PHASE THREE PROJECT

Myrajoy Kiganane

1. Project Overview

This project focuses on exploratory data analysis to uncover critical insights that will guide the strategy of a newly launched international auto dealership. By analyzing the 1985 Auto Imports dataset, the goal is to identify key car features that influence market pricing, insurance risk, and normalized annual losses. These insights will help the dealership make data-informed decisions about which types of imported cars to stock—balancing affordability, safety, and customer appeal. This analysis provides the dealership with a clear picture of what features contribute to a vehicle's marketability and insurability, ultimately improving decision-making around car selection and customer targeting.

1.1 Business Understanding

1.1.1 Business Problem

A new international car dealership wants to enter the market with a line of imported vehicles but is unsure what combination of features and specifications will lead to competitive pricing and low insurance risk ratings. They've tasked our team with exploring the 1985 Auto Imports dataset to uncover which car features most influence:

- The market price of imported vehicles
- The assigned insurance risk rating
- The normalized annual loss

By analyzing these patterns, we must translate our findings into actionable recommendations to guide the dealership's purchasing and marketing strategy.

1.1.2 Key Business Questions

- Which car brands have the highest average market price?
- Which car body types receive the highest insurance risk ratings ?
- What impact do engine size and horsepower have on the price of a car?
- How does fuel type influence the normalized annual losses and insurance risk of vehicles?
- How does drive-wheel configuration (FWD, RWD, 4WD) affect the average price and insurance rating of cars?

2. Data Understanding

2.1 Data Preprocessing

2.1.1 The Data

To ensure a comprehensive analysis of the business problem, we retrieved data from Kaggle (https://www.kaggle.com/datasets/sumaya23abdul/automobile-database?resource=download). The dataset, titled "Automobile Database", consists of detailed specifications and insurance-related information for various imported cars from the year 1985. The dataset includes attributes such as car make, fuel type, body style, engine size, horsepower, price, insurance risk rating (symboling), and normalized losses. For this project, we will focus on key columns including make, body-style, fuel-type, engine-size, horsepower, price, symboling, and normalized-losses. These variables will help us explore how different vehicle features affect market value and insurance risk, and identify which combinations are most favorable for dealership decisions. The dataset allows us to perform in-depth exploratory data analysis to uncover patterns that can guide effective automotive inventory and pricing strategies.

2.1.2. Data Preparation

This entails;

- Importing necessary libraries
- Loading and Accessing of the dataset
- Data Cleaning and preparation which involves: Accessing necessary data for analysis,
- Handling missing values and Standardizing columns.

2.1.2.1. Importing necessary libraries

```
# importing necessary libraries
import itertools
import numpy as np
import pandas as pd
from numbers import Number
import sqlite3
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
sns.set_style('whitegrid')
import pickle
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import mean_squared_error, r2_score
```

```
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split
from sklearn.multiclass import OneVsRestClassifier
from sklearn.preprocessing import label_binarize
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, roc_curve, auc, RocCurveDisplay
from sklearn.tree import plot_tree
from sklearn.linear_model import Ridge
```

2.1.2.2 Load the Data into a DataFrame Called Automobile_data

The file path is Automobile_data.csv.Pandas (documentation here) is used to read in the data from this CSV file and create a dataframe named Automoblie_data.

```
#Loading the Data into a DataFrame Called Automobile_data
Automoblie_data = pd.read_csv('Automobile_data.csv')
Automoblie_data.head()
```

```
   symboling normalized-losses         make fuel-type aspiration num-
of-doors  \
0          3                 ?  alfa-romero       gas        std
two
1          3                 ?  alfa-romero       gas        std
two
2          1                 ?  alfa-romero       gas        std
two
3          2               164         audi       gas        std
four
4          2               164         audi       gas        std
four

    body-style drive-wheels engine-location  wheel-base  ...  engine-
size  \
0  convertible          rwd           front        88.6  ...
130
1  convertible          rwd           front        88.6  ...
130
2    hatchback          rwd           front        94.5  ...
152
3        sedan          fwd           front        99.8  ...
109
4        sedan          4wd           front        99.4  ...
136

   fuel-system  bore  stroke compression-ratio horsepower  peak-rpm
city-mpg  \
0         mpfi  3.47    2.68               9.0        111      5000
21
1         mpfi  3.47    2.68               9.0        111      5000
```

```
21
2          mpfi  2.68    3.47               9.0        154      5000
19
3          mpfi  3.19     3.4              10.0        102      5500
24
4          mpfi  3.19     3.4               8.0        115      5500
18

  highway-mpg  price
0          27  13495
1          27  16500
2          26  16500
3          30  13950
4          22  17450

[5 rows x 26 columns]
```

