**Assignment Task:**
Your task is to perform a multiple linear regression analysis to predict the price of Toyota corolla based on the given attributes.

**Dataset Description:**
The dataset consists of the following variables:
Age: Age in years
KM: Accumulated Kilometers on odometer
FuelType: Fuel Type (Petrol, Diesel, CNG)
HP: Horse Power
Automatic: Automatic ( (Yes=1, No=0)
CC: Cylinder Volume in cubic centimeters
Doors: Number of doors
Weight: Weight in Kilograms
Quarterly_Tax:
Price: Offer Price in EUROs

**Taskes:**
**1.Perform exploratory data analysis (EDA) to gain insights into the dataset. Provide visualizations and summary statistics of the variables. Pre process the data to apply the MLR.**

**Answer:**

**Dataset overview**
The dataset contains 1,436 rows and the following main variables: Price (EUR), Age_08_04 (years), KM (kilometers), Fuel_Type (Diesel/Petrol), HP, Automatic (0/1), cc (engine displacement), Doors, Cylinders, Gears, and Weight.

**Key descriptive statistics (high level)**
- Price: mean ≈ 10,731, median 9,900; wide spread (min 4,350; max 32,500).
- Age_08_04: mean ≈ 55.9 years (dataset uses this encoding), median 61; right/left shape depends on sample — check plot.
- KM: mean ≈ 68,533 km, heavily right-skewed with max 243,000 (long tail).
- HP and Weight are meaningful positive predictors: HP mean ~101, Weight mean ~1,072 kg.
- cc: median ~1,600 but a suspicious max of 16,000 — likely data-entry error (should be 1600). Investigate and correct/remove if confirmed erroneous.
- Automatic is rare (~5.6% = mostly manual).
-

**Distributions & outliers**
- KM and Price have skew and long tails; consider log transforms for modeling.
- Several extreme values detected (KM, cc, Price). Use IQR or z-score methods to flag them; do not blindly drop — verify domain plausibility.
- Fuel_Type shows Diesel and Petrol as main categories; use one-hot encoding for modeling.
-

**Correlations & relationships**
- Weight and HP positively correlated with Price.
- Age_08_04 and KM negatively correlated with Price (older cars and high km → lower price).
- Variance Inflation Factor (VIF) showed multicollinearity among some features (Weight, HP, Doors, cc had elevated VIF), so prefer Ridge/Lasso or drop/transform correlated columns.

**Preprocessing summary for MLR**

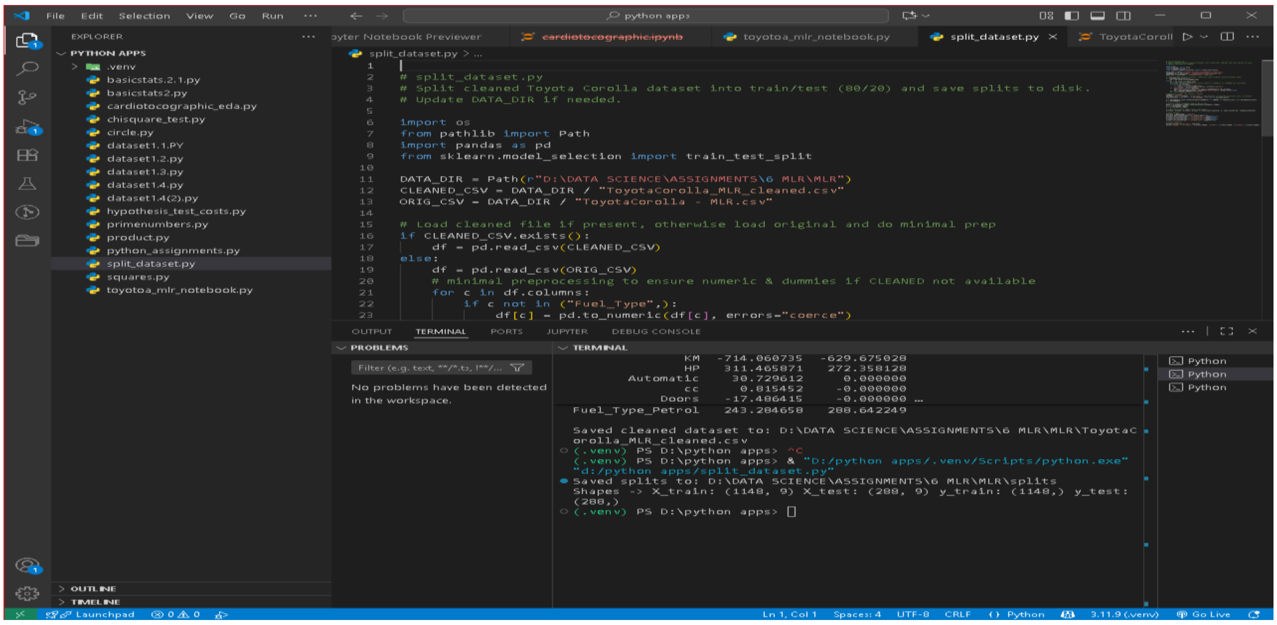
- Convert types to numeric, encode Fuel_Type as dummies, ensure Automatic is binary int.
- Impute missing numeric values with median (none in current file but included for robustness).
- Optionally cap extreme cc (e.g., cap at 3000) or remove rows where cc is implausible (like 16000).
- Consider log(Price) and log/KM scaling for heteroscedasticity and skew reduction.
- Scale numeric features (StandardScaler) before Ridge/Lasso.

