Welcome to the CoGrammar Data Cleaning

The session will start shortly...

Questions? Drop them in the chat. We'll have dedicated moderators answering questions.

Data Science Session Housekeeping

- The use of disrespectful language is prohibited in the questions, this is a supportive, learning environment for all - please engage accordingly. **(Fundamental British Values: Mutual Respect and Tolerance)**
- No question is daft or silly - **ask them!**
- There are **Q&A sessions** midway and at the end of the session, should you wish to ask any follow-up questions. Moderators are going to be answering questions as the session progresses as well.
- If you have any questions outside of this lecture, or that are not answered during this lecture, please do submit these for upcoming Academic Sessions. You can submit these questions here: [Questions]

Data Science Session Housekeeping cont.

- For all **non-academic questions**, please submit a query: www.hyperiondev.com/support

- Report a **safeguarding** incident: www.hyperiondev.com/safeguardreporting

- We would love your **feedback** on lectures: Feedback on Lectures

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Data Cleaning

April 2024

Learning objectives

- Describe techniques for **handling missing data** and when each is appropriate to use.
- Demonstrate how to identify and remove duplicate records in a dataset using Pandas.
- Explain the importance of **consistent data formatting and apply methods to standardise data.**
- Define **outliers** and discuss strategies for detecting and handling them appropriately based on the data context.

Handling Missing Data

- Missing data refers to the **absence of values in one or more variables in a dataset.**

- Identifying missing values:
  - Look for **null, NaN, or empty cells in the dataset**.
  - Use functions like **isnull() or isna()** in Pandas to detect missing values.

```
data.isnull().sum()
```

```
Name      0
Age       1
Salary    0
City      0
dtype: int64
```

Handling Missing Data

- Techniques for dealing with missing data:
  - **Deletion:** Remove records with missing values (only suitable if missing data is minimal and random).

```
data_deleted = data.dropna()
```

Handling Missing Data

- Techniques for dealing with missing data:
  - **Imputation:** Fill in missing values with estimated or calculated values.
    - **Simple imputation methods:** Mean, median, or mode imputation.

```
data_imputed_mean = data.fillna(data["Age"].mean())
```

    - **Advanced imputation methods:** K-Nearest Neighbors (KNN), Multiple Imputation by Chained Equations (MICE).

```
data_imputed_knn = imputer.fit_transform(data[['Age']])
```

Imputation Considerations

- The choice of imputation method depends on the **nature of the missing data** and the analysis requirements.

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Missing Completely at Random (MCAR)

- The probability of a value being missing is the **same for all cases** and does not depend on any other variables in the dataset.

- Example: In a survey, a participant accidentally skips a question. The missingness is unrelated to the participant's characteristics or other responses.

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Missing at Random (MAR)

- The probability of a value being missing **depends on other observed variables in the dataset but not on the missing values themselves.**

- Example: In a medical study, **younger participants are more likely to miss a follow-up appointment**. The missingness is r**elated to the observed variable "age" but not to the unobserved health outcomes**.

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Missing Not at Random (MNAR)

- The probability of a value being missing **depends on the missing values themselves,** even after accounting for other observed variables.

- Example: In an income survey, **high-income individuals are more likely to refuse to report their income**. The missingness is related to the unobserved income level itself.

Importance of Missing Data Mechanisms

- Understanding the type of missingness is crucial for selecting appropriate handling techniques.

- **MCAR:** Simple methods like deletion or mean imputation may be suitable.
- **MAR:** More advanced methods like multiple imputation can be used.
- **MNAR:** Requires careful consideration and modeling of the missingness mechanism.

Determining the Missing Data Mechanism

- ❖ Assess the relationship between missingness and other variables in the dataset.
- ❖ Consider domain knowledge and the data collection process.
- ❖ Conduct statistical tests to examine patterns of missingness.
- ❖ Be cautious and transparent about assumptions made regarding the missing data mechanism.

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Dealing with Duplicates

- ❖ Duplicate records are multiple instances of the same data point in a dataset.

4	David	40.0	80000	London
5	David	40.0	80000	London

- ❖ Identifying duplicates:
  - ➢ Use functions like **duplicated()** in Pandas to identify duplicate records.
    Specify the subset of columns to consider when identifying duplicates.

Dealing with Duplicates

- Strategies for handling duplicates:
  - **Removing duplicates:** Drop duplicate records from the dataset using drop_duplicates().
  - **Merging duplicates:** Combine duplicate records into a single record by aggregating or selecting relevant information.

```
data_deduplicated = data.drop_duplicates()
```

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Data Formatting and Standardisation

- ❖ Consistent data formatting is essential for **accurate analysis** and compatibility with different tools and algorithms.

- ❖ Common formatting issues:
  - ➢ **Date and time formats:** Ensure consistent representation (e.g., YYYY-MM-DD, HH:MM:SS).
  - ➢ **Text case inconsistencies:** Convert text to a consistent case (lowercase or uppercase).
  - ➢ **Inconsistent value representations:** Standardise values (e.g., "Yes"/"No" vs. "Y"/"N").