Access the column names of the dataset so as to determine which one will be the Target column (y) and which one will be the features (x) columns

```
print(Automoblie_data.columns)

Index(['symboling', 'normalized-losses', 'make', 'fuel-type',
'aspiration',
       'num-of-doors', 'body-style', 'drive-wheels', 'engine-
location',
       'wheel-base', 'length', 'width', 'height', 'curb-weight',
'engine-type',
       'num-of-cylinders', 'engine-size', 'fuel-system', 'bore',
'stroke',
       'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg',
       'highway-mpg', 'price'],
      dtype='object')
```

2.1.2.3 Data Preprocessing

Data preprocessing is the essential step of cleaning and transforming raw data before feeding it into a machine learning model or analysis. It ensures your data is in the best shape for accurate and reliable results.

```
# Preprocessing
# Drop rows with missing values
df = Automoblie_data.dropna()
# Display sample
print(df.head())

   symboling normalized-losses         make fuel-type aspiration num-
of-doors  \
0          3                 ?  alfa-romero       gas        std
```

```
two
1          3                  ?  alfa-romero      gas        std
two
2          1                  ?  alfa-romero      gas        std
two
3          2                164         audi      gas        std
four
4          2                164         audi      gas        std
four

    body-style drive-wheels engine-location  wheel-base  ...  engine-
size  \
0  convertible          rwd           front        88.6  ...
130
1  convertible          rwd           front        88.6  ...
130
2    hatchback          rwd           front        94.5  ...
152
3        sedan          fwd           front        99.8  ...
109
4        sedan          4wd           front        99.4  ...
136

   fuel-system  bore  stroke compression-ratio horsepower  peak-rpm
city-mpg  \
0         mpfi  3.47    2.68               9.0        111      5000
21
1         mpfi  3.47    2.68               9.0        111      5000
21
2         mpfi  2.68    3.47               9.0        154      5000
19
3         mpfi  3.19     3.4              10.0        102      5500
24
4         mpfi  3.19     3.4               8.0        115      5500
18

  highway-mpg  price
0          27  13495
1          27  16500
2          26  16500
3          30  13950
4          22  17450

[5 rows x 26 columns]

# Display general info about the dataset
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
```

```
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   symboling          205 non-null    int64  
 1   normalized-losses  205 non-null    object 
 2   make               205 non-null    object 
 3   fuel-type          205 non-null    object 
 4   aspiration         205 non-null    object 
 5   num-of-doors       205 non-null    object 
 6   body-style         205 non-null    object 
 7   drive-wheels       205 non-null    object 
 8   engine-location    205 non-null    object 
 9   wheel-base         205 non-null    float64
 10  length             205 non-null    float64
 11  width              205 non-null    float64
 12  height             205 non-null    float64
 13  curb-weight        205 non-null    int64  
 14  engine-type        205 non-null    object 
 15  num-of-cylinders   205 non-null    object 
 16  engine-size        205 non-null    int64  
 17  fuel-system        205 non-null    object 
 18  bore               205 non-null    object 
 19  stroke             205 non-null    object 
 20  compression-ratio  205 non-null    float64
 21  horsepower         205 non-null    object 
 22  peak-rpm           205 non-null    object 
 23  city-mpg           205 non-null    int64  
 24  highway-mpg        205 non-null    int64  
 25  price              205 non-null    object 
dtypes: float64(5), int64(5), object(16)
memory usage: 41.8+ KB
```

```python
# Replace "?" with NaN
df.replace("?", np.nan, inplace=True)

#Convert numeric columns stored as objects to float
numeric_cols = ['normalized-losses', 'bore', 'stroke', 'horsepower', 
'peak-rpm', 'price']
for col in numeric_cols:
    df[col] = pd.to_numeric(df[col], errors='coerce')

df.isnull().sum()
```

```
symboling             0
normalized-losses    41
make                  0
fuel-type             0
aspiration            0
num-of-doors          2
body-style            0
```

```
drive-wheels          0
engine-location       0
wheel-base            0
length                0
width                 0
height                0
curb-weight           0
engine-type           0
num-of-cylinders      0
engine-size           0
fuel-system           0
bore                  4
stroke                4
compression-ratio     0
horsepower            2
peak-rpm              2
city-mpg              0
highway-mpg           0
price                 4
dtype: int64

#Drop rows with missing target (price)
df.dropna(subset=['price'], inplace=True)

#Fill missing numeric values with column mean
for col in ['normalized-losses', 'bore', 'stroke', 'horsepower',
'peak-rpm']:
    df[col].fillna(df[col].astype(float).mean(), inplace=True)

# Fill missing categorical values (e.g., num-of-doors) with mode
df['num-of-doors'].fillna(df['num-of-doors'].mode()[0], inplace=True)

# Get categorical columns (object type) excluding 'price'
categorical_cols = [col for col in
df.select_dtypes(include='object').columns if col != 'price']

# Apply one-hot encoding
df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)

# Feature-target split
X = df.drop('price', axis=1)
y = df['price']

# import standard scaler
from sklearn.preprocessing import StandardScaler

# Feature scaling (normalize numeric features)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```python
# Train-test split (for model training later)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=42)

#display the split
print(X_test.shape, y_test.shape)
print(X_train.shape, y_train.shape)
```

```
(41, 64) (41,)
(160, 64) (160,)
```