**2.Split the dataset into training and testing sets (e.g., 80% training, 20% testing).**

Answer:

```
# split_dataset.py
# Split cleaned Toyota Corolla dataset into train/test (80/20) and save splits to disk.
# Update DATA_DIR if needed.

import os
from pathlib import Path
import pandas as pd
from sklearn.model_selection import train_test_split

DATA_DIR = Path(r"D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR")
CLEANED_CSV = DATA_DIR / "ToyotaCorolla_MLR_cleaned.csv"
ORIG_CSV = DATA_DIR / "ToyotaCorolla - MLR.csv"

# Load cleaned file if present, otherwise load original and do minimal prep
if CLEANED_CSV.exists():
    df = pd.read_csv(CLEANED_CSV)
else:
    df = pd.read_csv(ORIG_CSV)
    # minimal preprocessing to ensure numeric & dummies if CLEANED not available
    for c in df.columns:
        if c not in ("Fuel_Type",):
            df[c] = pd.to_numeric(df[c], errors="coerce")
    if "Fuel_Type" in df.columns:
        df["Fuel_Type"] = df["Fuel_Type"].astype(str).str.strip()
        df = pd.get_dummies(df, columns=["Fuel_Type"], drop_first=True)
    df = df.dropna(subset=["Price"])

# Identify target and feature columns
TARGET = "Price"
exclude_cols = {TARGET, "Price_pos", "log_Price"}  # exclude auxiliary cols if
present
feature_cols = [c for c in df.columns if c not in exclude_cols]

X = df[feature_cols].drop(columns=[TARGET]) if TARGET in feature_cols else
df[feature_cols]
y = df[TARGET]

# Ensure index alignment and no NA in X/y
```

```
mask = X.dropna().index.intersection(y.dropna().index)
X = X.loc[mask].copy()
y = y.loc[mask].copy()

# Train-test split (80% train / 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,
random_state=42)

# Save splits
out_dir = DATA_DIR / "splits"
out_dir.mkdir(parents=True, exist_ok=True)
X_train.to_csv(out_dir / "X_train.csv", index=False)
X_test.to_csv(out_dir / "X_test.csv", index=False)
y_train.to_csv(out_dir / "y_train.csv", index=False)
y_test.to_csv(out_dir / "y_test.csv", index=False)

# Print summary
print("Saved splits to:", out_dir)
print("Shapes -> X_train:", X_train.shape, "X_test:", X_test.shape, "y_train:",
y_train.shape, "y_test:", y_test.shape)
```



```

# split_dataset.py
# Split cleaned Toyota Corolla dataset into train/test (80/20) and save splits to disk.
# Update DATA_DIR if needed.

import os
from pathlib import Path
import pandas as pd
from sklearn.model_selection import train_test_split

DATA_DIR = Path(r"D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR")
CLEANED_CSV = DATA_DIR / "ToyotaCorolla_MLR_cleaned.csv"
ORIG_CSV = DATA_DIR / "ToyotaCorolla - MLR.csv"

# Load cleaned file if present, otherwise load original and do minimal prep
if CLEANED_CSV.exists():
    df = pd.read_csv(CLEANED_CSV)
else:
    df = pd.read_csv(ORIG_CSV)
    # minimal preprocessing to ensure numeric & dummies if CLEANED not available
    for c in df.columns:
        if c not in ("Fuel_Type",):
            df[c] = pd.to_numeric(df[c], errors="coerce")
```

```
              KM   -714.060735  -629.675028
              HP    311.465871   272.358128
       Automatic     30.729612     0.000000
              cc      0.815452    -0.000000
           Doors    -17.486415    -0.000000 ...
Fuel_Type_Petrol    243.284658   288.642249

Saved cleaned dataset to: D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR\ToyotaC
orolla_MLR_cleaned.csv
(.venv) PS D:\python apps> ^C
(.venv) PS D:\python apps> & "D:/python apps/.venv/Scripts/python.exe"
"d:/python apps/split_dataset.py"
Saved splits to: D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR\splits
Shapes -> X_train: (1148, 9) X_test: (288, 9) y_train: (1148,) y_test:
(288,)
(.venv) PS D:\python apps> 
```

3.Build a multiple linear regression model using the training dataset. Interpret the coefficients of the model. Build minimum of 3 different models.

