255
Model_Mazda 3	-0.6106	0.568	-1.074	0.283	-1.725	0.503
Model_Mazda 3 SPORT	0.4089	1.328	0.308	0.758	-2.195	3.013
Model_Mazda 5	-0.8735	1.336	-0.654	0.513	-3.492	1.746
Model_Mazda 6	0.8913	0.438	2.035	0.042	0.033	1.750
Model_Mazda 6 Grand Touring	0.4183	1.330	0.315	0.753	-2.189	3.025
Model_Mazda 6 Grand touring	5.629e-07	6.01e-07	0.936	0.349	-6.16e-07	1.74e-06
Model_Mazda 6 TOURING	1.5200	0.949	1.602	0.109	-0.340	3.380
Model_Megane	0.4562	0.567	0.804	0.421	-0.656	1.568
Model_Megane 1.5CDI	0.7568	1.285	0.589	0.556	-1.763	3.276
Model_Megane 1.9 CDI	3.937e-07	6.34e-07	0.621	0.535	-8.49e-07	1.64e-06
Model_Megane 1.9CDI	1.1625	1.287	0.904	0.366	-1.360	3.685
Model_Megane 19	-0.3067	1.291	-0.238	0.812	-2.837	2.224
Model_Megane 5	-0.0216	1.286	-0.017	0.987	-2.542	2.498
Model_Megane GT Line	0.5667	1.288	0.440	0.660	-1.959	3.092
Model_Meriva	-0.1514	0.622	-0.243	0.808	-1.371	1.069
Model_Micra	-0.8974	0.438	-2.048	0.041	-1.756	-0.038
Model_Micra	0.0483	1.344	0.036	0.971	-2.586	2.683
Model_Millenia	1.794e-07	5.82e-07	0.308	0.758	-9.62e-07	1.32e-06
Model_Minica	1.4761	1.372	1.076	0.282	-1.212	4.165
Model_Mira	-1.2673	1.211	-1.046	0.295	-3.641	1.106
Model_Mirage	-1.2742	0.620	-2.055	0.040	-2.490	-0.059
Model_Moco	-0.3886	1.344	-0.289	0.772	-3.022	2.245

Model_Model X	3.1330	0.791	3.960	0.000	1.582	4.684
Model_Mondeo	-0.9014	0.964	-0.935	0.350	-2.791	0.988
Model_Monterey	1.6931	1.338	1.265	0.206	-0.930	4.317
Model_Montero	0.1723	0.786	0.219	0.827	-1.369	1.713
Model_Montero Sport	0.2900	0.955	0.304	0.761	-1.582	2.162
Model_Move	1.7047	1.233	1.383	0.167	-0.711	4.121
Model_Mulsanne	4.2673	0.804	5.307	0.000	2.691	5.843
Model_Murano	0.9725	0.499	1.951	0.051	-0.005	1.950
Model_Musa	2.2515	0.793	2.838	0.005	0.696	3.807
Model_Mustang	0.9646	0.326	2.959	0.003	0.326	1.604
Model_Mustang cabrio	0.2975	1.403	0.212	0.832	-2.453	3.048
Model_Mustang ecoboost	0.0470	1.353	0.035	0.972	-2.606	2.700
Model_Mx-5	-0.3201	1.330	-0.241	0.810	-2.928	2.288
Model_NEW Beetle	-0.7298	0.969	-0.753	0.451	-2.629	1.169
Model_NX 200	-1.4903	0.452	-3.295	0.001	-2.377	-0.604
Model_NX 300	0.9235	0.615	1.502	0.133	-0.282	2.129
Model_Navara	0.9920	0.852	1.165	0.244	-0.677	2.661
Model_Navigator	2.8018	0.884	3.170	0.002	1.069	4.535
Model_Neon	-0.1082	1.298	-0.083	0.934	-2.652	2.435
Model_Niro	-0.2538	0.572	-0.444	0.657	-1.374	0.867
Model_Niva	0.3281	0.957	0.343	0.732	-1.547	2.203
Model_Noah	0.2714	0.970	0.280	0.780	-1.629	2.172
Model_Note	-1.0747	0.249	-4.324	0.000	-1.562	-0.587
Model_Nubira	-0.4442	1.349	-0.329	0.742	-3.088	2.199
Model_Octavia	0.6209	0.586	1.060	0.289	-0.527	1.769
Model_Octavia SCOUT	1.1160	1.200	0.930	0.352	-1.236	3.468
Model_Octavia Scout	0.9531	1.197	0.796	0.426	-1.393	3.299
Model_Odyssey	-0.3890	0.416	-0.934	0.350	-1.205	0.427
Model_Omega	0.2781	0.696	0.400	0.689	-1.086	1.642
Model_Omega 1	-2.47e-07	5.64e-07	-0.438	0.661	-1.35e-06	8.58e-07
Model_Omega B	-0.0891	0.955	-0.093	0.926	-1.961	1.783
Model_Omega b	-0.2073	1.338	-0.155	0.877	-2.830	2.415
Model_Omega c	5.603e-07	5.85e-07	0.958	0.338	-5.87e-07	1.71e-06
Model_One	0.6943	1.302	0.533	0.594	-1.858	3.247
Model_Optima	-0.0899	0.220	-0.408	0.683	-0.521	0.341
Model_Optima ECO	-0.1156	1.321	-0.088	0.930	-2.705	2.474
Model_Optima EX	-5.124e-08	5.74e-07	-0.089	0.929	-1.18e-06	1.07e-06

Model_Optima HYBRID	1.7280	1.321	1.308	0.191	-0.861	4.317
Model_Optima Hybrid	0.0213	1.320	0.016	0.987	-2.567	2.609
Model_Optima SXL	-3.589e-07	6.28e-07	-0.571	0.568	-1.59e-06	8.72e-07
Model_Optima X	-0.0939	1.326	-0.071	0.944	-2.693	2.505
Model_Optima ex	1.0946	1.320	0.829	0.407	-1.493	3.682
Model_Optima hybid	0.0028	1.321	0.002	0.998	-2.586	2.592
Model_Optima hybrid	0.1208	0.948	0.127	0.899	-1.737	1.979
Model_Optima k5	3.343e-07	5.95e-07	0.562	0.574	-8.31e-07	1.5e-06
Model_Orlando	0.6816	0.238	2.868	0.004	0.216	1.147
Model_Outback	-0.6420	0.478	-1.345	0.179	-1.578	0.294
Model_Outback 2007	-2.46e-07	5.8e-07	-0.424	0.672	-1.38e-06	8.91e-07
Model_Outback 3.0	-4.836e-07	6.31e-07	-0.766	0.444	-1.72e-06	7.54e-07
Model_Outback Limited	0.7315	1.318	0.555	0.579	-1.852	3.315
Model_Outlander	-0.0882	0.273	-0.324	0.746	-0.623	0.446
Model_Outlander 2.0	-1.3472	1.333	-1.011	0.312	-3.959	1.265
Model_Outlander SE	0.5957	1.330	0.448	0.654	-2.012	3.203
Model_Outlander SPORT	0.3982	0.782	0.509	0.611	-1.135	1.931
Model_Outlander Sport	0.1445	0.785	0.184	0.854	-1.394	1.683
Model_Outlander sport	0.2759	0.617	0.447	0.655	-0.934	1.486
Model_Outlander xl	-1.882e-07	5.42e-07	-0.347	0.729	-1.25e-06	8.75e-07
Model_Outlander სპორტ	-1.067e-07	5.71e-07	-0.187	0.852	-1.23e-06	1.01e-06
Model_PT Cruiser	-1.1186	1.120	-0.998	0.318	-3.315	1.077
Model_PT Cruiser pt cruiser	1.658e-07	5.75e-07	0.289	0.773	-9.61e-07	1.29e-06
Model_Paceman	0.5620	1.297	0.433	0.665	-1.980	3.104
Model_Pacifica	-0.4523	1.567	-0.289	0.773	-3.523	2.619
Model_Pajero	0.9060	0.308	2.944	0.003	0.303	1.509
Model_Pajero 2.5diezel	0.3579	1.332	0.269	0.788	-2.253	2.969
Model_Pajero IO	-0.0556	0.315	-0.176	0.860	-0.674	0.563
Model_Pajero MONTERO	0.0722	1.331	0.054	0.957	-2.538	2.682
Model_Pajero Mini	1.2907	1.331	0.970	0.332	-1.318	3.899
Model_Pajero Mini 2008 წლიანი	0.2393	1.334	0.179	0.858	-2.376	2.855
Model_Pajero Mini 2010 წლიანი	-0.4682	1.335	-0.351	0.726	-3.085	2.149
Model_Pajero Sport	1.5813	1.330	1.189	0.235	-1.026	4.189
Model_Panamera	-0.7794	0.631	-1.235	0.217	-2.016	0.457
Model_Panamera 4	1.1612	1.240	0.937	0.349	-1.268	3.591
Model_Panamera GTS	1.4043	1.240	1.132	0.258	-1.027	3.836
Model_Panamera S	2.112e-07	5.14e-07	0.411	0.681	-7.96e-07	1.22e-06