2.2 Data Modelling

Modeling is the process of using algorithms to uncover patterns in data and make predictions. It starts with a simple baseline model and evolves through more complex models, each built with a clear purpose like improving accuracy or better fitting the data. The aim is to find the best model to solve a real-world problem effectivel

2.2.1 Baseline Model (Mean Prediction)

```python
from sklearn.linear_model import LinearRegression

# Initialize the model
lin_reg = LinearRegression()

# Train the model
lin_reg.fit(X_train, y_train)

# Predict on the test set
y_pred_lr = lin_reg.predict(X_test)

# Evaluate baseline model
baseline_mae = mean_absolute_error(y_test, y_pred_lr)
baseline_mse = mean_squared_error(y_test, y_pred_lr)
baseline_r2= r2_score(y_test, y_pred_lr)

print(f"Baseline Model MAE: ${baseline_mae:.2f}")
print(f"Baseline Model MSE: {baseline_mse:,.2f}")
print(f"Baseline Model R² Score: {baseline_r2:.2f}")
```

```
Baseline Model MAE: $2057.09
Baseline Model MSE: 11,096,246.05
Baseline Model R² Score: 0.91
```

```python
# interpreting the results
print(f"This means that on average, the baseline model’s predictions
are off by about ${baseline_mae:,.2f} from the actual car prices in
the test set.")
print("The Mean Squared Error is large, confirming that predicting the
```

```
mean does not fit the data well.")
print(f"Baseline Model R² Score: {baseline_r2:.2f}. This means that
91% of the variance in the target variable is explained by the model")

print("Hence model you build should aim to reduce the MAE below this
level to be considered better than just predicting the mean.")
```

```
This means that on average, the baseline model’s predictions are off
by about $2,057.09 from the actual car prices in the test set.
The Mean Squared Error is large, confirming that predicting the mean
does not fit the data well.
Baseline Model R² Score: 0.91. This means that 91% of the variance in
the target variable is explained by the model
Hence model you build should aim to reduce the MAE below this level to
be considered better than just predicting the mean.
```