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Handling Outliers

❖ Outliers are data points that significantly deviate from the rest of the data distribution.

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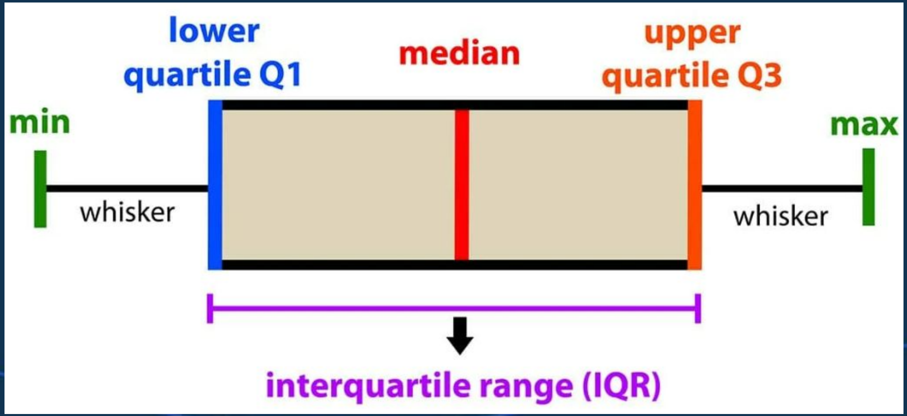
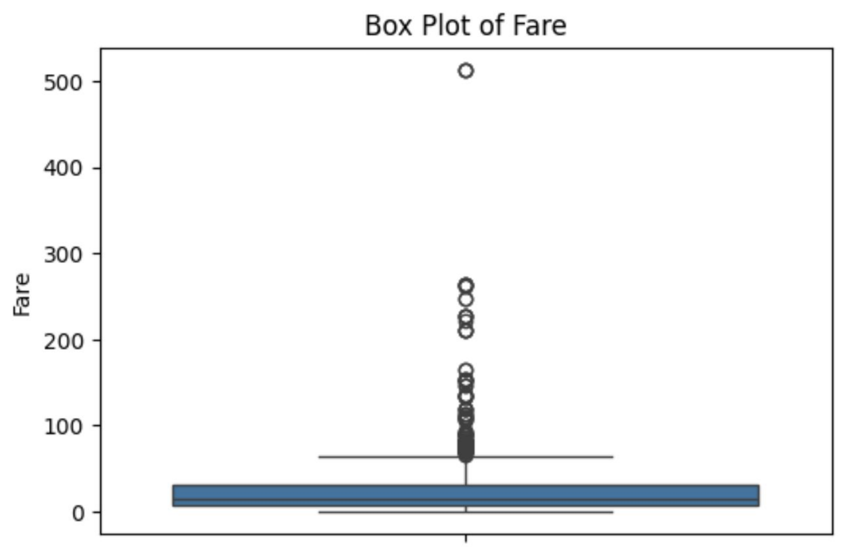
Handling Outliers

- Identifying outliers:
  - **Visual inspection:** Use plots like box plots, scatter plots, or histograms to identify extreme values.



Handling Outliers

Using a box plot to identify outliers.



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Handling Outliers

- Strategies for handling outliers:
  - **Removal:** Remove outliers from the dataset if they are erroneous or irrelevant to the analysis.
  - **Transformation:** Apply mathematical transformations (e.g., logarithmic, square root) to reduce the impact of outliers.
  - **Winsorisation:** Replace extreme values with the nearest non-outlier values.

```
data_winsorized['Salary'] = stats.mstats.winsorize(data_winsorized['Salary'], limits=0.2)
```

- Consider the context and domain knowledge when deciding how to handle outliers.

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Which of the following is NOT a common data quality issue?

A. Missing values
B. Duplicates
C. Inconsistent formatting
D. Small sample size

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Which technique is suitable for handling missing data only if the amount is minimal and missing at random?

A. Mean imputation

B. Deletion

C. K-Nearest Neighbours imputation

D. Multiple Imputation by Chained Equations

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In Pandas, which function can be used to identify duplicate records in a dataset?

A. find_duplicates()

B. duplicated()

C. is_duplicate()

D. has_duplicates()

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Which of the following is a technique for standardising inconsistent text case?

A. astype()

B. to_datetime()

C. upper() or lower()

D. strip()

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Which strategy replaces outlier values with the nearest non-outlier values?

A. Removal
B. Transformation
C. Winsorisation
D. Standardisation

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D. Standardisation

Conclusions

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Conclusions

- Recap of key points:
  - Data cleaning is an essential step in the data science pipeline.
  - It involves **handling missing data, duplicates, formatting issues, outliers, and data validation.**
  - Various techniques and tools are available for effective data cleaning.

Conclusions

- Importance of iterative data cleaning:
  - Data cleaning is an iterative process that may require multiple rounds.
  - Continuously assess and refine the cleaned data based on analysis results and feedback.

Further Learning

KDNuggets - Learn Data Cleaning and Preprocessing for Data Science with This Free eBook

Kaggle - Short Data Cleaning Course

Questions and Answers

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Thank you for attending

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