🏗️ Data Wrangling

Step 1: Load and Display the Dataset

First, we load the dataset and display the first few rows to understand its structure.

```
# Load the dataset
data = pd.read_csv("our_dataset.csv")

# Display the first 5 rows
data.head()
```

Explanation: The dataset is loaded using `pd.read_csv()`, and the first 5 rows are displayed using `data.head()`.

🔍 Raw Dataset Preview

	Date	Vehicle Category	GVWR Class	Fuel Type	Model Year	Fuel Technology	Electric Mile Range	Number of Vehicles Registered at the Same Address	Region
0	2,019	P	Not Applicable	Gasoline	2,020	ICE	Not Applicable	≥4	Statew
1	2,020	P	Not Applicable	Gasoline	2,020	ICE	Not Applicable	1	Statew
2	2,021	P	Not Applicable	Gasoline	2,020	ICE	Not Applicable	1	Statew
3	2,019	P	Not Applicable	Gasoline	2,019	ICE	Not Applicable	≥4	Statew
4	2,019	P	Not Applicable	Gasoline	2,018	ICE	Not Applicable	≥4	Statew

Step 2: Basic Information about the Dataset

Next, we check the dataset's shape, info, and missing values.

```
# Check dataset shape
print(f"Number of rows: {data.shape[0]}, Number of columns: {data.shape[1]}")

# Display dataset info
data.info()

# Check for missing values
data.isnull().sum()
```

Explanation: We use `data.shape` to get the dimensions, `data.info()` to see column types, and `data.isnull().sum()` to check for missing values.

Step 3: Handle Missing Values

We handle missing values by filling numerical columns with the median and categorical columns with the mode.

```
# Fill missing values in numerical columns with median
data['Model Year'].fillna(data['Model Year'].median(), inplace=True)

# Fill missing values in categorical columns with mode
for col in data.columns:
    if data[col].dtype == "object" or pd.api.types.is_categorical_dtype(data[col]):
        data[col].fillna(data[col].mode()[0], inplace=True)
```

Explanation: Missing values in numerical columns are filled with the median, while categorical columns are filled with the mode.

Step 4: Convert Data Types

We convert the 'Date' column to datetime format and categorical columns to the 'category' dtype.

```
# Convert 'Date' to datetime and extract the year
data['Date'] = pd.to_datetime(data['Date'], format='%Y').dt.year
```

```
# Convert categorical columns to 'category' dtype
categorical_columns = ['Vehicle Category', 'GVWR Class', 'Fuel Type', 'Fuel Technology', 'Electric Mile Range', 'Number of Veh
for col in categorical_columns:
    data[col] = data[col].astype('category')
```

Explanation: The 'Date' column is converted to datetime, and categorical columns are converted to the 'category' dtype for efficient memory usage.

Step 5: Remove Duplicates and Reset Index

We remove duplicate rows and reset the index for consistency.

```
# Remove duplicates
data.drop_duplicates(inplace=True)

# Reset index
data.reset_index(drop=True, inplace=True)
```

Explanation: Duplicates are removed using `drop_duplicates()`, and the index is reset using `reset_index()`.

📊 Exploratory Data Analysis

Step 6: Feature Engineering

We create a new feature called 'Vehicle Age' by subtracting the 'Model Year' from the 'Date'.

```
# Create 'Vehicle Age' feature
data["Vehicle Age"] = data["Date"] - data["Model Year"]
```

Explanation: The 'Vehicle Age' feature is created to represent the age of the vehicle in years.