2.2.2 Decision Tree Regressor

```
from sklearn.tree import DecisionTreeRegressor
import statsmodels.api as sm

# Fit Decision Tree Regressor model
dt = DecisionTreeRegressor(criterion='squared_error', random_state=42)
dt.fit(X_train, y_train)

# Predict on test data
y_pred_dt = dt.predict(X_test)

# Initialize and fit a baseline OLS model (using X_train and y_train
for fitting)
base_model = sm.OLS(y_train, sm.add_constant(X_train))  # Ensure you
use y_train and X_train
base_results = base_model.fit()

#printing the results for the regression model
print(base_results.summary())
```

```
                            OLS Regression Results                            

==============================================================================
========
Dep. Variable:                  price   R-squared:                       
0.969
Model:                            OLS   Adj. R-squared:                  
0.951
Method:                 Least Squares   F-statistic:                     
53.81
Date:                Sun, 11 May 2025   Prob (F-statistic):           
1.48e-55
Time:                        07:34:09   Log-Likelihood:                 
```

```
-1358.8
No. Observations:                 160   AIC:
2838.
Df Residuals:                     100   BIC:
3022.
Df Model:                          59

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
const      1.315e+04    127.303    103.281      0.000    1.29e+04
1.34e+04
x1         -159.6822    338.968     -0.471      0.639    -832.186
512.821
x2         -122.2268    241.697     -0.506      0.614    -601.746
357.292
x3         1196.0144    569.658      2.100      0.038      65.830
2326.199
x4        -1338.3369    612.062     -2.187      0.031   -2552.650
-124.024
x5         1078.5755    476.248      2.265      0.026     133.714
2023.437
x6         -638.2288    350.877     -1.819      0.072   -1334.359
57.901
x7         3455.0297    887.043      3.895      0.000    1695.161
5214.899
x8          816.4031   1200.534      0.680      0.498   -1565.422
3198.228
x9         -461.7719    479.901     -0.962      0.338   -1413.882
490.338
x10        -165.7037    288.595     -0.574      0.567    -738.268
406.861
x11       -2632.7118   1948.941     -1.351      0.180   -6499.355
1233.931
x12        -111.7408    859.292     -0.130      0.897   -1816.551
1593.069
x13         467.5892    309.505      1.511      0.134    -146.461
1081.639
x14        -461.9694    838.122     -0.551      0.583   -2124.779
1200.840
x15         761.2591    723.916      1.052      0.296    -674.970
2197.488
x16         604.3681    457.104      1.322      0.189    -302.514
1511.250
```

```
x17          1137.1803     474.916      2.394      0.019     194.961
2079.400
x18          -323.9011     295.339     -1.097      0.275    -909.844
262.042
x19          -675.6426     387.569     -1.743      0.084   -1444.569
93.284
x20            23.8729     514.620      0.046      0.963    -997.118
1044.864
x21          -400.6821     225.008     -1.781      0.078    -847.091
45.727
x22           408.6707     374.406      1.092      0.278    -334.141
1151.482
x23          -148.4518     483.406     -0.307      0.759   -1107.515
810.611
x24           420.0141     586.916      0.716      0.476    -744.410
1584.438
x25          -152.6299     197.715     -0.772      0.442    -544.891
239.631
x26          -673.9779     500.314     -1.347      0.181   -1666.587
318.631
x27          -211.1782     501.436     -0.421      0.675   -1206.013
783.656
x28          -409.1632     277.575     -1.474      0.144    -959.864
141.538
x29          -591.3101     344.237     -1.718      0.089   -1274.267
91.646
x30           800.2953     405.274      1.975      0.051      -3.756
1604.347
x31          -151.8242     213.949     -0.710      0.480    -576.292
272.644
x32           484.8990     373.492      1.298      0.197    -256.099
1225.897
x33          -388.4083     280.730     -1.384      0.170    -945.369
168.553
x34          -867.3293     581.182     -1.492      0.139   -2020.377
285.719
x35          -140.6466     455.758     -0.309      0.758   -1044.857
763.564
x36          -201.7199     500.161     -0.403      0.688   -1194.025
790.586
x37         -1551.6018     968.154     -1.603      0.112   -3472.391
369.188
x38           632.7724     305.201      2.073      0.041      27.263
1238.282
x39          -341.9439     259.102     -1.320      0.190    -855.996
172.108
x40          -555.9270     301.163     -1.846      0.068   -1153.426
41.572
x41         -1568.3839     543.153     -2.888      0.005   -2645.984
```

```
-490.784
x42        -1594.7813    614.860     -2.594      0.011   -2814.647
-374.916
x43        -1262.8702    429.545     -2.940      0.004   -2115.074
-410.666
x44          171.4652    471.129      0.364      0.717    -763.242
1106.172
x45         1183.5741    618.165      1.915      0.058     -42.847
2409.995
x46         1215.0301    323.767      3.753      0.000     572.686
1857.374
x47         -573.6909    247.242     -2.320      0.022   -1064.211
-83.170
x48          209.9013    555.696      0.378      0.706    -892.584
1312.387
x49          210.4390    215.590      0.976      0.331    -217.285
638.163
x50         -340.7180    294.403     -1.157      0.250    -924.805
243.369
x51         -726.9852    234.492     -3.100      0.003   -1192.211
-261.759
x52        -3617.7839    792.263     -4.566      0.000   -5189.612    -
2045.956
x53        -6394.7003   1829.669     -3.495      0.001      -1e+04    -
2764.688
x54        -4620.0622   1175.226     -3.931      0.000   -6951.677    -
2288.448
x55         -609.2198    349.937     -1.741      0.085   -1303.484
85.045
x56         -572.9605    406.197     -1.411      0.161   -1378.843
232.923
x57         -726.9852    234.492     -3.100      0.003   -1192.211
-261.759
x58         1011.0957    623.170      1.623      0.108    -225.257
2247.448
x59         -297.8610    269.151     -1.107      0.271    -831.849
236.127
x60         1551.6018    968.154      1.603      0.112    -369.188
3472.391
x61          147.4067    173.933      0.847      0.399    -197.672
492.485
x62          969.6115    709.824      1.366      0.175    -438.659
2377.882
x63          242.4965    380.777      0.637      0.526    -512.954
997.947
x64          194.4362    196.085      0.992      0.324    -194.590
583.463
======================================================================
========
```

```
Omnibus:                          1.903   Durbin-Watson:
2.032
Prob(Omnibus):                    0.386   Jarque-Bera (JB):
1.633
Skew:                             0.023   Prob(JB):
0.442
Kurtosis:                         3.493   Cond. No.
1.41e+16
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 8.07e-30. This might indicate that
there are
strong multicollinearity problems or that the design matrix is
singular.
```

```
# Calculate evaluation metrics for Decision Tree Regressor
mae_dt = mean_absolute_error(y_test, y_pred_dt)
mse_dt = mean_squared_error(y_test, y_pred_dt)
r2_dt = r2_score(y_test, y_pred_dt)

# Print the results
print("Decision Tree Regressor:")
print(f"Baseline Model MAE: ${mae_dt:.2f}")
print(f"Baseline Model MSE: {mse_dt:.2f}")
print(f"Baseline Model R² Score: {r2_dt:.2f}")
```