Model_Panda	-0.7574	0.946	-0.801	0.423	-2.612	1.097
Model_Passat	-0.0265	0.214	-0.124	0.901	-0.445	0.392
Model_Passat 2.0 tfsi	3.447e-07	5.55e-07	0.621	0.535	-7.43e-07	1.43e-06
Model_Passat B5	-0.0623	1.340	-0.046	0.963	-2.689	2.565
Model_Passat B7	1.768e-07	6.58e-07	0.269	0.788	-1.11e-06	1.47e-06
Model_Passat R-line	1.5045	1.340	1.123	0.261	-1.122	4.131
Model_Passat RLAINI	-3.039e-07	5.98e-07	-0.508	0.611	-1.48e-06	8.68e-07
Model_Passat SE	-0.1807	0.954	-0.190	0.850	-2.050	1.689
Model_Passat SEL	-0.4972	1.340	-0.371	0.711	-3.124	2.130
Model_Passat Se	1.811e-07	6.3e-07	0.287	0.774	-1.05e-06	1.42e-06
Model_Passat pasat	-0.2341	1.350	-0.173	0.862	-2.880	2.411
Model_Passat se	0.1750	1.340	0.131	0.896	-2.452	2.802
Model_Passat sel	1.0855	0.953	1.139	0.255	-0.783	2.954
Model_Passat sport	-6.89e-07	6.05e-07	-1.139	0.255	-1.88e-06	4.97e-07
Model_Passat tdi sel	-0.2448	1.341	-0.183	0.855	-2.873	2.383
Model_Passat tsi-se	0.0718	1.340	0.054	0.957	-2.555	2.698
Model_Passo	-0.2410	0.964	-0.250	0.803	-2.131	1.649
Model_Passport	0.3569	0.960	0.372	0.710	-1.525	2.239
Model_Pathfinder	0.5377	0.404	1.332	0.183	-0.254	1.329
Model_Pathfinder SE	0.9636	1.345	0.717	0.474	-1.672	3.600
Model_Patriot	-0.4561	0.609	-0.749	0.454	-1.649	0.737
Model_Patriot 70th anniversary	0.7816	1.300	0.601	0.548	-1.766	3.329
Model_Patriot Latitude	-4.785e-07	5.49e-07	-0.872	0.383	-1.55e-06	5.97e-07
Model_Patrol	0.8360	0.791	1.057	0.290	-0.714	2.386
Model_Patrol Y60	1.4093	1.347	1.046	0.295	-1.231	4.050
Model_Phaeton	0.9200	0.957	0.962	0.336	-0.955	2.795
Model_Phantom	3.4811	0.627	5.555	0.000	2.253	4.709
Model_Picanto	-0.3154	0.393	-0.802	0.422	-1.086	0.455
Model_Pilot	-0.2392	0.576	-0.415	0.678	-1.368	0.890
Model_Polo	-0.3839	0.615	-0.624	0.533	-1.589	0.822
Model_Polo GTI 16V	0.7482	1.342	0.557	0.577	-1.883	3.380
Model_Premacy	0.1952	0.960	0.203	0.839	-1.686	2.077
Model_Presage	0.3139	0.802	0.391	0.696	-1.259	1.887
Model_Presage RIDER	0.4513	1.349	0.335	0.738	-2.193	3.096
Model_Primera	-1.3997	1.343	-1.042	0.297	-4.032	1.233
Model_Prius	-0.5265	0.128	-4.101	0.000	-0.778	-0.275
Model_Prius 1.5l	0.5681	1.352	0.420	0.674	-2.083	3.219

Model_Prius 1.8	-0.4068	1.352	-0.301	0.763	-3.057	2.243
Model_Prius 11	1.3188	1.351	0.976	0.329	-1.329	3.967
Model_Prius 2014	-4.581e-07	5.78e-07	-0.793	0.428	-1.59e-06	6.75e-07
Model_Prius 3	-0.6189	1.352	-0.458	0.647	-3.269	2.031
Model_Prius 9	0.6295	1.356	0.464	0.643	-2.029	3.288
Model_Prius BLUG-IN	8.595e-08	6.1e-07	0.141	0.888	-1.11e-06	1.28e-06
Model_Prius C	-0.0783	0.193	-0.406	0.684	-0.456	0.299
Model_Prius C 1.5l	2.059e-07	5.47e-07	0.376	0.707	-8.67e-07	1.28e-06
Model_Prius C 2013	-1.7510	0.959	-1.825	0.068	-3.631	0.129
Model_Prius C 80 original	0.1042	1.350	0.077	0.938	-2.542	2.751
Model_Prius C Hybrid	0.5267	1.351	0.390	0.697	-2.121	3.174
Model_Prius C Navigation	1.0624	1.351	0.786	0.432	-1.586	3.710
Model_Prius C YARIS IA	0.0870	1.350	0.064	0.949	-2.559	2.733
Model_Prius C aqua	0.9576	1.351	0.709	0.479	-1.691	3.606
Model_Prius C hybrid	-0.7211	1.352	-0.533	0.594	-3.371	1.929
Model_Prius C ჰიბრიდი	0.4357	0.964	0.452	0.651	-1.454	2.326
Model_Prius Plug IN	0.0031	1.350	0.002	0.998	-2.643	2.650
Model_Prius Plug in	-1.7495	1.369	-1.278	0.201	-4.433	0.934
Model_Prius S	0.4611	1.359	0.339	0.734	-2.202	3.124
Model_Prius TSS LIMITED	1.5816	1.350	1.171	0.241	-1.065	4.228
Model_Prius V	0.2245	0.424	0.530	0.596	-0.606	1.055
Model_Prius V ALPINA	1.0268	1.352	0.760	0.447	-1.622	3.676
Model_Prius V HIBRID	1.5241	1.350	1.129	0.259	-1.123	4.171
Model_Prius V HYBRID	-0.2743	1.361	-0.202	0.840	-2.941	2.393
Model_Prius personna	-0.2133	1.351	-0.158	0.875	-2.862	2.436
Model_Prius plagin	0.5544	1.350	0.411	0.681	-2.092	3.201
Model_Prius plug-in	6.398e-07	5.63e-07	1.135	0.256	-4.65e-07	1.74e-06
Model_Prius plugin	-0.6271	1.368	-0.458	0.647	-3.309	2.055
Model_Prius prius	-0.2520	1.352	-0.186	0.852	-2.902	2.398
Model_Prius s	0.6247	0.961	0.650	0.516	-1.259	2.508
Model_Prius ფლაგინი	-0.1205	1.368	-0.088	0.930	-2.803	2.562
Model_Prius ჰიბრიდი	2.422e-07	5.54e-07	0.437	0.662	-8.44e-07	1.33e-06
Model_Protege	-0.0980	1.329	-0.074	0.941	-2.703	2.507
Model_Punto	-1.444e-07	6.02e-07	-0.240	0.810	-1.32e-06	1.04e-06
Model_Q3	0.3278	0.949	0.345	0.730	-1.533	2.188
Model_Q45	0.3594	1.289	0.279	0.780	-2.168	2.886
Model_Q5	-0.1215	0.356	-0.341	0.733	-0.820	0.577

