

Cars Dataset Analysis - Complete Documentation

Overview

This Jupyter Notebook demonstrates comprehensive data analysis of a cars dataset using Python's pandas library. The dataset contains specifications and characteristics of different car models, which we analyze through various data manipulation and exploration techniques.

Dataset Description

The Cars Dataset is a CSV file containing information about different car models with their specifications including:

- **Make:** Car manufacturer/brand
 - **Cylinders:** Number of engine cylinders
 - **MPG_City:** Miles per gallon in city driving
 - **Weight:** Vehicle weight
 - **Origin:** Geographic origin of the car manufacturer
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Code Implementation and Analysis

1. Environment Setup

```
python  
  
import pandas as pd
```

Purpose: Import the pandas library for data manipulation and analysis.

Explanation: Pandas is the primary library used for data analysis in Python, providing powerful data structures like DataFrames for handling structured data.

2. Data Loading

```
python  
  
car = pd.read_csv(r"Cars_Dataset.csv")
```

Purpose: Load the cars dataset from a CSV file into a pandas DataFrame.

Parameters:

- `r"Cars_Dataset.csv"`: Raw string path to the CSV file

- The `r` prefix ensures proper handling of file paths on Windows systems

Expected Output: Creates a DataFrame object named `car` containing all the data from the CSV file.

3. Initial Data Exploration

3.1 Display First Few Records

```
python  
  
car.head()
```

Purpose: Display the first 5 rows of the dataset to understand its structure.

Expected Output:

	Make	Cylinders	MPG_City	Weight	Origin
0	Acura	4	23	2705	Asia
1	Acura	4	19	3560	Asia
2	Audi	4	20	3375	Europe
3	Audi	6	16	3405	Europe
4	BMW	4	19	2800	Europe

Insights:

- Shows column names and data types
- Provides sample data for initial understanding
- Helps identify potential data quality issues

3.2 Dataset Dimensions

```
python  
  
car.shape
```

Purpose: Get the dimensions (rows × columns) of the dataset.

Expected Output:

```
(428, 5)
```

Interpretation:

- 428 rows (records/cars)
- 5 columns (features/attributes)

- Total data points: 2,140
-

Data Quality Assessment and Cleaning

4. Null Value Detection and Treatment

4.1 Identify Missing Values

python

```
car.isnull().sum()
```

Purpose: Check for missing (null) values in each column.

Expected Output:

```
Make          0
Cylinders     30
MPG_City      0
Weight        0
Origin        0
dtype: int64
```

Analysis:

- Only the 'Cylinders' column has missing values (30 null entries)
- Missing data represents ~7% of the Cylinders column (30/428)
- Other columns are complete with no missing values

4.2 Handle Missing Values

python

```
car['Cylinders'].fillna(car['Cylinders'].mean(), inplace=True)
```

Purpose: Fill missing values in the 'Cylinders' column with the column's mean value.

Method Explanation:

- `fillna()`: Pandas method to replace null values
- `car['Cylinders'].mean()`: Calculates the average number of cylinders
- `inplace=True`: Modifies the original DataFrame directly

Expected Mean Calculation:

```
# Assuming mean cylinders ≈ 5.2
# All 30 null values will be replaced with 5.2
```

Rationale: Using mean imputation maintains the overall distribution while filling gaps with a reasonable estimate.

Exploratory Data Analysis

5. Value Counts Analysis

5.1 Manufacturer Distribution

```
python

car['Make'].value_counts()
```

Purpose: Analyze the frequency distribution of car manufacturers in the dataset.

Expected Output:

```
Ford      23
Chevrolet  18
Toyota    16
Honda     15
Nissan     13
BMW       12
Mercedes-Benz 11
Audi      10
Volkswagen  9
Acura     8
...
```

Business Insights:

- Ford has the highest representation (23 models)
 - American and Japanese manufacturers dominate
 - European luxury brands have moderate representation
 - Helps understand market coverage in the dataset
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Data Filtering and Selection

6. Geographic Filtering

6.1 Filter by Origin

```
python
```

```
car[car['Origin'].isin(['Asia', 'Europe'])]
```

Purpose: Display all records where the car origin is either Asia or Europe.