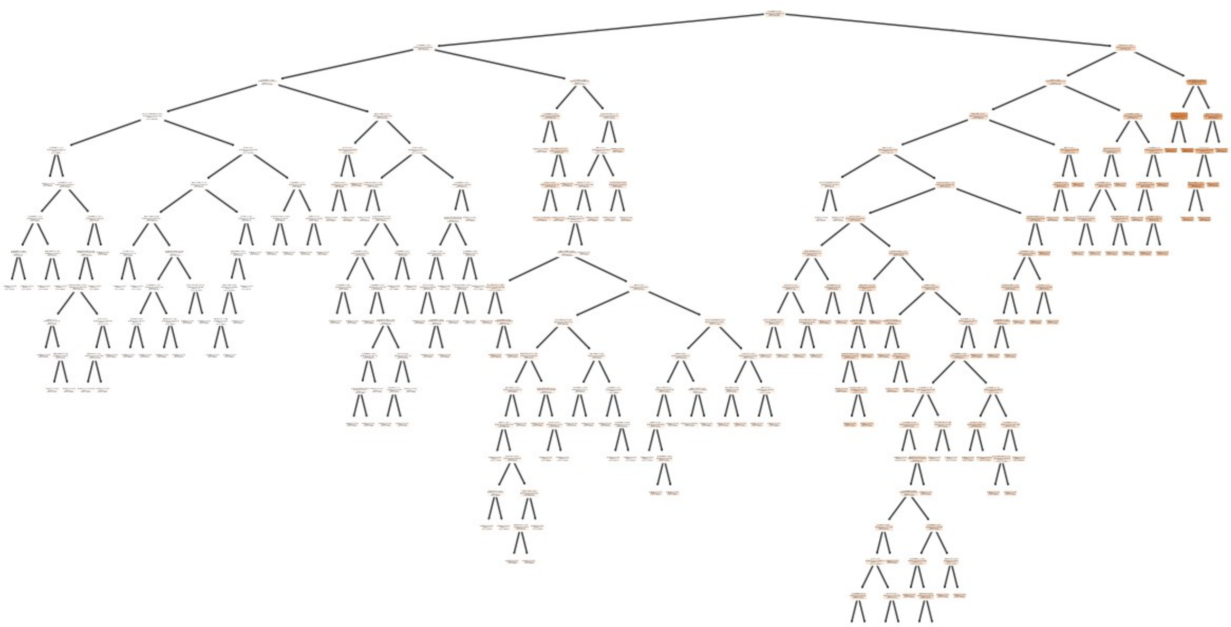
```
Decision Tree Regressor:
Baseline Model MAE: $1777.68
Baseline Model MSE: 6623956.02
Baseline Model R² Score: 0.95
```

```
#interpreting results
print(f"Compared to the baseline MAE of ${baseline_mae:,.2f}, the
Decision Tree model reduces the average prediction error by over $
{baseline_mae - mae_dt:,.2f}.")
print(f"There is a significant improvement from the baseline MSE of
{baseline_mse:,.2f}, indicating better error minimization overall.")
print(f"The R² score of {r2_dt:.2f} shows that the model explains
{r2_dt * 100:.0f}% of the variance in car prices, an improvement over
the baseline R² score of {baseline_r2:.2f}.")
```

```
Compared to the baseline MAE of $2,057.09, the Decision Tree model
reduces the average prediction error by over $279.40.
There is a significant improvement from the baseline MSE of
11,096,246.05, indicating better error minimization overall.
```