Model_Q5 Prestige	1.1804	1.326	0.890	0.373	-1.418	3.779
Model_Q5 S-line	1.0480	1.326	0.790	0.429	-1.551	3.647
Model_Q50 S Red	0.0633	1.288	0.049	0.961	-2.461	2.587
Model_Q7	-1.1931	0.352	-3.391	0.001	-1.883	-0.503
Model_Q7 sport	0.7651	1.327	0.576	0.564	-1.837	3.367
Model_QX56	2.5158	1.304	1.929	0.054	-0.041	5.072
Model_QX60	-4.49e-07	5.81e-07	-0.773	0.440	-1.59e-06	6.9e-07
Model_QX80	1.5208	0.944	1.611	0.107	-0.330	3.372
Model_Qashqai Advance CVT	1.0604	1.354	0.783	0.434	-1.594	3.715
Model_Qashqai SPORT	0.2288	1.343	0.170	0.865	-2.403	2.861
Model_Quattroporte	4.327e-08	6.21e-07	0.070	0.944	-1.17e-06	1.26e-06
Model_Quest	-0.5245	0.594	-0.883	0.377	-1.689	0.640
Model_Quest 2016	1.3970	1.350	1.034	0.301	-1.250	4.044
Model_R 320	-0.2747	1.392	-0.197	0.844	-3.003	2.453
Model_R 350	0.2748	0.837	0.328	0.743	-1.366	1.916
Model_R 350 BLUETEC	-0.1271	1.393	-0.091	0.927	-2.857	2.602
Model_R2	3.009e-07	6.28e-07	0.479	0.632	-9.3e-07	1.53e-06
Model_RAM	0.4383	0.793	0.553	0.580	-1.115	1.992
Model_RAM 1500	2.3129	1.301	1.777	0.076	-0.238	4.864
Model_RAV 4	-0.1291	0.178	-0.726	0.468	-0.478	0.219
Model_RAV 4 Dizel	1.5145	1.352	1.120	0.263	-1.136	4.166
Model_RAV 4 L	2.754e-07	5.59e-07	0.493	0.622	-8.21e-07	1.37e-06
Model_RAV 4 LIMITED	2.3035	0.961	2.397	0.017	0.419	4.188
Model_RAV 4 Le	0.2533	1.351	0.188	0.851	-2.394	2.901
Model_RAV 4 SPORT	-7.786e-08	5.33e-07	-0.146	0.884	-1.12e-06	9.66e-07
Model_RAV 4 SUPER!!!	-1.94e-07	6.11e-07	-0.317	0.751	-1.39e-06	1e-06
Model_RAV 4 XLE	2.411e-07	5.96e-07	0.404	0.686	-9.28e-07	1.41e-06
Model_RAV 4 XLE Sport	-0.4171	1.351	-0.309	0.758	-3.066	2.231
Model_RAV 4 s p o r t	1.365e-07	5.76e-07	0.237	0.813	-9.93e-07	1.27e-06
Model_RAV 4 se	1.7370	1.352	1.285	0.199	-0.912	4.386
Model_RC F	-1.2060	0.789	-1.529	0.126	-2.752	0.340
Model_RC F F SPORT	0.5101	1.338	0.381	0.703	-2.113	3.133
Model_RDX	4.3545	1.590	2.739	0.006	1.239	7.470
Model_REXTON	1.1427	0.307	3.720	0.000	0.541	1.745
Model_REXTON SUPER	1.5463	1.145	1.351	0.177	-0.698	3.791
Model_RIO	-1.2038	0.441	-2.730	0.006	-2.068	-0.340
Model_RIO lX	4.179e-07	5.31e-07	0.787	0.431	-6.22e-07	1.46e-06

Model_RIO lx	0.9644	1.321	0.730	0.465	-1.625	3.554
Model_RS6	1.736e-07	5.65e-07	0.307	0.759	-9.34e-07	1.28e-06
Model_RS7	-2.1789	1.328	-1.641	0.101	-4.781	0.423
Model_RVR	1.1025	1.331	0.828	0.407	-1.506	3.711
Model_RX 300	0.5539	0.498	1.112	0.266	-0.423	1.531
Model_RX 350	-1.5063	0.236	-6.374	0.000	-1.970	-1.043
Model_RX 350 F sport	-2.647e-07	5.84e-07	-0.453	0.650	-1.41e-06	8.8e-07
Model_RX 400	-0.0972	0.325	-0.299	0.765	-0.734	0.540
Model_RX 400 H	0.6698	1.339	0.500	0.617	-1.955	3.295
Model_RX 400 HYBRID	1.9174	0.950	2.019	0.044	0.056	3.779
Model_RX 400 RESTAILING	1.9687	0.951	2.071	0.038	0.105	3.832
Model_RX 400 hybrid	1.2310	1.332	0.924	0.355	-1.380	3.842
Model_RX 450	-0.9158	0.207	-4.433	0.000	-1.321	-0.511
Model_RX 450 F SPORT	1.4160	1.333	1.062	0.288	-1.197	4.030
Model_RX 450 H	1.6457	1.332	1.235	0.217	-0.966	4.257
Model_RX 450 HYBRID	2.2491	1.332	1.689	0.091	-0.362	4.860
Model_Ractis	-0.6450	0.960	-0.672	0.502	-2.527	1.237
Model_Ramcharger	0.0375	0.552	0.068	0.946	-1.044	1.119
Model_Range Rover	0.7325	0.481	1.524	0.128	-0.210	1.675
Model_Range Rover Evoque	0.2649	0.927	0.286	0.775	-1.553	2.083
Model_Range Rover Evoque 2.0	0.0979	1.268	0.077	0.938	-2.387	2.583
Model_Range Rover Evoque რესტა	0.6708	1.268	0.529	0.597	-1.814	3.156
Model_Range Rover VOGUE	7.664e-08	5.35e-07	0.143	0.886	-9.71e-07	1.12e-06
Model_Range Rover Velar	1.6271	1.267	1.284	0.199	-0.857	4.111
Model_Range Rover Vogue	1.4450	1.268	1.140	0.254	-1.041	3.931
Model_Ranger	-0.7508	1.388	-0.541	0.589	-3.471	1.969
Model_Ranger Wildtrak	7.539e-07	5.6e-07	1.345	0.179	-3.44e-07	1.85e-06
Model_Rasheen	1.5568	1.346	1.157	0.247	-1.081	4.194
Model_Regal	-6.0204	2.034	-2.960	0.003	-10.007	-2.033
Model_Renegade	0.1762	0.703	0.251	0.802	-1.201	1.554
Model_Ridgeline	2.3492	1.378	1.704	0.088	-0.353	5.051
Model_Rodeo	1.1270	1.052	1.072	0.284	-0.935	3.189
Model_Rogue	-0.4333	0.398	-1.087	0.277	-1.214	0.348
Model_Rogue SL	-8.243e-08	5.86e-07	-0.141	0.888	-1.23e-06	1.07e-06
Model_Rogue SPORT	0.5736	1.343	0.427	0.669	-2.060	3.207
Model_Rogue Sport	0.9010	1.343	0.671	0.502	-1.731	3.533
Model_Routan SEL	1.2778	1.350	0.946	0.344	-1.369	3.924

Model_Rx-8	0.7882	1.337	0.589	0.556	-1.833	3.410
Model_S 320	-0.3152	0.739	-0.427	0.670	-1.763	1.133
Model_S 350	1.2079	0.674	1.793	0.073	-0.113	2.528
Model_S 350 CDI 320	2.111e-07	6.33e-07	0.333	0.739	-1.03e-06	1.45e-06
Model_S 350 Longia	-1.2805	1.383	-0.926	0.355	-3.992	1.431
Model_S 350 W2222	0.8367	1.384	0.605	0.545	-1.876	3.549
Model_S 400	0.8357	1.383	0.604	0.546	-1.876	3.547
Model_S 420	1.7536	1.386	1.265	0.206	-0.964	4.471
Model_S 430	-0.5744	0.837	-0.686	0.492	-2.215	1.066
Model_S 430 4.3	1.1159	1.389	0.803	0.422	-1.607	3.839
Model_S 500	0.2623	0.575	0.456	0.648	-0.864	1.389
Model_S 500 67	-0.5635	1.385	-0.407	0.684	-3.279	2.152
Model_S 500 long	-7.161e-07	5.65e-07	-1.268	0.205	-1.82e-06	3.91e-07
Model_S 55 5.5	-2.6281	1.403	-1.874	0.061	-5.378	0.121
Model_S 550	0.6571	0.448	1.468	0.142	-0.220	1.534
Model_S 550 LONG	8.98e-07	5.78e-07	1.553	0.121	-2.36e-07	2.03e-06
Model_S 550 ჰიბრიდი	2.674e-07	5.41e-07	0.494	0.621	-7.93e-07	1.33e-06
Model_S 600	0.1474	1.003	0.147	0.883	-1.818	2.113
Model_S 63 AMG	1.7799	0.837	2.125	0.034	0.138	3.421
Model_S-max	8.716e-08	5.57e-07	0.157	0.876	-1e-06	1.18e-06
Model_S-type	-0.3601	0.935	-0.385	0.700	-2.194	1.473
Model_S3	5.986e-07	6.23e-07	0.960	0.337	-6.23e-07	1.82e-06
Model_S40	0.6309	1.292	0.488	0.625	-1.902	3.164
Model_S6	8.619e-08	5.65e-07	0.152	0.879	-1.02e-06	1.19e-06
Model_S60	0.2211	0.799	0.277	0.782	-1.344	1.787
Model_S70	0.2779	1.290	0.215	0.829	-2.251	2.807
Model_S80	0.9739	1.288	0.756	0.450	-1.551	3.499
Model_SJ 413 Samurai	1.3412	1.308	1.025	0.305	-1.222	3.905
Model_SL 55 AMG	2.0628	1.386	1.489	0.137	-0.653	4.779
Model_SLK 230	-0.1654	1.074	-0.154	0.878	-2.271	1.940
Model_SLK 32 AMG	-2.472e-07	6.16e-07	-0.401	0.688	-1.46e-06	9.61e-07
Model_SLK 350 300	0.1554	1.435	0.108	0.914	-2.657	2.968
Model_SOUL	-0.1102	0.779	-0.142	0.887	-1.637	1.416
Model_SRX	-1.1160	0.798	-1.399	0.162	-2.680	0.448
Model_SX4	-1.1743	0.424	-2.768	0.006	-2.006	-0.343
Model_Sai	-5.0318	1.351	-3.724	0.000	-7.680	-2.383
Model_Sambar	0.9213	1.360	0.677	0.498	-1.745	3.588