Step 7: Visualize Data

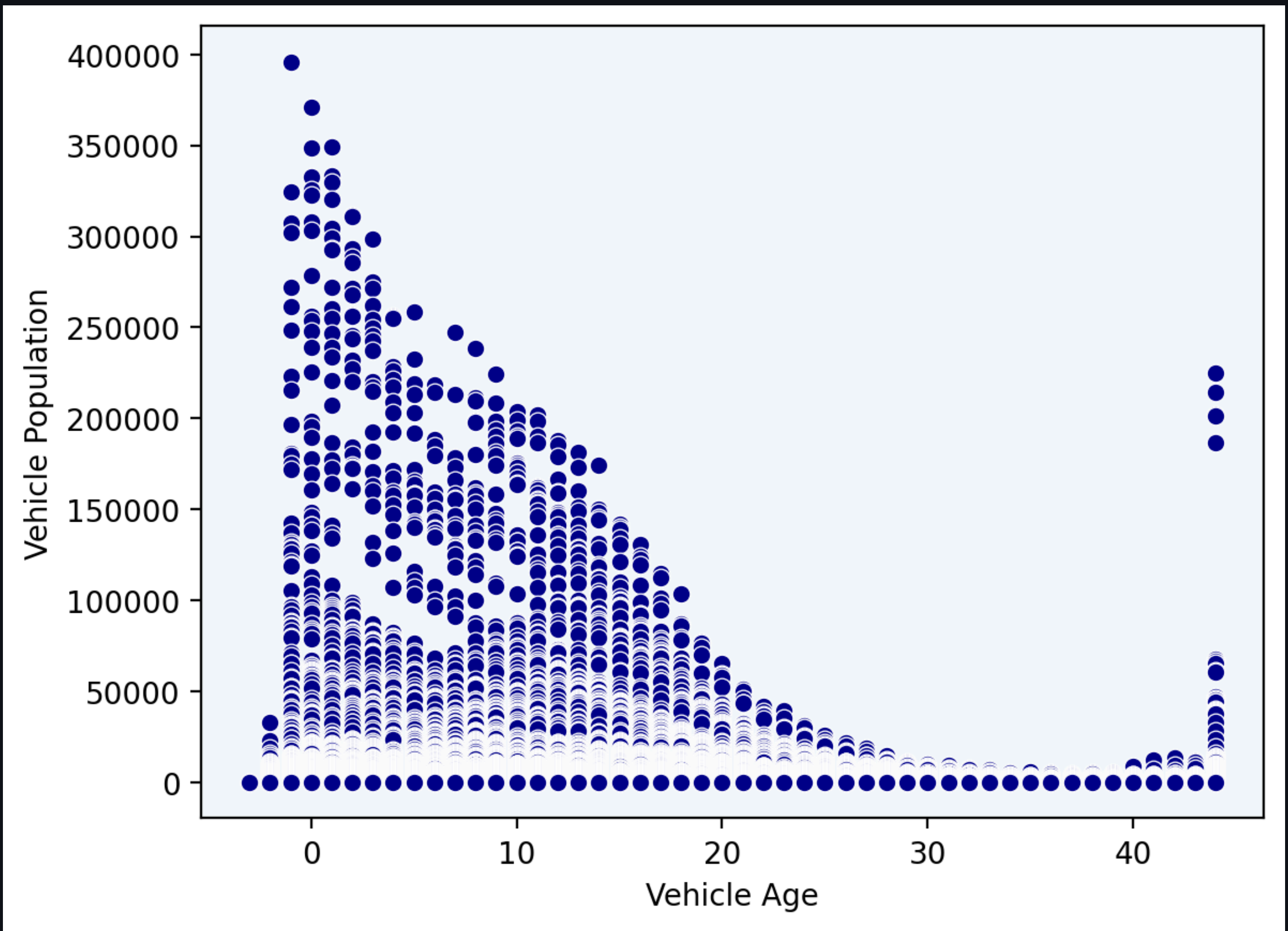
We visualize the relationship between 'Vehicle Age' and 'Vehicle Population' using a scatter plot.

```
import matplotlib.pyplot as plt
import seaborn as sns

# Scatter plot: Vehicle Age vs. Vehicle Population
plt.figure(figsize=(10, 6))
sns.scatterplot(x="Vehicle Age", y="Vehicle Population", data=data)
plt.title("Vehicle Age vs. Vehicle Population")
plt.xlabel("Vehicle Age")
plt.ylabel("Vehicle Population")
plt.grid(True)
plt.show()
```

Explanation: A scatter plot is created using `seaborn.scatterplot()` to visualize the relationship between 'Vehicle Age' and 'Vehicle Population'.

🔍 Vehicle Age vs. Population



📌 Insights

The Vehicle Population is highest for newer vehicles (age 0) and decreases significantly as the age increases. This trend indicates that newer vehicles dominate the population, while older vehicles (e.g., 30-40 years) are much rarer.

Step 8: Split Data into Training and Validation Sets

We split the dataset into training and validation sets for modeling.

```
from sklearn.model_selection import train_test_split

# Split data into features (X) and target (y)
X = data.drop(columns=["Vehicle Population"])
y = data["Vehicle Population"]

# Split into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
```

Explanation: The dataset is split into training and validation sets using `train_test_split()` with an 80-20 split.

Step 9: Final Check for Missing Values

We perform a final check to ensure no missing values remain in the dataset.

```
# Check for missing values
data.isnull().sum()
```

Explanation: A final check is performed to ensure all missing values have been handled.