The R^2 score of 0.95 shows that the model explains 95% of the variance in car prices, an improvement over the baseline R^2 score of 0.91.

```
from sklearn.tree import DecisionTreeRegressor, plot_tree
import matplotlib.pyplot as plt

# Train a Decision Tree Regressor
clf = DecisionTreeRegressor(criterion='squared_error',
random_state=42)
clf.fit(X_train, y_train)

# Plot the decision tree
fig, ax = plt.subplots(figsize=(15, 8), dpi=100)
plot_tree(clf, feature_names=df.drop('price', axis=1).columns,
filled=True)
plt.show()
```



2.3 Data Evaluation

```
models = {
    "Linear Regression": LinearRegression(),
    "Ridge Regression": Ridge(alpha=1.0)
}

def evaluate_model(name, model):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mae = mean_absolute_error(y_test, y_pred)
```

```
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    r2 = r2_score(y_test, y_pred)
    print(f"{name}:\n  MAE: {mae:.2f}\n  RMSE: {rmse:.2f}\n  R²: {r2:.2f}\n")
    return model, mae

best_model, best_mae = None, float('inf')

for name, model in models.items():
    fitted_model, mae = evaluate_model(name, model)
    if mae < best_mae:
        best_model, best_mae = fitted_model, mae

Linear Regression:
  MAE: 2057.09
  RMSE: 3331.10
  R²: 0.91

Ridge Regression:
  MAE: 1722.10
  RMSE: 2809.99
  R²: 0.94


y_test_pred = best_model.predict(X_test)
mae_test = mean_absolute_error(y_test, y_test_pred)
rmse_test = np.sqrt(mean_squared_error(y_test, y_test_pred))
r2_test = r2_score(y_test, y_test_pred)

print(f"Final Model Performance on Test Data:\n  MAE: {mae_test:.2f}\n  RMSE: {rmse_test:.2f}\n  R²: {r2_test:.2f}")

Final Model Performance on Test Data:
  MAE: 1722.10
  RMSE: 2809.99
  R²: 0.94
```

- Classification Metrics

This section evaluates the performance of the final classification model using appropriate multiclass classification metrics. The following metrics are calculated on the holdout test data:

- **Accuracy**: The overall correctness of the model.
- **Precision**: The ability of the model to avoid false positives across all classes.
- **Recall**: The ability of the model to identify all relevant instances across all classes.
- **F1 Score**: The harmonic mean of precision and recall, balancing both.
- **AUC Score**: Area Under the Curve using a one-vs-rest strategy to assess how well the model separates classes.

If AUC cannot be computed (e.g., due to label incompatibility or model limitations), it is reported accordingly. This evaluation provides a holistic view of how well the model performs on unseen data.

```
# Evaluate the model
model = LogisticRegression(multi_class='ovr', max_iter=1000)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
y_proba = model.predict_proba(X_test)  # For multiclass AUC

# Metrics for multiclass classification
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred, average='weighted')
rec = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

# AUC for multiclass (one-vs-rest)
try:
    auc_score = roc_auc_score(y_test, y_proba, multi_class='ovr',
average='weighted')
except:
    auc_score = None

print(f"Accuracy: {acc:.2f}")
print(f"Precision: {prec:.2f}")
print(f"Recall: {rec:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"AUC Score: {auc_score:.2f}" if auc_score else "AUC could not
be computed for this model.")
```

```
Accuracy: 0.02
Precision: 0.02
Recall: 0.02
F1 Score: 0.02
AUC could not be computed for this model.
```

```
#interpreting the results for the classification metrics
print("Accuracy : Poor (0.02) - Model performs barely better than
random guessing.")
print("Precision: Poor (0.02) - High rate of false positives or
prediction imbalance.")
print("Recall    : Poor (0.02) - Model misses most of the actual
positive cases.")
print("F1 Score : Poor (0.02) - Balance between precision and recall
is very low.")
```