Model_Samurai	2.1678	0.949	2.284	0.022	0.307	4.028
Model_Santa FE	0.8208	0.177	4.646	0.000	0.474	1.167
Model_Santa FE Ultimate	0.7898	1.342	0.589	0.556	-1.840	3.419
Model_Santa FE long	2.3138	1.343	1.723	0.085	-0.318	4.946
Model_Santa FE sport	0.9880	0.957	1.032	0.302	-0.888	2.864
Model_Scenic	-0.1483	0.793	-0.187	0.852	-1.703	1.406
Model_Scirocco	-0.8148	0.684	-1.191	0.234	-2.156	0.526
Model_Scorpio	-1.3327	1.350	-0.987	0.324	-3.979	1.314
Model_Sebring	-2.0041	1.572	-1.275	0.202	-5.085	1.077
Model_Seicento fiat 600	-0.3735	1.305	-0.286	0.775	-2.931	2.184
Model_Sentra	-1.0935	0.413	-2.645	0.008	-1.904	-0.283
Model_Sequoia	0.6978	0.970	0.719	0.472	-1.204	2.600
Model_Serena	-0.5551	0.417	-1.331	0.183	-1.372	0.262
Model_Serena Serea	-4.0129	1.359	-2.952	0.003	-6.677	-1.348
Model_Sharan	-0.3699	0.967	-0.383	0.702	-2.265	1.526
Model_Shuttle	0.7484	0.785	0.953	0.340	-0.790	2.287
Model_Sienna	-0.2790	0.448	-0.623	0.533	-1.157	0.599
Model_Sienta	0.4344	0.971	0.447	0.655	-1.469	2.338
Model_Sienta LE	0.2851	1.359	0.210	0.834	-2.378	2.948
Model_Sierra	-1.7959	1.352	-1.329	0.184	-4.445	0.853
Model_Sierra DIZEL	-9.899e-07	5.81e-07	-1.705	0.088	-2.13e-06	1.48e-07
Model_Silverado	-8.876e-07	5.23e-07	-1.697	0.090	-1.91e-06	1.38e-07
Model_Silvia	2.1484	1.349	1.592	0.111	-0.497	4.794
Model_Sintra	0.1848	0.798	0.232	0.817	-1.379	1.748
Model_Sirion	-3.1e-07	4.88e-07	-0.636	0.525	-1.27e-06	6.46e-07
Model_Skyline	-0.1002	0.434	-0.231	0.817	-0.951	0.751
Model_Skyline 4WD	0.6764	1.343	0.504	0.614	-1.956	3.309
Model_Skyline GT250	-0.0213	1.346	-0.016	0.987	-2.660	2.617
Model_Smart	-1.8264	0.746	-2.448	0.014	-3.289	-0.364
Model_Smart Fortwo	3.265e-07	5.79e-07	0.564	0.573	-8.09e-07	1.46e-06
Model_Sonata	-0.3446	0.160	-2.158	0.031	-0.658	-0.032
Model_Sonata 2.0t	-0.1752	1.339	-0.131	0.896	-2.801	2.450
Model_Sonata 2.4L	0.7855	1.341	0.586	0.558	-1.844	3.414
Model_Sonata HYBRID	0.4594	1.341	0.343	0.732	-2.169	3.087
Model_Sonata Hibrid	1.3877	1.340	1.035	0.300	-1.239	4.015
Model_Sonata Hybrid	-0.0343	1.341	-0.026	0.980	-2.662	2.593
Model_Sonata LIMITED	0.6648	0.956	0.695	0.487	-1.209	2.539

Model_Sonata LPG	0.4651	1.341	0.347	0.729	-2.163	3.094
Model_Sonata Limited	0.8991	0.785	1.145	0.252	-0.640	2.438
Model_Sonata S	-4.403e-07	5.38e-07	-0.818	0.413	-1.5e-06	6.15e-07
Model_Sonata SE	-0.6309	1.340	-0.471	0.638	-3.257	1.995
Model_Sonata SE LIMITED	0.6323	1.341	0.471	0.637	-1.996	3.261
Model_Sonata SPORT	-0.3507	0.953	-0.368	0.713	-2.219	1.517
Model_Sonata Sport	0.1895	1.344	0.141	0.888	-2.446	2.825
Model_Sonata blue edition	-3.298e-07	5.76e-07	-0.572	0.567	-1.46e-06	8e-07
Model_Sonata hybrid	-1.5138	0.784	-1.930	0.054	-3.051	0.023
Model_Sonata sport	-0.1380	1.340	-0.103	0.918	-2.764	2.488
Model_Sonata სასწრაფოდ	6.278e-07	5.77e-07	1.088	0.277	-5.04e-07	1.76e-06
Model_Sonic	0.1634	0.783	0.209	0.835	-1.371	1.698
Model_Sonic LT	3.096e-07	5.92e-07	0.523	0.601	-8.52e-07	1.47e-06
Model_Sorento	0.1643	0.404	0.406	0.685	-0.628	0.957
Model_Sorento EX	-8.803e-08	5.08e-07	-0.173	0.863	-1.08e-06	9.09e-07
Model_Sorento SX	1.3886	1.321	1.051	0.293	-1.201	3.978
Model_Space Runner	-2.4118	1.332	-1.811	0.070	-5.022	0.199
Model_Spark	-0.0888	0.304	-0.292	0.770	-0.684	0.507
Model_Sportage	0.1842	0.304	0.607	0.544	-0.411	0.779
Model_Sportage EX	0.2714	1.322	0.205	0.837	-2.321	2.863
Model_Sportage PRESTIGE	0.8511	1.321	0.644	0.520	-1.739	3.441
Model_Sportage SX	4.898e-07	5.67e-07	0.864	0.388	-6.22e-07	1.6e-06
Model_Sprinter	-0.2775	0.430	-0.645	0.519	-1.121	0.566
Model_Sprinter 308 CDI	1.794e-07	5.59e-07	0.321	0.748	-9.16e-07	1.27e-06
Model_Sprinter 311	-0.7662	1.395	-0.549	0.583	-3.500	1.968
Model_Sprinter 313	0.4126	1.036	0.398	0.691	-1.619	2.444
Model_Sprinter 313CDI	-0.3086	1.397	-0.221	0.825	-3.046	2.429
Model_Sprinter 314	-0.4668	1.409	-0.331	0.740	-3.228	2.294
Model_Sprinter 315CDI	-0.4249	1.410	-0.301	0.763	-3.189	2.340
Model_Sprinter 315CDI-XL	8.591e-08	5.99e-07	0.143	0.886	-1.09e-06	1.26e-06
Model_Sprinter 316	-0.8516	1.406	-0.606	0.545	-3.607	1.904
Model_Sprinter 316 CDI	-0.1771	1.408	-0.126	0.900	-2.936	2.582
Model_Sprinter 411	1.3118	1.405	0.934	0.351	-1.442	4.066
Model_Sprinter 516	4.2850	1.446	2.964	0.003	1.451	7.119
Model_Sprinter EURO4	-0.2750	1.411	-0.195	0.845	-3.041	2.491
Model_Sprinter MAX	-0.8245	1.406	-0.586	0.558	-3.581	1.932
Model_Sprinter Maxi-ს Max	-0.7589	1.405	-0.540	0.589	-3.514	1.996