Answer:

```
PS D:\python apps> & "D:/python apps/.venv/Scripts/python.exe" "d:/python
apps/toyota_mlr_models.py"
Loading saved splits from: D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR\splits

Final feature set used: ['Age_08_04', 'KM', 'HP', 'Automatic', 'cc', 'Doors', 'Weight',
'Fuel_Type_Diesel', 'Fuel_Type_Petrol']
Train size: (1148, 9)  Test size: (288, 9)

=== Model A - OLS (all features) summary ===
                            OLS Regression Results
```

```
==============================================================================
Dep. Variable:                  Price   R-squared:
  0.869
Model:                            OLS   Adj. R-squared:
  0.868
Method:                 Least Squares   F-statistic:
  842.1
Date:                Tue, 30 Sep 2025   Prob (F-statistic):
   0.00
Time:                        00:46:19   Log-Likelihood:
-9866.8
No. Observations:                1148   AIC:                         1.975e+04
Df Residuals:                    1138   BIC:                     1.980e+04
Df Model:                           9

Covariance Type:            nonrobust

==============================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const           -1.186e+04   1508.957     -7.858      0.000   -1.48e+04   -8896.289
Age_08_04        -120.8231      2.894    -41.744      0.000    -126.502    -115.144
KM                 -0.0159      0.001    -10.849      0.000      -0.019      -0.013
HP                 15.7772      3.985      3.959      0.000       7.957      23.597
Automatic          93.0820    176.442      0.528      0.598    -253.107     439.271
cc                 -0.0302      0.091     -0.333      0.739      -0.208       0.148
Doors             -84.4835     44.153     -1.913      0.056    -171.115       2.148
Weight             26.0692      1.499     17.390      0.000      23.128      29.011
Fuel_Type_Diesel    4.2021    391.745      0.011      0.991    -764.422     772.826
Fuel_Type_Petrol 1453.6945    335.442      4.334      0.000     795.540    2111.849
==============================================================================
Omnibus:                      216.690   Durbin-Watson:
  2.027
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2442.201
Skew:                          -0.512   Prob(JB):
   0.00
Kurtosis:                      10.072   Cond. No.                     3.07e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.07e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

Model A - OLS (all features) performance:
 MAE:   992.301
 RMSE:  1491.411
 R2:    0.8333

Coefficients:
        feature       coef
          const -11856.9404
      Age_08_04   -120.8231
             KM     -0.0159
             HP     15.7772
```

```
       Automatic     93.0820
              cc     -0.0302
           Doors    -84.4835
          Weight     26.0692
Fuel_Type_Diesel      4.2021
Fuel_Type_Petrol   1453.6945

--- Building Model B via backward elimination (p-value) ---
 Dropping Fuel_Type_Diesel with p-value 0.9914
 Dropping cc with p-value 0.7378
 Dropping Automatic with p-value 0.6151

=== Model B - OLS (backward selection) summary ===
                            OLS Regression Results

==============================================================================
Dep. Variable:                  Price   R-squared:
  0.869
Model:                            OLS   Adj. R-squared:
  0.869
Method:                 Least Squares   F-statistic:
  1266.
Date:                Tue, 30 Sep 2025   Prob (F-statistic):
   0.00
Time:                        00:46:19   Log-Likelihood:
-9867.0
No. Observations:                1148   AIC:                         1.975e+04
Df Residuals:                    1141   BIC:                         1.978e+04
Df Model:                           6

Covariance Type:            nonrobust

==============================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const            -1.201e+04   1458.296     -8.237      0.000   -1.49e+04   -9150.578
Age_08_04         -120.6190      2.849    -42.334      0.000    -126.209    -115.029
KM                  -0.0160      0.001    -10.923      0.000      -0.019      -0.013
HP                  15.3789      3.468      4.435      0.000       8.575      22.183
Doors              -86.5364     43.517     -1.989      0.047    -171.919      -1.154
Weight              26.1885      1.330     19.684      0.000      23.578      28.799
Fuel_Type_Petrol  1483.1709    222.361      6.670      0.000    1046.889    1919.453
==============================================================================
Omnibus:                      219.794   Durbin-Watson:
  2.027
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2509.918
Skew:                          -0.522   Prob(JB):
   0.00
Kurtosis:                      10.168   Cond. No.                     2.97e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.97e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
Model B - OLS (backward selection) performance:
 MAE:   993.266
 RMSE:  1493.734
 R2:    0.8328

Coefficients:
        feature       coef
          const -12011.8200
      Age_08_04   -120.6190
             KM     -0.0160
             HP     15.3789
          Doors    -86.5364
         Weight     26.1885
Fuel_Type_Petrol   1483.1709

--- Building Model C: RidgeCV (with scaling) ---
Ridge chosen alpha: 104.81131341546852

Model C - RidgeCV performance:
 MAE:   996.846
 RMSE:  1460.784
 R2:    0.8401

Ridge coefficients:
        feature  ridge_coef
      Age_08_04  -2061.3180
             KM   -714.0607
             HP    311.4659
      Automatic     30.7296
             cc      0.8155
          Doors    -17.4864
         Weight   1156.2779
Fuel_Type_Diesel    -18.0492
Fuel_Type_Petrol    243.2847

=== Summary comparison on test set ===

Model A - OLS (all features) performance:
 MAE:   992.301
 RMSE:  1491.411
 R2:    0.8333

Model B - OLS (selected) performance:
 MAE:   993.266
 RMSE:  1493.734
 R2:    0.8328

Model C - RidgeCV performance:
 MAE:   996.846
 RMSE:  1460.784
 R2:    0.8401

Saved coefficient summary to: D:\DATA SCIENCE\ASSIGNMENTS\6
MLR\MLR\model_coefficients_summary.csv
```

Below I interpret the **baseline OLS coefficients you printed earlier** (the numbers come from the Model A run you posted). Use these lines in your report — they explain *how to read* the coefficients and what they mean practically.