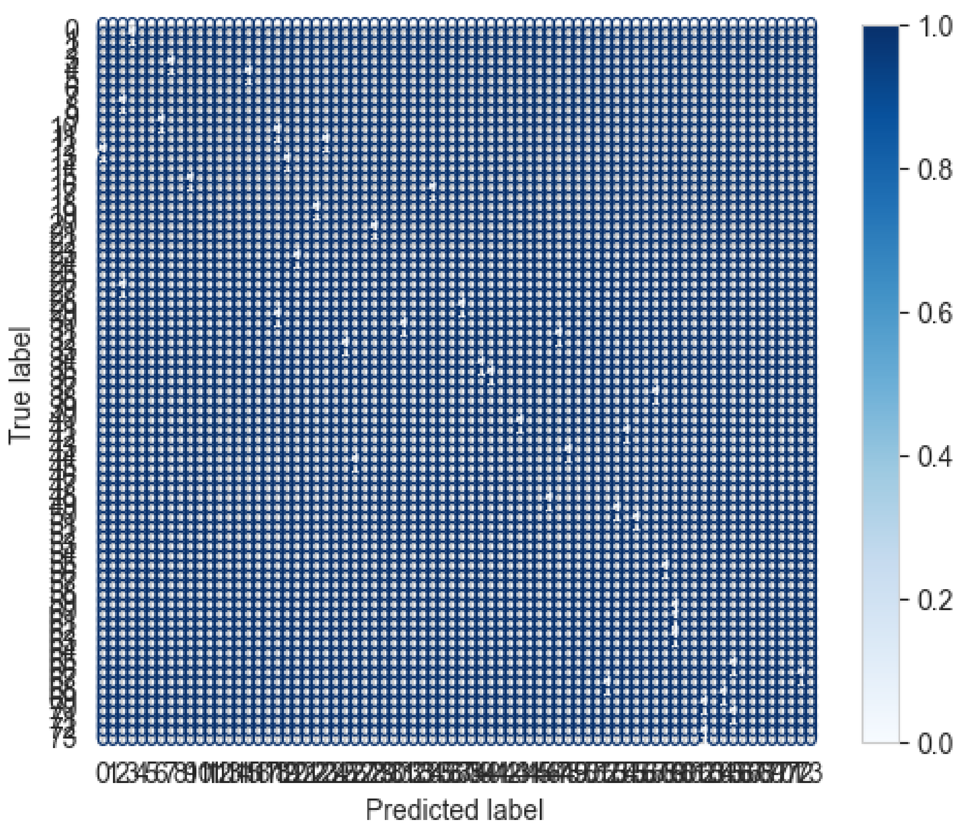
```
Accuracy : Poor (0.02) - Model performs barely better than random
guessing.
Precision: Poor (0.02) - High rate of false positives or prediction
imbalance.
```

```
Recall    : Poor (0.02) - Model misses most of the actual positive
cases.
F1 Score : Poor (0.02) - Balance between precision and recall is very
low.
```