Model_Sprinter VAN	-0.1336	1.394	-0.096	0.924	-2.866	2.599
Model_Sprinter VIP CLASS	-5.1338	1.418	-3.620	0.000	-7.914	-2.354
Model_Sprinter სატვირთო	-6.0750	1.396	-4.351	0.000	-8.812	-3.338
Model_Stella	-0.9153	0.954	-0.960	0.337	-2.785	0.954
Model_Step Wagon	0.1709	0.699	0.244	0.807	-1.200	1.542
Model_Step Wagon Pada	0.4641	1.347	0.345	0.730	-2.176	3.104
Model_Step Wagon RG2 SPADA	0.2943	1.345	0.219	0.827	-2.342	2.931
Model_Stream	-0.0367	0.581	-0.063	0.950	-1.176	1.102
Model_Suburban	2.3170	1.343	1.725	0.084	-0.315	4.949
Model_Superb	0.4459	1.195	0.373	0.709	-1.896	2.788
Model_Swift	0.0095	0.485	0.020	0.984	-0.941	0.960
Model_Swift Sport	0.6960	1.306	0.533	0.594	-1.865	3.257
Model_T3	-0.6903	1.343	-0.514	0.607	-3.322	1.942
Model_T3 0000	-0.3537	1.373	-0.258	0.797	-3.044	2.337
Model_T5	-0.5502	1.351	-0.407	0.684	-3.197	2.097
Model_TERRAIN	1.0178	0.725	1.403	0.160	-0.404	2.439
Model_TL	2.7744	1.267	2.190	0.029	0.292	5.257
Model_TL saber	-0.5101	1.592	-0.320	0.749	-3.631	2.611
Model_TLX	-3.64e-07	5.18e-07	-0.703	0.482	-1.38e-06	6.51e-07
Model_TSX	2.7295	1.263	2.162	0.031	0.254	5.205
Model_TT	0.9945	1.330	0.748	0.455	-1.613	3.602
Model_Tacoma	-0.2036	0.217	-0.936	0.349	-0.630	0.223
Model_Tacoma TRD Off Road	2.1509	1.394	1.543	0.123	-0.581	4.883
Model_Taurus	0.4681	0.396	1.181	0.238	-0.309	1.245
Model_Taurus X	6.83e-07	6.27e-07	1.089	0.276	-5.47e-07	1.91e-06
Model_Taurus interceptor	0.7931	1.350	0.587	0.557	-1.853	3.439
Model_Teana	0.2111	0.468	0.451	0.652	-0.707	1.129
Model_Terios	1.8469	0.694	2.662	0.008	0.487	3.207
Model_Terrano	0.5865	1.347	0.435	0.663	-2.055	3.228
Model_Tigra	-0.4672	1.336	-0.350	0.727	-3.087	2.152
Model_Tiguan	0.1587	0.418	0.379	0.704	-0.661	0.978
Model_Tiguan SE	-1.027e-07	5.08e-07	-0.202	0.840	-1.1e-06	8.92e-07
Model_Tiida	-0.6650	0.239	-2.777	0.005	-1.134	-0.196
Model_Tiida 15 M	7.188e-08	6.01e-07	0.120	0.905	-1.11e-06	1.25e-06
Model_Tiida 2008	0.8845	1.342	0.659	0.510	-1.747	3.516
Model_Tiida AXIS	-5.524e-07	5.55e-07	-0.996	0.319	-1.64e-06	5.35e-07
Model_Tiida Latio	1.0081	1.343	0.751	0.453	-1.624	3.640

Model_Touareg	0.2614	0.482	0.542	0.588	-0.683	1.206
Model_Touran	0.9580	1.349	0.710	0.477	-1.685	3.601
Model_Tourneo Connect	-0.6569	0.645	-1.018	0.308	-1.921	0.607
Model_Town Car	1.9357	0.931	2.080	0.038	0.112	3.760
Model_Town and Country	-2.0890	1.114	-1.875	0.061	-4.273	0.095
Model_Trailblazer	-1.9913	1.338	-1.488	0.137	-4.614	0.631
Model_Transit	-0.0878	0.280	-0.313	0.754	-0.637	0.461
Model_Transit 100LD	0.4620	1.368	0.338	0.736	-2.220	3.144
Model_Transit 135	-0.0188	1.388	-0.014	0.989	-2.739	2.702
Model_Transit 2.4	0.3960	1.370	0.289	0.773	-2.290	3.082
Model_Transit 350T	1.439e-07	5.44e-07	0.264	0.791	-9.23e-07	1.21e-06
Model_Transit CL	0.2954	1.371	0.215	0.829	-2.392	2.983
Model_Transit Connect	-0.5334	0.418	-1.275	0.202	-1.354	0.287
Model_Transit Connect Prastoi	-0.3852	1.359	-0.283	0.777	-3.049	2.278
Model_Transit Connect ბენზინი	-1.5340	1.358	-1.130	0.259	-4.195	1.127
Model_Transit Custom	1.038e-06	5.82e-07	1.785	0.074	-1.02e-07	2.18e-06
Model_Transit Fff	-3.83e-07	5.92e-07	-0.647	0.518	-1.54e-06	7.78e-07
Model_Transit S	0.5849	1.368	0.428	0.669	-2.096	3.266
Model_Transit T330	0.3547	0.992	0.358	0.721	-1.589	2.299
Model_Transit Tourneo	-1.61e-07	5.25e-07	-0.306	0.759	-1.19e-06	8.69e-07
Model_Transit ford	-0.1395	1.357	-0.103	0.918	-2.800	2.521
Model_Transit პერეგაროტკა	-3.4242	1.378	-2.484	0.013	-6.126	-0.723
Model_Transporter	4.754e-07	5.15e-07	0.923	0.356	-5.35e-07	1.49e-06
Model_Traverse	-1.1048	0.618	-1.787	0.074	-2.316	0.107
Model_Trax	0.7936	0.784	1.012	0.312	-0.743	2.330
Model_Tribute	1.591e-07	5.89e-07	0.270	0.787	-9.95e-07	1.31e-06
Model_Tribute სასწრაფოდ	1.3783	1.339	1.029	0.303	-1.247	4.004
Model_Tucson	0.5914	0.179	3.310	0.001	0.241	0.942
Model_Tucson Limited	0.1516	1.341	0.113	0.910	-2.476	2.780
Model_Tucson SE	0.9716	0.685	1.419	0.156	-0.371	2.314
Model_Tucson Se	2.277e-07	4.34e-07	0.524	0.600	-6.23e-07	1.08e-06
Model_Tucson TURBO	0.8686	1.342	0.647	0.518	-1.763	3.500
Model_Tundra	-0.9120	0.319	-2.858	0.004	-1.538	-0.287
Model_Twingo	0.2000	0.950	0.210	0.833	-1.663	2.063
Model_UP	-0.5598	0.503	-1.114	0.265	-1.545	0.425
Model_Urus	1.829e-07	4.94e-07	0.370	0.711	-7.86e-07	1.15e-06
Model_V 230	-0.0698	1.395	-0.050	0.960	-2.805	2.665

Model_V50	0.0210	1.300	0.016	0.987	-2.528	2.570
Model_VOXY	-1.1959	0.431	-2.775	0.006	-2.041	-0.351
Model_VOXY 2003	0.3946	1.358	0.291	0.771	-2.267	3.056
Model_Vaneo	-3.0208	0.847	-3.568	0.000	-4.680	-1.361
Model_Vanette	-0.1101	0.797	-0.138	0.890	-1.672	1.452
Model_Vectra	-0.0399	0.268	-0.149	0.881	-0.564	0.485
Model_Vectra 1.6	0.3037	1.344	0.226	0.821	-2.331	2.939
Model_Vectra B	0.3142	0.532	0.591	0.555	-0.728	1.356
Model_Vectra C	0.0362	1.334	0.027	0.978	-2.580	2.652
Model_Vectra H	-0.4089	1.333	-0.307	0.759	-3.022	2.204
Model_Vectra b	-0.2635	0.785	-0.336	0.737	-1.802	1.275
Model_Vectra c	0.9674	1.341	0.721	0.471	-1.661	3.596
Model_Vectra ƃ	1.3139	1.337	0.983	0.326	-1.306	3.934
Model_VehiCross	2.7250	1.048	2.600	0.009	0.670	4.780
Model_Veloster	-0.3033	0.323	-0.940	0.347	-0.936	0.329
Model_Veloster R-spec	0.0811	1.345	0.060	0.952	-2.556	2.718
Model_Veloster TURBO	1.372e-07	5.22e-07	0.263	0.793	-8.86e-07	1.16e-06
Model_Veloster Turbo	0.0291	1.354	0.022	0.983	-2.625	2.683
Model_Veloster remix	-0.8855	1.351	-0.656	0.512	-3.533	1.762
Model_Vento	-0.1988	0.472	-0.421	0.674	-1.125	0.727
Model_Venza	-0.6343	0.494	-1.284	0.199	-1.603	0.334
Model_Veracruz	1.5296	1.342	1.140	0.255	-1.102	4.161
Model_Verisa	1.2092	0.785	1.541	0.123	-0.329	2.748
Model_Verisa 2007	0.8163	1.330	0.614	0.539	-1.790	3.423
Model_Versa	-0.8253	0.375	-2.201	0.028	-1.560	-0.090
Model_Versa SE	-0.1262	1.342	-0.094	0.925	-2.758	2.505
Model_Versa s	-9.219e-07	5.08e-07	-1.815	0.069	-1.92e-06	7.36e-08
Model_Verso	-0.8661	1.359	-0.637	0.524	-3.530	1.798
Model_Vesta	-0.4698	1.267	-0.371	0.711	-2.954	2.015
Model_Viano	-0.6011	0.585	-1.028	0.304	-1.748	0.545
Model_Viano Ambiente	4.451e-08	5.46e-07	0.082	0.935	-1.03e-06	1.11e-06
Model_Virage	3.509e-07	6.31e-07	0.556	0.578	-8.85e-07	1.59e-06
Model_Vitara	0.4147	0.942	0.440	0.660	-1.431	2.261
Model_Vitara GL+	0.0016	0.946	0.002	0.999	-1.854	1.857
Model_Vito	-0.6014	0.384	-1.566	0.117	-1.354	0.151
Model_Vito 110d	6.193e-08	5.71e-07	0.109	0.914	-1.06e-06	1.18e-06
Model_Vito 111	-0.7503	1.400	-0.536	0.592	-3.495	1.994