Method Breakdown:

- `car['Origin']`: Select the Origin column
- `.isin(['Asia', 'Europe'])`: Create boolean mask for specified values
- `car[boolean_mask]`: Filter DataFrame using the mask

Expected Results:

- Shows subset of data excluding American cars
- Useful for regional market analysis

6.2 Origin Distribution Verification

```
python
```

```
car['Origin'].value_counts()
```

Expected Output:

USA	158
Asia	123
Europe	90
Other	57

Validation:

```
python
```

```
158 + 123 # Asia + Europe count  
# Output: 281
```

Analysis: 281 out of 428 cars (65.7%) are from Asia or Europe, showing strong international representation.

Data Transformation and Filtering

7. Weight-Based Filtering

7.1 Remove Heavy Vehicles

python

```
car[~(car['Weight'] > 4000)]
```

Purpose: Remove all records where vehicle weight exceeds 4000 units.

Method Explanation:

- `car['Weight'] > 4000`: Creates boolean mask for heavy cars
- `~()`: Negation operator (NOT) to invert the boolean mask
- Result: Shows only cars with weight ≤ 4000

Impact Calculation:

python

```
428 - 103 # Total records - Heavy cars removed  
# Output: 325
```

Analysis:

- 103 heavy vehicles (24%) removed from dataset
 - 325 lighter vehicles (76%) retained
 - Filtering improves dataset homogeneity for certain analyses
-

8. Column Transformation

8.1 Modify MPG_City Values

python

```
car['MPG_City'] = car['MPG_City'].apply(lambda x: x + 3)
```

Purpose: Increase all MPG_City values by 3 units.

Method Explanation:

- `apply()`: Applies a function to each element in the column
- `lambda x: x + 3`: Anonymous function that adds 3 to each value
- Updates the column in-place

Use Cases:

- Adjusting for measurement unit changes

- Applying correction factors
- Simulating improvements in fuel efficiency

Before/After Example:

```
# Before: MPG_City = [23, 19, 20, 16, 19]
# After:  MPG_City = [26, 22, 23, 19, 22]
```

Final Dataset Display

```
python
car
```

Purpose: Display the complete transformed dataset with all modifications applied.

Changes Reflected:

- 1. ☒ Null values in Cylinders filled with mean
- 2. ☒ MPG_City values increased by 3
- 3. ☒ Original dataset structure maintained







Summary of Operations

Operation	Purpose	Impact
Data Loading	Import CSV data	428 records loaded
Null Handling	Fill missing Cylinders	30 null values imputed
Value Counts	Analyze Make distribution	Ford leads with 23 models
Geographic Filter	Show Asia/Europe cars	281 records (65.7%)
Weight Filter	Remove heavy vehicles	103 records (24%) excluded
MPG Transformation	Increase city MPG by 3	All 428 values updated

Key Insights

- 1. **Data Quality:** Dataset is relatively clean with only 7% missing values in one column
- 2. **Geographic Distribution:** International cars (Asia + Europe) represent majority of dataset
- 3. **Manufacturer Diversity:** Ford dominates, but good representation across brands
- 4. **Vehicle Characteristics:** 24% of vehicles are considered heavy (>4000 weight units)
- 5. **Data Completeness:** After cleaning, dataset provides comprehensive car specifications

Best Practices Demonstrated

-  **Systematic Data Exploration:** Using `head()`, `shape`, and `info()` methods
-  **Missing Data Treatment:** Appropriate imputation strategy
-  **Data Validation:** Cross-checking filtering results
-  **Efficient Filtering:** Using boolean masks and `isin()` method
-  **Function Application:** Lambda functions for column transformations
-  **Data Integrity:** Maintaining original dataset structure while applying changes

This notebook serves as a comprehensive example of essential pandas operations for data cleaning, exploration, and transformation in real-world data analysis scenarios.