

DATA CLEANING CHECKLIST

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Understand the Dataset Start by thoroughly reviewing the dataset to understand its structure and purpose.	<input type="checkbox"/> Review the dataset's documentation and metadata.	NOTES
	<input type="checkbox"/> Familiarize yourself with key variables and data types.	
	<input type="checkbox"/> Identify the expected ranges and formats for each column.	
Handling Missing Data Detect and handle any missing values to ensure your dataset is complete and accurate.	<input type="checkbox"/> Identify missing values using <code>.isnull()</code> (Python) or <code>is.na()</code> (R).	NOTES
	<input type="checkbox"/> Analyze if the missing data follows any patterns.	
	<input type="checkbox"/> Impute missing data (mean, median, or mode), or remove rows/columns with excessive missing data.	
Fix Data Types Ensure all variables are correctly formatted to avoid errors during analysis.	<input type="checkbox"/> Check that numeric, categorical, and date columns are correctly typed.	NOTES
	<input type="checkbox"/> Convert columns to appropriate data types (e.g., <code>pd.to_numeric()</code>).	
	<input type="checkbox"/> Format date/time columns for consistency (e.g., <code>pd.to_datetime()</code>).	
Handling Duplicates Detect and eliminate duplicate rows to prevent redundancy in your data.	<input type="checkbox"/> Detect duplicate rows using <code>.duplicated()</code> (Python) or <code>duplicated()</code> (R).	NOTES
	<input type="checkbox"/> Remove duplicates using <code>.drop_duplicates()</code> (Python).	
	<input type="checkbox"/> Ensure key columns are unique where necessary (e.g., IDs).	
Outliers Detection and Treatment Identify and assess outliers. Remove or retain them based on your analysis goals.	<input type="checkbox"/> Use statistical methods (e.g., z-scores, IQR) or boxplots to identify outliers.	NOTES
	<input type="checkbox"/> Analyze outliers to determine if they are valid or data entry errors.	
	<input type="checkbox"/> Remove or transform outliers (e.g., apply log transformation if necessary).	
Handle Inconsistent Data Standardize inconsistent entries, especially in categorical data, to ensure uniformity.	<input type="checkbox"/> Detect inconsistent values (e.g., 'USA' vs 'United States').	NOTES
	<input type="checkbox"/> Standardize categories and ensure text formatting (e.g., all lowercase).	
	<input type="checkbox"/> Cross-check categories for spelling or case sensitivity issues.	

Remove Unwanted Characters Clean up unnecessary spaces, special characters, and formatting errors.	<input type="checkbox"/> Remove leading/trailing spaces using <code>.strip()</code> (Python) or <code>trimws()</code> (R).	NOTES
	<input type="checkbox"/> Eliminate special characters using regex or string replacement.	
	<input type="checkbox"/> Ensure uniform formatting for text fields.	

Normalize and Standardize Data Scale numeric data to make it comparable across different units or ranges.	<input type="checkbox"/> Normalize data to bring all values into a similar range (e.g., Min-Max scaling).	NOTES
	<input type="checkbox"/> Standardize data (mean = 0, standard deviation = 1) for algorithms that require standardized inputs.	
	<input type="checkbox"/> Apply appropriate scaling methods based on analysis needs.	

Create and Validate Derived Variables Generate new features and validate their correctness before analysis.	<input type="checkbox"/> Create new variables (e.g., age from date of birth).	NOTES
	<input type="checkbox"/> Validate derived variables with cross-checks and summary statistics.	
	<input type="checkbox"/> Ensure that new variables follow consistent formatting and logical rules.	

Ensure No Data Leakage Double-check data. Remove information that would be unavailable in real-world analysis.	<input type="checkbox"/> Ensure no target variables or future data are included in the training set.	NOTES
	<input type="checkbox"/> Review features to prevent information leaks during model training.	
	<input type="checkbox"/> Split your data into training, validation, and test sets before performing feature engineering.	

Ensure Consistent Formatting Ensure dates, text, and other formatted fields follow consistent patterns.	<input type="checkbox"/> Standardize date formats (e.g., YYYY-MM-DD).	NOTES
	<input type="checkbox"/> Ensure consistent text formatting (e.g., same case, punctuation, etc.).	
	<input type="checkbox"/> Check for and correct any formatting irregularities in all columns.	

Validate Data Use summary statistics and external references to verify the accuracy of your cleaned data.	<input type="checkbox"/> Run summary statistics (<code>.describe()</code> in Python) to verify data ranges and distributions.	NOTES
	<input type="checkbox"/> Cross-check your data with external sources or domain expertise.	
	<input type="checkbox"/> Investigate any values that fall outside expected ranges.	

Backup the Cleaned Data Safeguard your progress by creating a backup of your cleaned dataset.	<input type="checkbox"/> Create a backup copy of the cleaned dataset.	NOTES
	<input type="checkbox"/> Store backups securely (e.g., cloud storage, version control system).	
	<input type="checkbox"/> Keep a version history to track changes in case of errors.	

SNIPPETS / TIPS

Use Pandas Profiling for Quick Data Insights	<pre>import pandas_profiling profile = pandas_profiling.ProfileReport(df) profile.to_file("data_report.html")</pre>
Tip: Generate a comprehensive report of your dataset using the pandas_profiling package in Python. It provides an overview of missing values, statistics, correlations, and more.	<i>Use this to get a quick overview of your dataset before cleaning.</i>
Detect and Replace Outliers Efficiently	<pre>Q1 = df['column_name'].quantile(0.25) Q3 = df['column_name'].quantile(0.75) IQR = Q3 - Q1 lower_bound = Q1 - 1.5 * IQR upper_bound = Q3 + 1.5 * IQR df = df[(df['column_name'] >= lower_bound) & (df['column_name'] <= upper_bound)]</pre>
Tip: Use the IQR (Interquartile Range) method to detect outliers and handle them by capping or removing them.	<i>This method helps you handle outliers in numerical data.</i>
Fill Missing Data Using Interpolation	<pre>df['column_name'].interpolate(method='linear', inplace=True)</pre>
Tip: For time series data, you can use interpolation to fill in missing values in a logical way based on surrounding data.	<i>Use this when missing values are within a time sequence and can be estimated using surrounding points.</i>
Normalize Data Easily	<pre>from sklearn.preprocessing import MinMaxScaler scaler = MinMaxScaler() df[['column1', 'column2']] = scaler.fit_transform(df[['column1', 'column2']])</pre>
Tip: Use the MinMaxScaler from scikit-learn to scale numeric values to a range between 0 and 1.	<i>This is useful for preparing data for machine learning models.</i>
Split Data Properly	<pre>from sklearn.model_selection import train_test_split train, test = train_test_split(df, test_size=0.2, random_state=42)</pre>
Tip: Always split your dataset into training, validation, and test sets to avoid data leakage.	<i>This ensures your model is evaluated on unseen data.</i>

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Let's clean data the smart way!