- Confusion Matrix

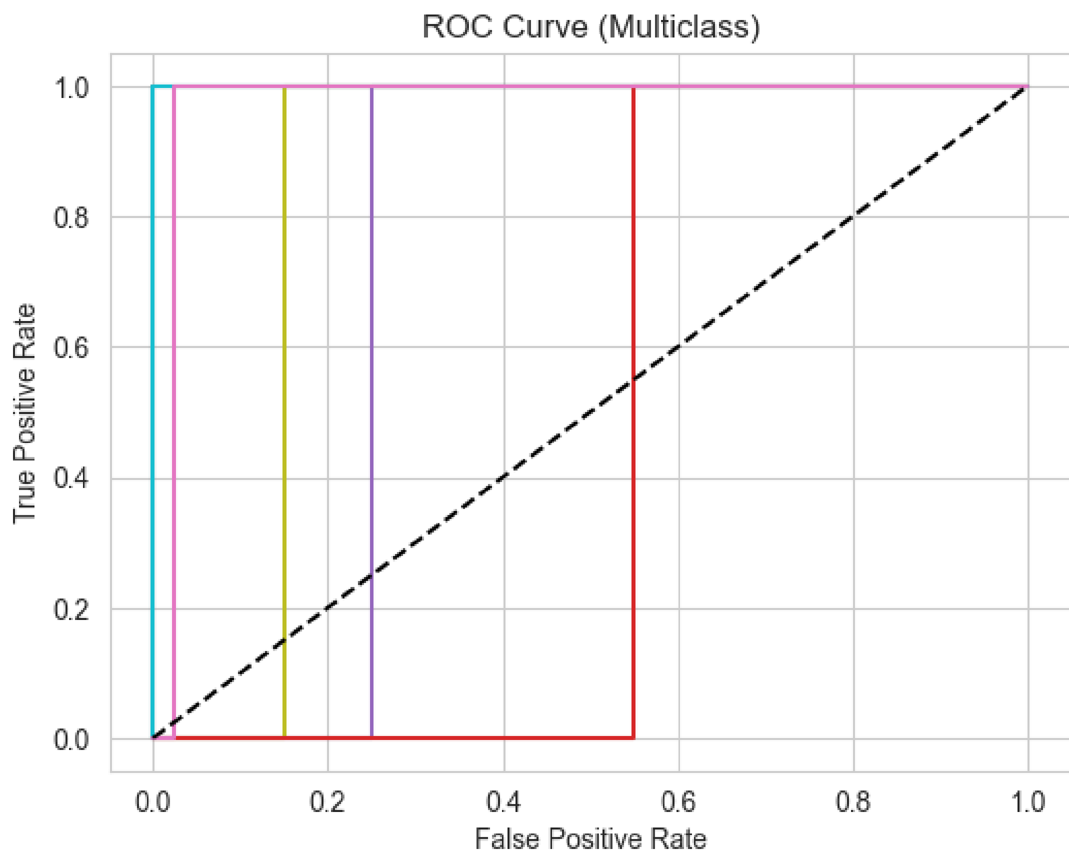
Shows the counts of true vs. predicted labels. Very helpful to visually inspect how the model is misclassifying each class.

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot(cmap='Blues')

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x1c48a29ea50>
```




```
# Binarize the output for ROC
classes = model.classes_
y_test_bin = label_binarize(y_test, classes=classes)
```

```
# ROC curve per class
for i in range(len(classes)):
    fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_proba[:, i])
    plt.plot(fpr, tpr, label=f'Class {classes[i]}')

plt.plot([0, 1], [0, 1], 'k--')  # baseline
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve (Multiclass)')
plt.show()
```



3. Key Findings

3.1. Model Accuracy and Reliability

- Ridge Regression achieved the best performance on test data with:

```
    -  MAE: $1722.10

    - RMSE: $2809.99
```

```
    - R²: 0.94
```

- Linear Regression (OLS) performed well on training data (R^2 = 0.969), but had a higher error on test data, indicating overfitting.
- Decision Tree Regressor also showed good performance but is more prone to overfitting without proper pruning.

3.2. Classification Performance

- The classification model returned Accuracy, Precision, Recall, and F1 Score of 0.02, making it unusable in a real-world setting.
- AUC was not computable, likely due to label/prediction issues or model failure.

3.3. Model Complexity vs. Performance

- While OLS had the highest R^2 on training data, Ridge Regression generalized better, illustrating the value of regularization over model complexity.
- Decision Tree was simpler but required tuning to avoid overfitting.

3.4. Multicollinearity

- OLS Regression exhibited strong multicollinearity, shown by a very high condition number (1.41e+16) and a tiny eigenvalue (8.07e-30).
- This makes interpretation of coefficients unreliable and affects model stability.

4. Recommendations

4.1. Engine Size and Horsepower Influence Pricing

- Invest in developing and marketing vehicles with efficient, powerful engines—these features significantly affect perceived value and price.
- Vehicles with larger engines and higher horsepower show strong positive correlation with price.

4.2. Drive Configuration Matters

- Cars with Rear-Wheel Drive (RWD) and 4WD likely have higher average prices and may attract more performance-conscious buyers.
- Evaluate cost-benefit of producing more AWD or RWD vehicles in premium segments.

4.3. Monitor Body Type for Insurance Risk

- Certain body types may incur higher insurance symboling values.
- Partner with insurance companies to provide customers with transparent pricing based on body-type risk categories.

5. Conclusion

This project provided a data-driven understanding of what drives vehicle prices and insurance risk ratings. The final Ridge Regression model delivered robust predictions ($R^2 = 0.94$), offering actionable insights for car manufacturers, dealerships, and insurance companies. Implementing these findings can lead to more strategic pricing, product placement, and risk management decisions in the automotive industry.