Conclusion

The dataset has been cleaned, preprocessed, and is now ready for modeling. The EDA process included handling missing values, converting data types, removing duplicates, creating new features, and visualizing relationships between variables.

📌 Processed Dataset Preview

	Date	GVWR Class	Model Year	Number of Vehicles Registered at the Same Address	Vehicle Category_B	Vehicle Category_BS	Vehicle Category_BT	Vehicle Catego
0	2,019	1	2,014	4	0	0	0	
1	2,022	-1	1,999	4	1	0	0	
2	2,023	7	2,007	3	0	0	0	
3	2,020	3	1,996	2	0	0	0	
4	2,022	2	2,023	2	0	0	0	

📌 Intuition: We aim to predict the vehicle population using machine learning models. We'll train Random Forest, CatBoost, and XGBoost models, tune hyperparameters, and stack models to improve performance. The reason why we chose these models is that they are robust, handle non-linear relationships well, and are suitable for regression tasks, especially all the features are categorical data.

⚙️ Random Forest

Step 1: Train Random Forest Model

First, we train a basic Random Forest model and evaluate its performance on both the validation and test sets.

```
# Train Random Forest model
random_forest_model = RandomForestRegressor(random_state=28)
random_forest_model.fit(X_train, y_train)

# Shuffle validation and test data
X_test, y_test = shuffle(X_test, y_test, random_state=42)

# Evaluate on Validation Set
y_pred_val = random_forest_model.predict(X_val)
print("VALIDATION SET")
print("Mean Absolute Error (MAE):", mean_absolute_error(y_val, y_pred_val))
print("Root Mean Squared Error (RMSE):", math.sqrt(mean_squared_error(y_val, y_pred_val)))
print("R-squared (R2):", r2_score(y_val, y_pred_val))

# Evaluate on Test Set
y_pred = random_forest_model.predict(X_test)
print("TEST SET")
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Root Mean Squared Error (RMSE):", math.sqrt(mean_squared_error(y_test, y_pred)))
print("R-squared (R2):", r2_score(y_test, y_pred))
```

Step 2: Hyperparameter Tuning with GridSearchCV

Now we tune the hyperparameters of the Random Forest model using **GridSearchCV**.

```
param_grid = {
    "n_estimators": [50, 100, 200],
    "max_depth": [None, 10, 20, 30],
    "min_samples_split": [2, 5, 10],
    "min_samples_leaf": [1, 2, 4],
    "max_features": ["sqrt", "log2"],
    "bootstrap": [True, False]
}

grid_search = GridSearchCV(estimator=random_forest_model, param_grid=param_grid, cv=5,
                        scoring="neg_mean_squared_error", n_jobs=-1, verbose=3)

grid_search.fit(X_train, y_train)
print(f"Best Parameters: {grid_search.best_params_}")
print(f"Best RMSE from GridSearchCV: {math.sqrt(-grid_search.best_score_)}")
```

Step 3: Random State Tuning for Optimizing RMSE

Next, we experiment with different random states to find the one that minimizes the RMSE.

```
list_rmse = []
min_rmse = float('inf')
for i in tqdm(range(1, 100)):
    rf = RandomForestRegressor(random_state=i)
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)
    rmse_now = math.sqrt(mean_squared_error(y_test, y_pred))
    if rmse_now < min_rmse:
        min_rmse = rmse_now
        print(f"New Min RMSE: {min_rmse} at state {i}")
```

```
    list_rmse.append({"state": i, "rmse": rmse_now})

top_5_rmse = sorted(list_rmse, key=lambda x: x['rmse'])[:5]
for top_rmse in top_5_rmse:
    print(f"State: {top_rmse['state']}, RMSE: {top_rmse['rmse']}")
```

⚙️ CatBoost

Step 1: Train CatBoost Model

In this step, we train a CatBoost model, perform hyperparameter tuning, and evaluate its performance.

```
from catboost import CatBoostRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import math

# Define best parameters for CatBoost
best_params_catboost = {
    'iterations': 1000,
    'learning_rate': 0.1,
    'depth': 8,
    'l2_leaf_reg': 1,
    'random_strength': 0.5,
    'bagging_temperature': 1,
    'border_count': 32,
    'verbose': False,
    'random_state': 42
}

# Initialize CatBoost model with best parameters
catboost_model = CatBoostRegressor(**best_params_catboost)

# Train the model
catboost_model.fit(X_train_cat, y_train_full, cat_features=categorical_cols)

# Predictions
catboost_preds = catboost_model.predict(X_test_cat)

# Evaluate on Test Set
catboost_rmse = np.sqrt(mean_squared_error(y_test_cat, catboost_preds))
print(f"CatBoost RMSE: {catboost_rmse}")
print("*" * 50)
print("TEST SET")
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test_cat, catboost_preds))
print("Root Mean Squared Error (RMSE):", catboost_rmse)
print("R-squared (R2):", r2_score(y_test_cat, catboost_preds))
```