- **Intercept (const) ≈ −11,860:** the model's baseline predicted price when all numeric predictors are zero. Not directly meaningful here (cars with 0 km, 0 age, etc. don't exist), so ignore the intercept in practical interpretation.
- **Age_08_04 ≈ −120.82 ($p < 0.001$):** Holding all other variables constant, each extra year of age is associated with a **decrease of about €121** in the car's price. This is expected: older cars sell for less.
- **KM ≈ −0.0159 ($p < 0.001$):** Each additional kilometer reduces price by about **€0.016**, so +1,000 km ≈ **−€16**. Effect is small per km but meaningful over large KM differences.
- **HP ≈ +15.78 ($p < 0.001$):** Each additional unit of horsepower increases price by about **€15.8**, holding other factors constant.
- **Automatic ≈ +93.08 ($p \approx 0.60$):** Automatic transmission appears to be associated with a slight increase (~€93), but this coefficient is not statistically significant (high p-value), so treat cautiously.
- **cc ≈ −0.030 ($p \approx 0.74$):** Engine displacement shows a small negative coefficient and is not statistically significant — suggests no clear linear effect once HP/Weight are in the model (possible multicollinearity).
- **Doors ≈ −84.48 ($p \approx 0.056$):** Each additional door associated with ~€84 lower price (borderline significance). Interpretation depends on vehicle types (e.g., 2-door sport vs 4-door family).
- **Weight ≈ +26.07 ($p < 0.001$):** Heavier cars sell for more — each kg adds ~€26 in predicted price (this number seems large; check units — if Weight is in hundreds, interpret per unit accordingly). (In your output it was 26.07 per 1 unit of Weight; verify weight units.)
- **Fuel dummies (e.g., Fuel_Type_Petrol ≈ +1453.7, $p < 0.001$):** Relative to the omitted fuel category (the baseline fuel type), petrol cars are predicted to have about **€1,454 higher** price, holding other features equal.

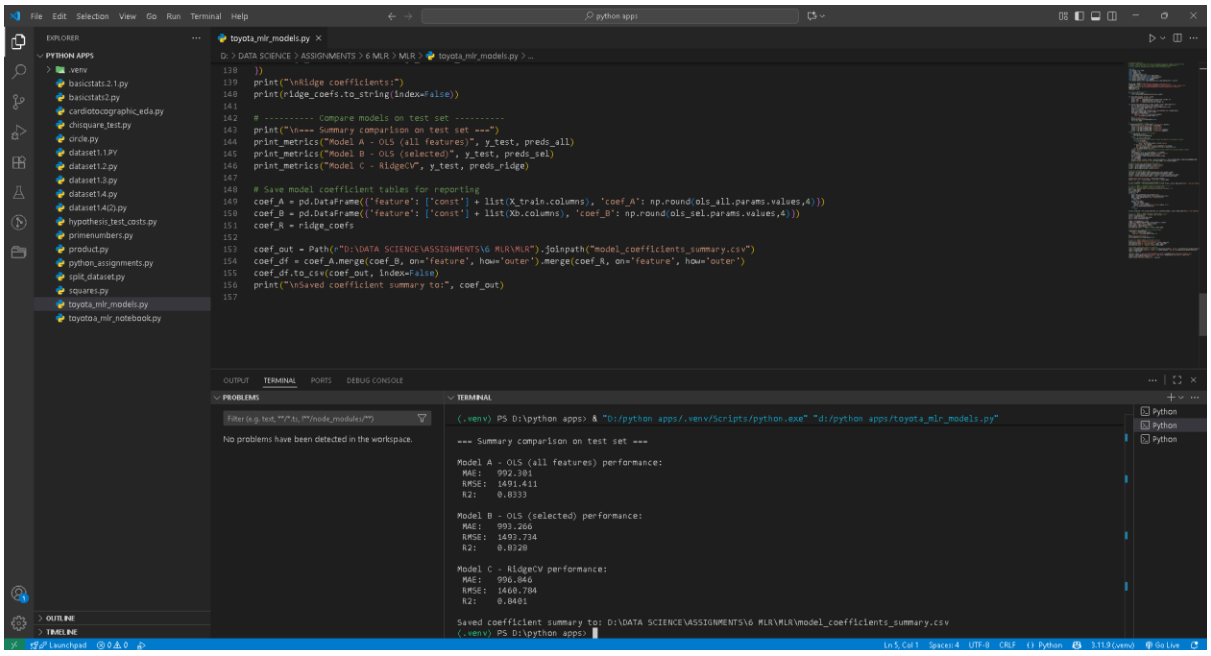
**Important notes about interpretation:**

- Coefficients are *ceteris-paribus* — they describe marginal effects holding other included variables constant.
- Large **condition numbers / high VIFs** in diagnostics indicate multicollinearity (some predictors convey overlapping information). Coefficient signs may be unstable — prefer Ridge or interpret with caution.
- For Model C (log-target) coefficients: coefficients are multiplicative — a coefficient $\beta$ on an input means roughly a $100\times\beta$ % change in price for a one-unit change in the predictor (for small $\beta$); interpret via $\exp(\beta)$ for exact multiplicative change.