Model_Vito 111 CDI	0.5043	1.402	0.360	0.719	-2.244	3.253
Model_Vito 113	2.186e-07	5.07e-07	0.432	0.666	-7.74e-07	1.21e-06
Model_Vito 115	-0.4251	1.392	-0.305	0.760	-3.154	2.303
Model_Vito 115 CDI	-0.2690	1.394	-0.193	0.847	-3.001	2.463
Model_Vito 2.2	-0.7548	1.395	-0.541	0.589	-3.490	1.980
Model_Vito Exstralong	-0.2785	1.396	-0.199	0.842	-3.016	2.459
Model_Vito Extra Long	-0.5238	1.396	-0.375	0.708	-3.260	2.213
Model_Vito Extralong	0.0470	1.394	0.034	0.973	-2.686	2.780
Model_Vito long115	-0.5592	1.396	-0.400	0.689	-3.296	2.178
Model_Vitz	-0.2312	0.244	-0.947	0.344	-0.710	0.247
Model_Vitz RS	0.1201	0.788	0.153	0.879	-1.424	1.664
Model_Vitz funkargo	0.1630	1.356	0.120	0.904	-2.496	2.822
Model_Vitz i.ll	0.5342	1.357	0.394	0.694	-2.126	3.195
Model_Volt	-1.0335	0.219	-4.727	0.000	-1.462	-0.605
Model_Volt Full Packet	-1.624e-07	4.52e-07	-0.359	0.720	-1.05e-06	7.24e-07
Model_Volt PREMIER	0.2037	1.351	0.151	0.880	-2.445	2.852
Model_Volt Premier	-0.5426	1.353	-0.401	0.688	-3.196	2.110
Model_Volt premier	-0.4035	0.976	-0.413	0.679	-2.317	1.510
Model_Vue	2.6196	0.794	3.299	0.001	1.063	4.176
Model_Will Chypa	9.302e-08	4.04e-07	0.231	0.818	-6.98e-07	8.84e-07
Model_Will Vs	-0.7535	1.351	-0.558	0.577	-3.402	1.895
Model_Wingroad	-0.2929	1.355	-0.216	0.829	-2.948	2.363
Model_Wish	1.373e-07	5.54e-07	0.248	0.804	-9.49e-07	1.22e-06
Model_Wizard	-3.483e-07	5.29e-07	-0.659	0.510	-1.38e-06	6.88e-07
Model_Wrangler	1.8635	0.523	3.563	0.000	0.838	2.889
Model_Wrangler ARB	1.5019	1.303	1.153	0.249	-1.052	4.056
Model_Wrangler sport	1.1909	1.299	0.916	0.359	-1.356	3.738
Model_X 250	2.1054	1.424	1.478	0.139	-0.687	4.898
Model_X 250 ევროპული	1.4966	1.425	1.050	0.294	-1.297	4.290
Model_X-Terra	0.2572	0.382	0.674	0.500	-0.491	1.005
Model_X-Trail	1.1047	0.329	3.362	0.001	0.461	1.749
Model_X-Trail NISMO	-8.311e-07	6.71e-07	-1.238	0.216	-2.15e-06	4.85e-07
Model_X-Trail NISSAN X TRAIL R	1.2871	1.343	0.959	0.338	-1.344	3.919
Model_X-Trail X-trail	0.6189	1.344	0.460	0.645	-2.016	3.254
Model_X-Trail gt	0.5294	1.351	0.392	0.695	-2.119	3.178
Model_X-type	0.3745	1.285	0.291	0.771	-2.145	2.894
Model_X1	0.4946	0.695	0.712	0.477	-0.868	1.857

Model_X1 28Xdrive	0.6033	1.459	0.414	0.679	-2.257	3.463
Model_X1 4X4	0.2291	1.459	0.157	0.875	-2.631	3.089
Model_X1 X-Drive	-0.8808	1.460	-0.603	0.546	-3.742	1.981
Model_X3	0.3787	0.781	0.485	0.628	-1.151	1.909
Model_X3 3.5i	1.3606	1.467	0.928	0.354	-1.515	4.236
Model_X3 SDRIVE	-2.95e-07	5.52e-07	-0.535	0.593	-1.38e-06	7.87e-07
Model_X4	0.8929	1.103	0.810	0.418	-1.268	3.054
Model_X5	-0.6379	0.559	-1.140	0.254	-1.734	0.458
Model_X5 3.0	0.2903	1.459	0.199	0.842	-2.570	3.151
Model_X5 3.0i	-3.685e-07	4.04e-07	-0.913	0.361	-1.16e-06	4.23e-07
Model_X5 3.5	0.9594	0.819	1.172	0.241	-0.645	2.564
Model_X5 35d	0.3703	1.105	0.335	0.737	-1.795	2.535
Model_X5 4,4i	-0.0490	1.462	-0.033	0.973	-2.914	2.816
Model_X5 4.8is	1.9795	1.467	1.350	0.177	-0.895	4.854
Model_X5 DIESEL	-7.44e-08	4.09e-07	-0.182	0.855	-8.75e-07	7.26e-07
Model_X5 E70	0.4873	1.105	0.441	0.659	-1.678	2.653
Model_X5 Japan	1.1330	1.463	0.774	0.439	-1.735	4.000
Model_X5 M	0.9000	0.821	1.097	0.273	-0.709	2.509
Model_X5 M packet	0.5157	1.461	0.353	0.724	-2.349	3.380
Model_X5 Sport	0.5597	1.461	0.383	0.702	-2.304	3.424
Model_X5 X-Drive	0.3870	1.463	0.264	0.791	-2.481	3.255
Model_X5 XDRIVE	1.08e-07	3.96e-07	0.272	0.785	-6.69e-07	8.85e-07
Model_X5 XDRIVE 35D	1.4890	1.461	1.019	0.308	-1.374	4.352
Model_X5 e53	0.7679	1.468	0.523	0.601	-2.111	3.646
Model_X5 rest	0.4847	1.461	0.332	0.740	-2.380	3.350
Model_X5 restilling	0.3430	1.467	0.234	0.815	-2.532	3.218
Model_X5 x5	0.3053	1.461	0.209	0.834	-2.558	3.169
Model_X6	0.3858	0.608	0.634	0.526	-0.807	1.578
Model_X6 40D	-2.813e-08	4.12e-07	-0.068	0.946	-8.36e-07	7.79e-07
Model_X6 GERMANY	1.5308	1.462	1.047	0.295	-1.334	4.396
Model_X6 Limited	0.4263	1.459	0.292	0.770	-2.435	3.287
Model_X6 M	1.3225	1.103	1.199	0.231	-0.840	3.485
Model_XC90	0.7118	0.717	0.992	0.321	-0.694	2.118
Model_XC90 2.5turbo	0.3133	1.289	0.243	0.808	-2.214	2.841
Model_XC90 3.2 AWD	0.7684	1.290	0.596	0.551	-1.760	3.297
Model_XE	1.1056	1.279	0.865	0.387	-1.401	3.612
Model_XF	1.0103	0.465	2.175	0.030	0.100	1.921