Step 2: Hyperparameter Tuning with GridSearchCV or RandomizedSearchCV

You can further fine-tune the hyperparameters using **GridSearchCV** or **RandomizedSearchCV**. Here's how:

```
from sklearn.model_selection import GridSearchCV

# Define parameter grid for hyperparameter tuning
param_grid = {
    'iterations': [500, 1000, 1500],
    'learning_rate': [0.01, 0.05, 0.1],
    'depth': [4, 6, 8],
    'l2_leaf_reg': [1, 3, 5],
    'random_strength': [0.1, 0.5, 1],
    'bagging_temperature': [0, 0.5, 1],
    'border_count': [32, 64, 128],
    'verbose': [False]
}

# Initialize the CatBoost model
catboost_model = CatBoostRegressor(random_state=42, cat_features=categorical_cols)

# Perform GridSearchCV for hyperparameter tuning
grid_search = GridSearchCV(catboost_model, param_grid, cv=3, n_jobs=-1, scoring='neg_root_mean_squared_error')
```

```
grid_search.fit(X_train_cat, y_train_full)

# Get the best parameters found by GridSearchCV
best_params_catboost = grid_search.best_params_
print("Best parameters found by GridSearchCV:", best_params_catboost)

# Train the model with the best parameters
best_catboost_model = grid_search.best_estimator_

# Evaluate on Test Set
catboost_preds = best_catboost_model.predict(X_test_cat)
catboost_rmse = np.sqrt(mean_squared_error(y_test_cat, catboost_preds))
print(f"CatBoost RMSE: {catboost_rmse}")
print("*" * 50)
print("TEST SET")
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test_cat, catboost_preds))
print("Root Mean Squared Error (RMSE):", catboost_rmse)
print("R-squared (R2):", r2_score(y_test_cat, catboost_preds))
```

⚙️ Stacking Multiple Models

📌 Intuition: Leveraging the strengths of multiple models to enhance overall performance. CatBoost is highly sensitive to extreme values, while Random Forest struggles with very small values. By combining these models, we aim to balance their strengths, improving both accuracy and robustness in our predictions.

Method 1: Stacking Random Forest and CatBoost with Meta-Model (Linear Regression)

In this method, we combine the predictions of Random Forest and CatBoost models by stacking them and then use a meta-model (Linear Regression) to make final predictions.

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import numpy as np

# Step 1: Fit the trained model with the training data
rf_preds = random_forest_model.predict(X_train)
cb_preds = best_catboost_model.predict(X_train_cat)

# Step 2: Create a new dataset using model predictions as features
stacked_features_1 = np.column_stack((rf_preds, cb_preds))

# Step 3: Train the meta-model on training data(using RF predictions as the main guidance)
meta_model = LinearRegression()
meta_model.fit(stacked_features_1, y_train)

# Step 4: Predict using the meta-model
rf_preds_test = random_forest_model.predict(X_test)
cb_preds_test = best_catboost_model.predict(X_test_cat)
stacked_features_1_test = np.column_stack((rf_preds_test, cb_preds_test))
stacked_preds_1_test = meta_model.predict(stacked_features_1_test)

# Step 5: Ensure non-negative predictions (since vehicle population can't be negative)
stacked_preds_1 = np.maximum(stacked_preds_1_test, 0)

# Step 6: Evaluate performance
rmse_stacked = np.sqrt(mean_squared_error(y_test, stacked_preds_1_test))
mae_stacked = mean_absolute_error(y_test, stacked_preds_1_test)
r2_stacked = r2_score(y_test, stacked_preds_1_test)