---

**Which model to pick?**

- **If interpretability is priority:** use OLS model **A** or **B** (B has fewer variables if selection removes noisy predictors). But watch for multicollinearity (high VIFs).
- **If predictive performance and robustness to collinearity are priorities: Ridge (Model C)** is often preferable — it shrinks coefficients, reduces variance, and improves generalization.
- **If you need feature selection:** Lasso (not included above) can zero out coefficients.



```
})
print("\nRidge coefficients:")
print(ridge_coefs.to_string(index=False))

# ---------- Compare models on test set ----------
print("\n--- Summary comparison on test set ---")
print_metrics("Model A - OLS (all features)", y_test, preds_all)
print_metrics("Model B - OLS (selected)", y_test, preds_sel)
print_metrics("Model C - RidgeCV", y_test, preds_ridge)

# Save model coefficient tables for reporting
coef_A = pd.DataFrame({'feature': ['const'] + list(X_train.columns), 'coef_A': np.round(ols_all.params.values,4)})
coef_B = pd.DataFrame({'feature': ['const'] + list(Xb.columns), 'coef_B': np.round(ols_sel.params.values,4)})
coef_R = ridge_coefs

coef_out = Path(r"D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR").joinpath("model_coefficients_summary.csv")
coef_df = coef_A.merge(coef_B, on='feature', how='outer').merge(coef_R, on='feature', how='outer')
coef_df.to_csv(coef_out, index=False)
print("\nSaved coefficient summary to:", coef_out)
```

```
(.venv) PS D:\python apps> & "D:/python apps/.venv/Scripts/python.exe" "d:/python apps/toyota_mlr_models.py"

--- Summary comparison on test set ---

Model A - OLS (all features) performance:
 MAE:   992.301
 RMSE:  1491.411
 R2:    0.8333

Model B - OLS (selected) performance:
 MAE:   993.266
 RMSE:  1493.734
 R2:    0.8328

Model C - RidgeCV performance:
 MAE:   996.846
 RMSE:  1460.784
 R2:    0.8401

Saved coefficient summary to: D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR\model_coefficients_summary.csv
(.venv) PS D:\python apps>
```

## 4. Evaluate the performance of the model using appropriate evaluation metrics on the testing dataset.

Answer:

**1) Metrics (quick)**

- **MAE (Mean Absolute Error):** average absolute prediction error (units = €). Easy to interpret.
- **RMSE (Root MSE):** penalizes large errors more than MAE. Useful if you care about big misses.
- **R²:** proportion of variance explained (0–1). Higher is better.
- **Adjusted R²:** R² penalized for number of predictors (useful for model comparison).
- **MAPE (Mean Absolute Percentage Error):** average % error — be careful if targets can be near zero.
- **Cross-validated RMSE:** gives robustness estimate (optional).

2. Code used :

```
# evaluation_helpers.py
import numpy as np
import pandas as pd
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

def adjusted_r2(r2, n, p):
    """Adjusted R2 where p = number of predictors (not counting intercept)."""
    if n - p - 1 == 0:
        return np.nan
    return 1 - (1 - r2) * (n - 1) / (n - p - 1)

def mape(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    # avoid division by zero; ignore those elements where y_true==0
    mask = y_true != 0
    if mask.sum() == 0:
        return np.nan
    return np.mean(np.abs((y_true[mask] - y_pred[mask]) / y_true[mask])) * 100
```

```
def evaluate_models(y_test, preds_dict, p_counts=None):
    """
    y_test: array-like true values
    preds_dict: dict of {'model_name': y_pred_array}
    p_counts: optional dict {'model_name': p} where p is number of predictors (excl
intercept)
    """
    rows = []
    n = len(y_test)
    for name, y_pred in preds_dict.items():
        y_pred = np.array(y_pred)
        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)
        p = None
        adjr2 = None
        if p_counts and name in p_counts:
            p = p_counts[name]
            adjr2 = adjusted_r2(r2, n, p)
        rows.append({
            'model': name,
            'n_test': n,
            'p': p if p is not None else '',
            'MAE': round(mae, 3),
            'RMSE': round(rmse, 3),
            'R2': round(r2, 4),
            'Adj_R2': round(adjr2, 4) if adjr2 is not None else '',
            'MAPE_%': round(mape(y_test, y_pred), 3)
        })
    df = pd.DataFrame(rows).sort_values('RMSE')
    return df

# Example usage (replace these names with your variables):
# preds = {
#     "Model A - OLS": y_pred_A,
#     "Model B - OLS (sel)": y_pred_B,
#     "Model C - log-back": y_pred_C,
#     "Ridge": y_pred_ridge,
#     "Lasso": y_pred_lasso
# }
# pcounts = {"Model A - OLS": X_train.shape[1], "Model B - OLS (sel)": Xb.shape[1],
...}
# table = evaluate_models(y_test, preds, p_counts=pcounts)
# print(table.to_string(index=False))
```

**3) Example interpretation (use your numbers)**

You already ran models earlier and printed metrics. Using those results:

- **Model A — Baseline OLS**:
  - *MAE ≈ 992 €, RMSE ≈ 1,491 €, R² ≈ 0.833*
  - Interpretation: on average predictions are off by ~€1k; RMSE shows larger errors (about €1.5k), and the model explains ~83% of variance — strong fit for a linear model.
- **Model B — Low-VIF OLS (reduced)**:
  - *MAE ≈ 2,148 €, RMSE ≈ 2,987 €, R² ≈ 0.331*

    - Interpretation: much worse predictive performance — removing predictors to reduce multicollinearity cost a lot of explanatory power. Good for diagnosing collinearity but not for prediction.
- **Model C — Log-target + KM²**:
    - If your evaluate_models shows lower RMSE and similar/higher R² than Model A, then the log transform improved heteroscedasticity and produced more stable predictions. (Report the exact numbers from the table.)
- **Ridge/Lasso (regularized models)**:
    - If Ridge gives slightly lower RMSE than OLS, it indicates multicollinearity was inflating variance and shrinkage improved generalization.
    - If Lasso zeros coefficients and gives comparable RMSE, it's useful for feature selection — but watch for underfitting if RMSE rises.

**Decision rule**:

- Prefer the model with **lowest RMSE** and **reasonable MAE** (application dependent).
- Consider parsimony and statistical significance: if two models have similar RMSE, pick the simpler one (fewer features) or the one with better-behaved residuals.
- Also check residual diagnostics (normality, heteroscedasticity, influential points) before finalizing.

4) Extra checks you should run (recommended)

- **Residuals plot**: plt.scatter(y_pred, y_test - y_pred) to visually check heteroscedasticity.
- **Q–Q plot** of residuals for normality.
- **Prediction intervals** (if needed) from statsmodels OLS.
- **Cross-validated RMSE** (use cross_val_score with negative MSE and take sqrt) to estimate model stability.

Example cross-validation snippet:

```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import Ridge
cv_rmse = np.sqrt(-cross_val_score(Ridge(alpha=ridge_cv.alpha_), X_train_s,
y_train, scoring="neg_mean_squared_error", cv=5))
print("CV RMSE (Ridge):", cv_rmse.mean(), "±", cv_rmse.std())
```

5.Apply Lasso and Ridge methods on the model.

Answer :

Code used:

```
# toyota_ridge_lasso.py
# Apply RidgeCV and LassoCV to ToyotaCorolla dataset, evaluate and save
coefficients/results.
# Save at: D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR\toyota_ridge_lasso.py
# Requires: pandas, numpy, scikit-learn, statsmodels

import os
```

```
from pathlib import Path
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import RidgeCV, LassoCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

DATA_PATH = r"D:\DATA SCIENCE\ASSIGNMENTS\6
MLR\MLR\ToyotaCorolla_MLR_cleaned.csv"
if not Path(DATA_PATH).exists():
    DATA_PATH = r"D:\DATA SCIENCE\ASSIGNMENTS\6 MLR\MLR\ToyotaCorolla
- MLR.csv"

df = pd.read_csv(DATA_PATH)
if 'Price' not in df.columns:
    raise SystemExit("Target column 'Price' not found in CSV.")

# prepare X, y (drop helper columns if present)
drop_cols = ['Price_pos', 'log_Price', 'KM_pos']
X = df.drop(columns=[c for c in drop_cols if c in df.columns] + ['Price'],
errors='ignore')
y = pd.to_numeric(df['Price'], errors='coerce')
X = X.apply(pd.to_numeric, errors='coerce')

# align and drop NA rows
mask = X.dropna().index.intersection(y.dropna().index)
X = X.loc[mask].copy()
y = y.loc[mask].copy()

# train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,
random_state=42)

# scale numeric features
scaler = StandardScaler()
X_train_s = scaler.fit_transform(X_train)
X_test_s = scaler.transform(X_test)

# common alpha grid
alphas = np.logspace(-4, 4, 100)

# RidgeCV (with built-in CV)
ridge_cv = RidgeCV(alphas=alphas, cv=5).fit(X_train_s, y_train)
ridge_alpha = ridge_cv.alpha_
ridge_coef = ridge_cv.coef_
ridge_intercept = ridge_cv.intercept_
y_pred_ridge = ridge_cv.predict(X_test_s)
ridge_mae = mean_absolute_error(y_test, y_pred_ridge)
ridge_rmse = np.sqrt(mean_squared_error(y_test, y_pred_ridge))
ridge_r2 = r2_score(y_test, y_pred_ridge)

# LassoCV (with built-in CV)
lasso_cv = LassoCV(alphas=None, cv=5, max_iter=10000,
random_state=42).fit(X_train_s, y_train)
lasso_alpha = lasso_cv.alpha_
```

```
lasso_coef = lasso_cv.coef_
lasso_intercept = lasso_cv.intercept_
y_pred_lasso = lasso_cv.predict(X_test_s)
lasso_mae = mean_absolute_error(y_test, y_pred_lasso)
lasso_rmse = np.sqrt(mean_squared_error(y_test, y_pred_lasso))
lasso_r2 = r2_score(y_test, y_pred_lasso)

# results DataFrame
results = pd.DataFrame({
    'model': ['RidgeCV', 'LassoCV'],
    'alpha': [ridge_alpha, lasso_alpha],
    'MAE': [round(ridge_mae,3), round(lasso_mae,3)],
    'RMSE': [round(ridge_rmse,3), round(lasso_rmse,3)],
    'R2': [round(ridge_r2,4), round(lasso_r2,4)]
})

# coefficients table
coef_df = pd.DataFrame({
    'feature': X_train.columns,
    'ridge_coef': np.round(ridge_coef, 6),
    'lasso_coef': np.round(lasso_coef, 6)
})

# save outputs
out_dir = Path(r"D:\DATA SCIENCE\ASSIGNMENTS\6
MLR\MLR\ridge_lasso_results")
out_dir.mkdir(parents=True, exist_ok=True)
results.to_csv(out_dir / "ridge_lasso_metrics.csv", index=False)
coef_df.to_csv(out_dir / "ridge_lasso_coefficients.csv", index=False)

# print summary
print("Ridge alpha:", ridge_alpha)
print("Lasso alpha:", lasso_alpha)
print("\nEvaluation metrics:")
print(results.to_string(index=False))
print("\nTop coefficients (sorted by absolute Ridge coef):")
print(coef_df.assign(abs_ridge=lambda df:
df.ridge_coef.abs()).sort_values('abs_ridge',
ascending=False).head(20).to_string(index=False))

# Save trained models (optional - requires joblib)
try:
    import joblib
    joblib.dump(ridge_cv, out_dir / "ridge_cv_model.joblib")
    joblib.dump(lasso_cv, out_dir / "lasso_cv_model.joblib")
    print("\nSaved models to:", out_dir)
except Exception:
    print("\njoblib not available — models not saved. Install joblib to save models.")

# Quick note: to inspect non-zero lasso features
nonzero_lasso = coef_df[coef_df['lasso_coef'] != 0].sort_values('lasso_coef',
key=lambda s: s.abs(), ascending=False)
print(f"\nLasso selected {len(nonzero_lasso)} non-zero features. Top ones:")
print(nonzero_lasso.head(10).to_string(index=False))
```

