

2. Handle Missing Data

Why It's Important

Missing data can bias results or reduce model performance. Handling it effectively ensures data integrity.

Steps to Handle Missing Data

1. Identify Missing Values:

- Look for null, NaN, or placeholder values like 999 or -1.
- Summarize missing data as percentages or counts for each column.
- Example: If 30% of entries in a column are missing, consider if that feature is still valuable.

2. Decide How to Handle Missing Data:

- **Remove Rows/Columns:**
 - If a row has too many missing values (>50%), consider removing it.
 - If a column has >30% missing data and no easy way to impute, consider dropping it.
- **Imputation:**
 - For numerical data:
 - Mean or median for symmetric distributions.
 - Mode for categorical or binary data.
 - For categorical data:
 - Most frequent value or "Unknown" category.
- **Domain-Specific Handling:**
 - For example, forward-fill or backward-fill for time-series data ensures continuity.

Best Practices:

- Impute missing values only in the training set to avoid data leakage.
 - Document imputation methods for reproducibility.
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3. Remove Duplicates

Why It's Important

Duplicate data skews analysis by overrepresenting patterns. Removing duplicates ensures accurate modeling.

Steps to Handle Duplicates:

1. Identify Duplicates:

- Check rows where all columns have identical values.
- For partial duplicates, focus on key columns like IDs or combinations (e.g., customer ID and timestamp).

2. Decide on Removal:

- Retain only the first occurrence of a duplicate.
- If duplicates have slight differences (e.g., timestamps), use domain knowledge to decide which one to keep.

3. Verify After Removal:

- Ensure important records were not mistakenly dropped.
- Keep a backup before removing duplicates for safety.

Best Practices:

- Check for duplicates after merging datasets or concatenating rows.
 - Log removal criteria for transparency.
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4. Handle Outliers

Why It's Important

Outliers can distort model predictions, especially in algorithms sensitive to scale, like linear regression.

Steps to Handle Outliers:

1. Detect Outliers:

- Statistical methods:
 - **Interquartile Range (IQR):**
 - Define outliers as values $< Q1 - 1.5IQR$ or $> Q3 + 1.5IQR$.
 - **Z-Score:**
 - Treat values with $|z| > 3$ as outliers.
- Visual methods:
 - Box plots, scatter plots, or histograms.

2. Decide on Outlier Handling:

- **Remove:**

- For data entry errors or when the outlier is irrelevant to the analysis.
- **Transform:**
 - Apply logarithmic, square-root, or similar transformations to reduce the effect.
- **Cap Values:**
 - Set thresholds to replace extreme outliers with fixed values (e.g., 1st and 99th percentiles).
- **Analyze Separately:**
 - If outliers are valuable (e.g., high-spending customers), analyze them in a separate context.

Best Practices:

- Treat each feature independently for outlier detection.
 - Use domain expertise to determine if an outlier is truly erroneous or meaningful.
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5. Fix Data Types

Why It's Important

Incorrect data types cause errors during analysis or modeling. Fixing them ensures consistency and compatibility.

Steps to Fix Data Types:

1. **Inspect Data Types:**
 - Check all columns for mismatched types (e.g., dates stored as strings or numerical IDs stored as text).
2. **Convert Data Types:**
 - **Numerical Conversion:**
 - Convert numerical strings (e.g., "123.45") to float or integer.
 - **Date Conversion:**
 - Transform date strings (e.g., "2024-12-28") into datetime objects for easier analysis.
 - **Categorical Conversion:**
 - Ensure categorical features are stored as appropriate data types for better memory usage and compatibility with encoding.
3. **Verify After Conversion:**
 - Validate the changes by summarizing the dataset to check for errors.

- Perform a quick analysis (e.g., histograms or unique values) to confirm correctness.

Best Practices:

- Consistently format similar features (e.g., prices in dollars and cents).
- Use metadata or domain expertise to ensure proper type assignments.