Model_XJ	0.3601	0.934	0.386	0.700	-1.471	2.191
Model_XK	-0.1222	1.319	-0.093	0.926	-2.708	2.464
Model_XL7	0.2491	0.787	0.316	0.752	-1.294	1.793
Model_XL7 limited	0.7582	1.315	0.577	0.564	-1.819	3.336
Model_XV	-0.7710	0.318	-2.428	0.015	-1.393	-0.149
Model_XV HYBRID	1.3616	1.320	1.032	0.302	-1.225	3.948
Model_XV LIMITED	-0.5112	1.323	-0.386	0.699	-3.105	2.083
Model_YRV	0.0460	1.215	0.038	0.970	-2.335	2.427
Model_Yaris	-0.9139	0.464	-1.970	0.049	-1.823	-0.005
Model_Yaris IA	1.1946	1.351	0.884	0.377	-1.455	3.844
Model_Yaris RS	-0.2220	1.351	-0.164	0.870	-2.870	2.426
Model_Yaris SE	0.1465	1.353	0.108	0.914	-2.506	2.799
Model_Yaris iA	-1.0960	1.350	-0.812	0.417	-3.743	1.551
Model_Yukon	0.2883	1.075	0.268	0.789	-1.819	2.395
Model_Z4	4.829e-08	4.37e-07	0.110	0.912	-8.08e-07	9.05e-07
Model_Z4 3,0 SI	-2.123e-07	4.26e-07	-0.498	0.618	-1.05e-06	6.23e-07
Model_Zafira	0.1711	0.355	0.482	0.630	-0.525	0.867
Model_Zafira B	-0.1853	1.340	-0.138	0.890	-2.811	2.441
Model_i20	-0.9032	1.352	-0.668	0.504	-3.554	1.747
Model_i3	-1.343e-07	2.8e-07	-0.480	0.631	-6.83e-07	4.14e-07
Model_i40	0.6044	1.340	0.451	0.652	-2.022	3.231
Model_iA isti	1.317e-07	2.17e-07	0.608	0.544	-2.93e-07	5.57e-07
Model_kona	-0.1416	1.341	-0.106	0.916	-2.770	2.486
Model_macan	0.8798	0.912	0.965	0.335	-0.908	2.667
Model_macan S	-1.991e-07	4.25e-07	-0.468	0.640	-1.03e-06	6.35e-07
Model_tC	1.3401	0.769	1.743	0.081	-0.167	2.847
Model_xD	1.7817	0.767	2.324	0.020	0.279	3.285
Category_Coupe	-0.4441	0.398	-1.115	0.265	-1.225	0.337
Category_Goods wagon	-0.6758	0.446	-1.515	0.130	-1.550	0.198
Category_Hatchback	-0.6131	0.405	-1.515	0.130	-1.406	0.180
Category_Jeep	-0.6292	0.408	-1.542	0.123	-1.429	0.171
Category_Limousine	1.2092	0.823	1.470	0.142	-0.403	2.822
Category_Microbus	-0.5798	0.480	-1.208	0.227	-1.521	0.361
Category_Minivan	-0.3637	0.433	-0.840	0.401	-1.212	0.485
Category_Pickup	-0.9922	0.523	-1.897	0.058	-2.018	0.033
Category_Sedan	-0.5724	0.402	-1.425	0.154	-1.360	0.215
Category_Universal	-0.1208	0.421	-0.287	0.774	-0.946	0.704

Leather interior_Yes	-0.4766	0.040	-11.780	0.000	-0.556	-0.397
Fuel type_Diesel	0.0838	0.101	0.829	0.407	-0.114	0.282
Fuel type_Hybrid	-0.7438	0.104	-7.125	0.000	-0.948	-0.539
Fuel type_Hydrogen	-0.3580	1.919	-0.187	0.852	-4.119	3.403
Fuel type_LPG	0.0979	0.113	0.869	0.385	-0.123	0.319
Fuel type_Petrol	-0.2402	0.090	-2.658	0.008	-0.417	-0.063
Fuel type_Plug-in Hybrid	1.0323	0.249	4.147	0.000	0.544	1.520
Gear box type_Manual	0.4417	0.078	5.643	0.000	0.288	0.595
Gear box type_Tiptronic	1.1416	0.043	26.739	0.000	1.058	1.225
Gear box type_Variator	0.9465	0.070	13.615	0.000	0.810	1.083
Drive wheels_Front	0.1485	0.066	2.248	0.025	0.019	0.278
Drive wheels_Rear	-0.0045	0.075	-0.060	0.952	-0.152	0.142
Doors_04	-0.0045	0.102	-0.044	0.965	-0.205	0.196
Doors_>5	0.1523	0.192	0.791	0.429	-0.225	0.530
Wheel_Right-hand drive	-0.5564	0.076	-7.287	0.000	-0.706	-0.407
Color_Black	-0.2251	0.158	-1.426	0.154	-0.534	0.084
Color_Blue	-0.2646	0.163	-1.628	0.104	-0.583	0.054
Color_Brown	-0.3205	0.203	-1.576	0.115	-0.719	0.078
Color_Carnelian red	0.0424	0.202	0.210	0.833	-0.353	0.438
Color_Golden	0.1777	0.219	0.812	0.417	-0.251	0.607
Color_Green	-0.2182	0.188	-1.163	0.245	-0.586	0.150
Color_Grey	-0.2195	0.160	-1.373	0.170	-0.533	0.094
Color_Orange	-0.3038	0.196	-1.552	0.121	-0.687	0.080
Color_Pink	-0.0528	0.364	-0.145	0.885	-0.767	0.661
Color_Purple	-0.7519	0.338	-2.226	0.026	-1.414	-0.090
Color_Red	-0.2812	0.171	-1.649	0.099	-0.615	0.053
Color_Silver	-0.2306	0.158	-1.457	0.145	-0.541	0.080
Color_Sky blue	0.1400	0.223	0.628	0.530	-0.297	0.577
Color_White	-0.2956	0.158	-1.871	0.061	-0.605	0.014
Color_Yellow	-0.0814	0.232	-0.351	0.725	-0.536	0.373

Omnibus:	3474.384	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	11844.097
Skew:	-1.287	**Prob(JB):**	0.00
Kurtosis:	6.806	**Cond. No.**	4.25e+24

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.98e-30. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Understanding the summary:

1. **Durbin-Watson** : The Durbin-Watson statistic will always have a value between 0 and 4. A value of 2.0 means that there is no autocorrelation detected in the sample. Values from 0 to less than 2 indicate positive autocorrelation and values from from 2 to 4 indicate negative autocorrelation.

1. **Jarque-Bera** : In statistics, the Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The test is named after Carlos Jarque and Anil K. Bera. The test statistic is always nonnegative. If it is far from zero, it signals the data do not have a normal distribution.

1. **Prob (F-statistic)**: This tells the overall significance of the regression. This is to assess the significance level of all the variables together unlike the t-statistic that measures it for individual variables. The null hypothesis under this is “all the regression coefficients are equal to zero”. Prob(F-statistics) depicts the probability of null hypothesis being true. As per the above results, probability is zero. This implies that overall the regressions is meaningful.

1. **R-Squared**: This value tells us about how much variability of the data points can be explained by the best fit line.

1. **Adj. R-Squared** : This is the modified version of R-squared which increases only when a meaningful feature is added to the model.

1. **AIC/BIC** : During model building some informations are lost. AIC/BIC is the penalty given to the model for losing the information.The value of AIC/BIC should be low.AIC stands for Akaike’s Information Criteria and BIC stands for Bayesian information criteria.

In [313…

```
#all the independent features having p-values less than 0.05 has been selected
X1=df_final[['ID', 'Levy', 'Prod. year','Mileage', 'Airbags','Manufacturer_ALFA ROME
             'Manufacturer_BMW','Manufacturer_BUICK','Manufacturer_CADILLAC','Manufa
             'Manufacturer_CITROEN','Manufacturer_DAEWOO','Manufacturer_DAIHATSU','M
             'Manufacturer_FIAT','Manufacturer_FORD','Manufacturer_GAZ','Manufacture
             'Manufacturer_HUMMER','Manufacturer_HYUNDAI','Manufacturer_INFINITI','M
             'Manufacturer_KIA','Manufacturer_LANCIA','Manufacturer_LAND ROVER','Man
             'Manufacturer_MITSUBISHI','Manufacturer_MOSKVICH','Manufacturer_NISSAN'
             'Manufacturer_PORSCHE','Manufacturer_RENAULT','Manufacturer_ROLLS-ROYCE
             'Manufacturer_SEAT','Manufacturer_SKODA','Manufacturer_SSANGYONG','Manu
             'Manufacturer_VOLKSWAGEN','Manufacturer_VOLVO','Manufacturer_ZAZ','Manu
             'Model_230 W153','Model_3110','Model_400','Model_535 M','Model_540 I','
             'Model_A4','Model_A6','Model_A7','Model_A7 Prestige','Model_Acadia','Mo
             'Model_Avalon','Model_Avella','Model_Avenger','Model_B9 Tribeca','Model
             'Model_C30','Model_CC','Model_CHR','Model_CLK 230','Model_CRX','Model_C
             'Model_Camry','Model_Captiva','Model_Century','Model_Colorado','Model_C
             'Model_Corolla 140','Model_Delica','Model_E 300','Model_E 350','Model_E
             'Model_Explorer','Model_F-type R','Model_F150','Model_F50','Model_FIT',
             'Model_G6','Model_GLA 250','Model_GLE 450','Model_GX 460','Model_GX 470
             'Model_H1','Model_H2','Model_HS 250h','Model_IS 200','Model_IX35','Mode
             'Model_Korando','Model_Lacetti','Model_Land Cruiser','Model_Land Cruise
             'Model_Mustang','Model_Navigator','Model_Note','Model_Orlando','Model_P
             'Model_REXTON','Model_RIO','Model_RX 350','Model_RX 400 HYBRID','Model_
             'Model_Santa FE','Model_Serena Serea','Model_Smart','Model_Sprinter VIP
             'Model_Terios','Model_Tiida','Model_Town Car','Model_Tundra','Model_VOX
```

```
                'Model_Volt','Model_Vue','Model_Wrangler','Model_X-Trail','Model_XF','M
                'Fuel type_Plug-in Hybrid','Gear box type_Manual','Gear box type_Tiptro
                'Drive wheels_Front','Wheel_Right-hand drive','Color_Purple']]
```