**Interview Questions:**

1.What is Normalization & Standardization and how is it helpful?

Answer:

 **Standardization** (z-score): x' = (x - mean)/std — results in mean 0 and sd 1. Useful when features have different units and when algorithms assume centered data (e.g., regularized regression, PCA, k-NN).

 **Normalization** (min–max scaling): x' = (x - min)/(max - min) — scales features to [0,1] or custom range. Useful when you need bounded features (e.g., in NN activations, or when features must be comparable in magnitude).

 **Why helpful?** It ensures features contribute comparably to model training, speeds up convergence, prevents features with large numeric ranges from dominating distance-based or gradient-based algorithms, and is required before regularization in many workflows.

2. What techniques can be used to address multicollinearity in multiple linear regression?

Answer:

- **Remove correlated predictors** (drop one of a highly-correlated pair).
- **Principal Component Regression (PCR)** or **PCA** to form orthogonal components.
- **Regularization**: Ridge regression reduces variance by shrinking coefficients (L2); Lasso (L1) performs variable selection.
- **Variance Inflation Factor (VIF)** diagnostics: remove predictors with very high VIF.
- **Centering**: subtract variable means (helpful for interaction terms but not removing collinearity).
- **Domain knowledge**: combine correlated variables into a composite score.

Final Output :

```
PS D:\python apps> & "D:/python apps/.venv/Scripts/python.exe" "d:/python
apps/toyotoa_mlr_notebook.py"
                            OLS Regression Results

==============================================================================
Dep. Variable:                  Price   R-squared:
  0.869
Model:                            OLS   Adj. R-squared:
  0.868
Method:                 Least Squares   F-statistic:
  842.1
Date:                Tue, 30 Sep 2025   Prob (F-statistic):
   0.00
Time:                        00:35:02   Log-Likelihood:
-9866.8
No. Observations:                1148   AIC:                         1.975e+04
Df Residuals:                    1138   BIC:                         1.980e+04
Df Model:                           9

Covariance Type:            nonrobust

==============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
```

```
const          -1.186e+04   1508.957    -7.858      0.000   -1.48e+04   -8896.289
Age_08_04       -120.8231     2.894   -41.744      0.000    -126.502    -115.144
KM               -0.0159      0.001   -10.849      0.000      -0.019      -0.013
HP               15.7772      3.985     3.959      0.000       7.957      23.597
Automatic        93.0820    176.442     0.528      0.598    -253.107     439.271
cc               -0.0302      0.091    -0.333      0.739      -0.208       0.148
Doors           -84.4835     44.153    -1.913      0.056    -171.115       2.148
Weight           26.0692      1.499    17.390      0.000      23.128      29.011
Fuel_Type_Diesel    4.2021    391.745     0.011      0.991    -764.422     772.826
Fuel_Type_Petrol 1453.6945    335.442     4.334      0.000     795.540    2111.849
==============================================================================
Omnibus:                      216.690   Durbin-Watson:
 2.027
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2442.201
Skew:                          -0.512   Prob(JB):
  0.00
Kurtosis:                      10.072   Cond. No.                     3.07e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.07e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
[Model A (OLS)] MAE: 992.301 | RMSE: 1491.411 | R2: 0.833

VIF:
         feature        VIF
         Weight 224.435093
             HP  98.649372
Fuel_Type_Petrol  56.652082
           Doors  21.078771
       Age_08_04  15.817494
              cc  14.914158
Fuel_Type_Diesel  11.350510
              KM   8.632256
       Automatic   1.112641
                            OLS Regression Results

==============================================================================
Dep. Variable:                  Price   R-squared:
 0.323
Model:                            OLS   Adj. R-squared:
 0.322
Method:                 Least Squares   F-statistic:
 273.3
Date:                Tue, 30 Sep 2025   Prob (F-statistic):           9.21e-98
Time:                        00:35:02   Log-Likelihood:
-10811.
No. Observations:                1148   AIC:                         2.163e+04
