

# Data Science Workflow Report

Here is a detailed response that covers each aspect of the data science workflow for the given dataset:

## 1. Data Preprocessing & Cleaning

### - Missing Values:

+ ``normalized-losses``: 41 missing values (20.5% of total). Suggest median imputation, as it is more robust to outliers than mean imputation.

+ ``bore``, ``stroke``, ``horsepower``, ``peak-rpm``, and ``price``: 4 missing values each (2% of total). Suggest mean imputation, as the missing values are relatively few and the columns are numeric.

+ ``num-of-doors``: 2 missing values (1% of total). Suggest mode imputation, as it is a categorical column.

- Duplicate Records: No duplicate records detected.

- Inconsistent Data: No obvious inconsistencies detected. However, it's essential to review the data manually to ensure consistency in formatting and units.

## 2. Exploratory Data Analysis (EDA)

### - Numeric Columns:

+ ``horsepower``, ``wheel-base``, ``length``, ``width``, ``height``, ``curb-weight``, ``engine-size``, ``bore``, ``stroke``, ``compression-ratio``, ``peak-rpm``, ``city-mpg``, and ``highway-mpg``: Histograms and box plots can help visualize distributions and identify outliers.

+ ``normalized-losses``: A scatter plot can help visualize the relationship between ``normalized-losses`` and other numeric columns.

### - Categorical Columns:

+ ``fuel-type``, ``aspiration``, ``num-of-doors``, ``body-style``, ``drive-wheels``, ``engine-location``, ``engine-type``, ``fuel-system``, and ``make``: Bar charts or count plots can help visualize the distribution of each category.

### - Relationships between Columns:

+ Correlation matrices can help identify relationships between numeric columns, such as the relationship between ``horsepower`` and ``engine-size``.

+ Pair plots can help visualize relationships between multiple columns, such as ``wheel-base``,

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`length`, and `width`.

## 3. Machine Learning Algorithm Selection

- Classification:

- + If the target variable is `fuel-type`, suggest logistic regression, decision trees, or random forests, as they are suitable for categorical classification tasks.

- + If the target variable is `make`, suggest logistic regression or multinomial logistic regression, as they are suitable for multi-class classification tasks.

- Regression:

- + If the target variable is `price`, suggest linear regression, decision trees, or gradient boosting, as they are suitable for regression tasks.

- + If the target variable is `normalized-losses`, suggest linear regression or random forests, as they are suitable for regression tasks.

- Supervised vs. Unsupervised:

- + Supervised learning is more suitable for this dataset, as there are clear target variables (e.g., `fuel-type`, `price`) that can be predicted.

- Model Evaluation Metrics:

- + For classification tasks, suggest accuracy, precision, recall, and F1-score.

- + For regression tasks, suggest mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R-squared).

## 4. Model Optimization & Feature Engineering

- Feature Engineering:

- + For numeric columns, suggest normalization (e.g., standardization, min-max scaling) to reduce the effect of outlier values.

- + For categorical columns, suggest one-hot encoding or label encoding to convert categorical values into numeric features.

- + For `engine-size` and `horsepower`, suggest log transformation to reduce skewness.

- Hyperparameter Tuning:

- + Suggest GridSearchCV or RandomizedSearchCV to perform hyperparameter tuning for machine

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learning algorithms.

- Ensemble Learning:

+ Suggest bagging, boosting, or stacking to improve model performance by combining multiple base models.

## 5. Deployment & Real-World Considerations

- Model Deployment:

+ Suggest deploying models as APIs or cloud services to make predictions accessible to users.

- Data Drift:

+ Suggest monitoring data distribution and retraining models periodically to adapt to changes in the data distribution.

- Model Monitoring:

+ Suggest tracking model performance metrics (e.g., accuracy, MSE) and retraining models when performance degrades.

- Real-World Applications:

+ Suggest using the trained models to predict fuel efficiency, engine performance, or vehicle prices in real-world applications.

I hope this detailed response helps! Let me know if you have any questions or need further clarification.