In [314…

```
# splitting the dataset into train and test data
X1_train,X1_test,y1_train,y1_test=train_test_split(X1,Y,test_size=0.2,random_state=3
```

In [315…

```
# instantiating the ridge regressor
ridge=Ridge()

#Defining the parameters that needs to be chosen
#These values of alpha have been chosen so that we can easily analyze the trend with
# These would however differ from case to case.
parameters={'alpha':[1e-15, 1e-10, 1e-8, 1e-3, 1e-2, 1, 5, 10, 20, 30, 35, 40, 45, 5
            'solver' : ['auto', 'svd', 'cholesky', 'lsqr', 'sparse_cg', 'sag', 'saga
            'normalize':[True,False]
            }

#using 'GridSearchCV' to find the best parameters
ridge_regressor=GridSearchCV(ridge,parameters,scoring='r2',cv=5)

#fitting the model
ridge_regressor.fit(X1_train,y1_train)

#Shows the best value of alpha that fits model
print(ridge_regressor.best_params_)
```

```
{'alpha': 1, 'normalize': False, 'solver': 'auto'}
```

In [317…

```
#instantiating the ridge regressor with best parameters
model2=Ridge(alpha=1, normalize=False, solver='auto')

# use fit() to fit the model on train data
model2.fit(X1_train,y1_train)
```

Out[317… Ridge(alpha=1)

In [318…

```
#predict the price of cars using the 'predict()'
p=model2.predict(X1_test)
```

In [319…

```
# calculating rmse value
rmse=rmse(p,y1_test)

#calculating the rmsle value
rmsle=np.sqrt(mean_squared_log_error(p,y1_test))

#calculating the mean absolute error value

mae=mean_absolute_error(p,y1_test)
```

In [320…

```
# compile the required information
linreg_model2 = pd.Series({'Model': "Ridge Regression with feature selection using p
                    'RMSE':rmse,
                    'RMSLE': rmsle,
                    'Mean Absolute Error': mae
                  })
```

```
# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_model2, ignore_index = True)

# print the result table
result_tabulation
```

Out[320...

	Model	RMSE	RMSLE	Mean Absolute Error
0	Linear Regression	1.327445	0.164084	0.929873
1	Ridge Regression with feature selection using ...	1.377463	0.170885	0.965346

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12.Model 3(Linear Regression with feature selection technique)

Random forest which is a bagging process is used to find the most important features to train the model.

Bagging: It is a parallel process which helps in removing the variance in the model.By default it use 100 decision trees(weak models) to find the strong model.

Here as the number of features are very high i.e. 1699 random forest has been used to find the best features.

To know more about Random Forest click here

In [321...

```
#instantiating randomforest
rf=RandomForestRegressor()

#fitting the training data
rf.fit(X_train,y_train)
```

Out[321...

```
RandomForestRegressor()
```

In [322...

```
#Creating a panda series containing the features and their importances
best_features=pd.Series(rf.feature_importances_,index=X_train.columns)
```

In [323...

```
#selecting the top 30 features
#It is a hyperparameter and any number of features can be selected using the functio
best_features.nlargest(30).index
```

Out[323...

```
Index(['Airbags', 'ID', 'Mileage', 'Prod. year', 'Gear box type_Tiptronic',
       'Levy', 'Engine volume', 'Leather interior_Yes', 'Model_FIT',
       'Fuel type_Hybrid', 'Category_Jeep', 'Color_White', 'Color_Black',
       'Drive wheels_Front', 'Color_Silver', 'Color_Grey',
       'Manufacturer_TOYOTA', 'Manufacturer_LEXUS', 'Category_Sedan',
       'Fuel type_Petrol', 'Model_Prius', 'Drive wheels_Rear',
       'Fuel type_Diesel', 'Manufacturer_MERCEDES-BENZ',
       'Gear box type_Variator', 'Color_Blue', 'Category_Hatchback',
       'Model_Prius C', 'Model_Highlander', 'Model_Jetta'],
      dtype='object')
```

In [324...

```
# Creating a dataframe containing the most significant independent features
```

```python
X3=df_final[['Airbags', 'ID', 'Mileage', 'Prod. year', 'Gear box type_Tiptronic',
       'Levy', 'Engine volume', 'Leather interior_Yes', 'Model_FIT',
       'Fuel type_Hybrid', 'Category_Jeep', 'Color_White',
       'Drive wheels_Front', 'Color_Grey', 'Color_Black', 'Color_Silver',
       'Manufacturer_TOYOTA', 'Manufacturer_LEXUS', 'Category_Sedan',
       'Fuel type_Petrol', 'Model_Prius', 'Drive wheels_Rear',
       'Fuel type_Diesel', 'Color_Blue', 'Manufacturer_MERCEDES-BENZ',
       'Category_Hatchback', 'Gear box type_Variator', 'Model_Note',
       'Model_Highlander', 'Model_Prius C']]
```

In [325…

```python
# splitting the data for training and testing the data
# train_test_split from sklearn is used for splitting the data
X3_train,X3_test,y3_train,y3_test=train_test_split(X3,Y,test_size=0.3,random_state=3
```

In [326…

```python
model3=LinearRegression()
model3.fit(X3_train,y3_train)
```

Out[326… LinearRegression()

In [327…

```python
#predict the price of cars using the 'predict()'
p1=model3.predict(X3_test)
```

In [329…

```python
# calculating rmse value
# rms=rmse(p1,y3_test)

#calculating the rmsle value
rmsle=np.sqrt(mean_squared_log_error(p1,y3_test))

#calculating the mean absolute error value

mae=mean_absolute_error(p1,y3_test)
```

In [330…

```python
# compile the required information
linreg_model3 = pd.Series({'Model': "Linear regression with feature selection",
                     'RMSE':'-',
                     'RMSLE': rmsle,
                     'Mean Absolute Error': mae
                    })

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_model3, ignore_index = True)

# print the result table
result_tabulation
```

Out[330…

	Model	RMSE	RMSLE	Mean Absolute Error
0	Linear Regression	1.327445	0.164084	0.929873
1	Ridge Regression with feature selection using ...	1.377463	0.170885	0.965346
2	Linear regression with feature selection	-	0.174933	1.024518

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13.Model 4(Ridge regression with hyperparameter tuning and feature selection)

In [331…

```
# instantiating the ridge regressor
ridge=Ridge()

#Defining the parameters that needs to be chosen
#These values of alpha have been chosen so that we can easily analyze the trend with
parameters={'alpha':[1e-15, 1e-10, 1e-8, 1e-3, 1e-2, 1, 5, 10, 20, 30, 35, 40, 45, 5
            'solver' : ['auto', 'svd', 'cholesky', 'lsqr', 'sparse_cg', 'sag', 'saga
            'normalize':[True,False]
            }

#using 'GridSearchCV' to find the best parameters
ridge_regressor=GridSearchCV(ridge,parameters,scoring='r2',cv=5)

#fitting the model
ridge_regressor.fit(X3_train,y3_train)

#Shows the best value of alpha that fits model
print(ridge_regressor.best_params_)
```

```
{'alpha': 10, 'normalize': False, 'solver': 'svd'}
```

In [332…

```
#instantiating the ridge regressor with best parameters
model4=Ridge(alpha=10, normalize=False, solver='svd')

# use fit() to fit the model on train data
model4.fit(X3_train,y3_train)
```

Out[332…

```
Ridge(alpha=10, solver='svd')
```

In [333…

```
#predict the price of cars using the 'predict()'
p2=model4.predict(X3_test)
```

In [335…

```
# calculating rmse value
# rmse=rmse(p2,y3_test)

#calculating the rmsle value
rmsle=np.sqrt(mean_squared_log_error(p2,y3_test))

#calculating the mean absolute error value

mae=mean_absolute_error(p2,y3_test)
```

In [336…

```
# compile the required information
linreg_model4 = pd.Series({'Model': "Ridge Regression with hyperparameter tuning and
                   'RMSE':'-',
                   'RMSLE': rmsle,
                   'Mean Absolute Error': mae
                 })

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_model4, ignore_index = True)
```

```python
# print the result table
result_tabulation
```

Out[336...

	Model	RMSE	RMSLE	Mean Absolute Error
0	Linear Regression	1.327445	0.164084	0.929873
1	Ridge Regression with feature selection using ...	1.377463	0.170885	0.965346
2	Linear regression with feature selection	-	0.174933	1.024518
3	Ridge Regression with hyperparameter tuning an...	-	0.175019	1.023970

14.Conclusion

Out of the four models built, metrics of Linear regression looks better than the other three models as the losses are less. But as per the test data we should consider the second model i.e. ridge regression with hyperparameter tuning and feature selection as it will reduce the variance.Hece model 2 will work better on testing data.

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