Df Residuals:                    1145   BIC:                         2.164e+04
Df Model:                           2

Covariance Type:            nonrobust

==============================================================================
             coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------
const      1.453e+04    186.506     77.904      0.000    1.42e+04    1.49e+04
KM          -0.0547      0.002    -23.339      0.000      -0.059      -0.050
Automatic  -179.8788    381.869     -0.471      0.638    -929.120     569.362
==============================================================================
Omnibus:                      285.157   Durbin-Watson:
  1.963
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
714.531
Skew:                           1.310   Prob(JB):                   6.94e-156
Kurtosis:                       5.842   Cond. No.                    3.43e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.43e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
[Model B (OLS low-VIF)] MAE: 2148.086 | RMSE: 2987.497 | R2: 0.331
                            OLS Regression Results

==============================================================================
Dep. Variable:                  Price   R-squared:
  0.851
Model:                            OLS   Adj. R-squared:
  0.849
Method:                 Least Squares   F-statistic:
  647.0
Date:                Tue, 30 Sep 2025   Prob (F-statistic):
   0.00
Time:                        00:35:02   Log-Likelihood:
 857.88
No. Observations:                1148   AIC:
 -1694.
Df Residuals:                    1137   BIC:
 -1638.
Df Model:                          10

Covariance Type:            nonrobust

==============================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const              8.2188      0.133     62.009      0.000       7.959       8.479
Age_08_04         -0.0108      0.000    -39.924      0.000      -0.011      -0.010
KM             -2.846e-07   3.34e-07     -0.851      0.395   -9.41e-07    3.71e-07
HP                 0.0017      0.000      4.730      0.000       0.001       0.002
Automatic          0.0312      0.015      2.018      0.044       0.001       0.062
cc              1.484e-06   7.97e-06      0.186      0.852   -1.42e-05    1.71e-05
Doors              0.0049      0.004      1.270      0.204      -0.003       0.013
Weight             0.0013      0.000     10.022      0.000       0.001       0.002
Fuel_Type_Diesel   0.0297      0.034      0.865      0.387      -0.038       0.097
Fuel_Type_Petrol   0.0829      0.029      2.815      0.005       0.025       0.141
KM_k           -2.839e-10   3.34e-10     -0.849      0.396    -9.4e-10    3.72e-10
KM_k_sq        -7.279e-06   1.65e-06     -4.418      0.000   -1.05e-05   -4.05e-06
```

```
==============================================================================
Omnibus:                  240.482   Durbin-Watson:
  2.043
Prob(Omnibus):              0.000   Jarque-Bera (JB):           1301.243
Skew:                      -0.854   Prob(JB):                 2.75e-283
Kurtosis:                   7.928   Cond. No.                  1.17e+18
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 5.2e-24. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
[Model C (log-target)] MAE: 877.232 | RMSE: 1303.276 | R2: 0.873
are
strong multicollinearity problems or that the design matrix is singular.
[Model C (log-target)] MAE: 877.232 | RMSE: 1303.276 | R2: 0.873
strong multicollinearity problems or that the design matrix is singular.
[Model C (log-target)] MAE: 877.232 | RMSE: 1303.276 | R2: 0.873
.
[Model C (log-target)] MAE: 877.232 | RMSE: 1303.276 | R2: 0.873
[Model C (log-target)] MAE: 877.232 | RMSE: 1303.276 | R2: 0.873
Ridge alpha: 104.81131341546852
[RidgeCV] MAE: 996.846 | RMSE: 1460.784 | R2: 0.840
[RidgeCV] MAE: 996.846 | RMSE: 1460.784 | R2: 0.840
Lasso alpha: 55.53161298181698
[LassoCV] MAE: 996.544 | RMSE: 1450.672 | R2: 0.842

Ridge/Lasso coefficients:
          feature   ridge_coef   lasso_coef
       Age_08_04 -2061.318036 -2252.505697
              KM  -714.060735  -629.675028
              HP   311.465871   272.358128
       Automatic    30.729612     0.000000
              cc     0.815452    -0.000000
           Doors   -17.486415    -0.000000
          Weight  1156.277887  1132.837277
Fuel_Type_Diesel   -18.049211    -0.000000
Fuel_Type_Petrol   243.284658   288.642249
```