print("TEST SET")
print("Mean Absolute Error (MAE):", mae_stacked)
print("Root Mean Squared Error (RMSE):", rmse_stacked)
print("R-squared (R2):", r2_stacked)
```

Method 2: Stacking Predictions from Two Random Forest Models and CatBoost with Meta Model (Random Forest) - BEST SELECTION

In this method, we stack the predictions from one/two Random Forest models and a CatBoost model and use two Random Forest meta-models to make final predictions.

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import numpy as np

# Step 1: Generate features using the trained models
rf_preds_1 = random_forest_model.predict(X_train)  # First Random Forest model
rf_preds_2 = random_forest_model_2.predict(X_train)  # Second Random Forest model (with different hyperparameters)
cb_preds = best_catboost_model.predict(X_train_cat)  # CatBoost predictions

# Step 2: Stack the predictions from the base models
stacked_features_rf_only = np.column_stack((rf_preds_1, cb_preds))
stacked_features_rf_cb = np.column_stack((rf_preds_1, rf_preds_2, cb_preds))

# Step 3: Train the meta-model (Random Forest)
meta_rf_only = RandomForestRegressor(random_state=28)
meta_rf_only.fit(stacked_features_rf_only, y_train)
meta_rf_cb = RandomForestRegressor(random_state=28)
meta_rf_cb.fit(stacked_features_rf_cb, y_train)

# Step 4: Make final predictions
rf_preds_1_test = random_forest_model.predict(X_test)  # First Random Forest model
rf_preds_2_test = random_forest_model_2.predict(X_test)  # Second Random Forest model
cb_preds_test = best_catboost_model.predict(X_test_cat)  # CatBoost predictions

stacked_features_rf_only_test = np.column_stack((rf_preds_1_test, rf_preds_2_test))
stacked_features_rf_cb_test = np.column_stack((rf_preds_1_test, rf_preds_2_test, cb_preds_test))

stacked_preds_rf_only_test = meta_rf_only.predict(stacked_features_rf_only_test)
stacked_preds_rf_cb_test = meta_rf_cb.predict(stacked_features_rf_cb_test)

# Step 5: Evaluate performance
mae_stacked_rf_only = mean_absolute_error(y_test, stacked_preds_rf_only_test)
rmse_stacked_rf_only = np.sqrt(mean_squared_error(y_test, stacked_preds_rf_only_test))
r2_stacked_rf_only = r2_score(y_test, stacked_preds_rf_only_test)

mae_stacked_rf_cb = mean_absolute_error(y_test, stacked_preds_rf_cb_test)
rmse_stacked_rf_cb = np.sqrt(mean_squared_error(y_test, stacked_preds_rf_cb_test))
r2_stacked_rf_cb = r2_score(y_test, stacked_preds_rf_cb_test)
```

📈 Result Interpretation

📌 Understanding Model Performance

Model Performance Metrics

Below is a table summarizing the performance metrics of different models.

	Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	R-squared (R2)
0	CatBoost Only	2,092.98	5,661.89	0.9154
1	Base Random Forest	559.86	3,730.61	0.9633
2	Random Forest + CatBoost -> Linear Regression	564.66	3,757.97	0.9627
3	Two Random Forests -> Random Forest	559.9	3,719.93	0.9635
4	Two Random Forests + CatBoost -> Random Forest	563.79	3,736.97	0.9631
5	Tuned XGBoost	1,075.45	6,006.13	0.9061

Sample Predictions from Test Set

The table below shows a few examples of the actual vs. predicted values from the test set for each model.

CatBoost Model Predictions

	y_test	y_pred
0	47	-1,523.39
1	11,999	4,759.2
2	1	3,439.39
3	7	195.64
4	183,742	165,083.7
5	7	-2,978.96
6	7	-1,004.15
7	6	-167.97
8	2,551	-394.54
9	1	644.07

Base Random Forest Predictions

	y_test	y_pred
0	1	2.28
1	58	83.85
2	3,425	3,426.17
3	112	142.89
4	5,771	6,087.88
5	3	2.12
6	3	3.39
7	853	1,032.91
8	495	480.7
9	70	79.69

Random Forest + CatBoost → Linear Regression Predictions

	y_test	y_pred
0	316,065	292,402.11
1	315,986	297,319.85
2	306,487	292,453.54
3	284,754	266,745.41
4	284,153	280,101.62
5	1	-11.02
6	1	-9.43
7	1	-10.49
8	1	-8.6
9	1	-9.77

Two Random Forests → Random Forest Predictions

	y_test	y_pred
0	316,065	279,491.9
1	315,986	294,791.51
2	306,487	288,526.82
3	284,754	257,626.26
4	284,153	276,024.33
5	1	1.58
6	1	2.75
7	1	2.57
8	1	3.35
9	1	2.82

Tuned XGBoost Predictions

	y_test	y_pred
0	16	36.09
1	582	303.4
2	73	31.57
3	4	1.42
4	16	22.95
5	520	-77.27
6	15	129.97
7	44,018	162.68
8	508	-147.48
9	500	52.6

🤖 AI Assistant

📌 AI Assistant Features

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