Statistics and Data Analysis

Unit 01 – Lecture 03: Preprocessing Pipelines and Exploratory Data Analysis (EDA)

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https://github.com/tali7c/Statistics-and-Data-Analysis

Quick Links

Workflow EDA Checklist Plots Demo Summary

Agenda

Learning Outcomes

- Explain what a preprocessing pipeline is and why it matters

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- Apply a simple end-to-end workflow: load $\rightarrow$ clean $\rightarrow$ validate $\rightarrow$ summarize
- Perform basic EDA: missingness, summary stats, group summaries, correlations
- Choose appropriate plots for numeric and categorical variables

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- Makes analysis **reproducible** (same input $\Rightarrow$ same output)
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- Helps avoid **data leakage** (train/test separation)

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6. EDA: summary tables + plots + simple relationships
7. Save outputs (cleaned dataset, plots, summary tables)

Example: "Pipeline" in Code (Concept)

```
df = read_raw()
df = clean_strings(df)
df = coerce_types(df)
df = range_check(df)
df = impute_missing(df)
save_clean(df)
eda_report(df)
```

This is a simple pipeline: each step has a clear purpose.

Exercise 1: Put Steps in Order

Arrange these steps in a reasonable order:

1. EDA plots
2. Load raw data
3. Fix data types + invalid ranges
4. Save cleaned dataset
5. Check missingness

Solution 1

One reasonable order:

1. Load raw data
2. Check missingness
3. Fix data types + invalid ranges
4. EDA plots
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- Understand distribution (shape, spread, outliers)
- Understand relationships (scatter plots, correlation)
- Compare groups (e.g., program-wise summaries)
- Identify issues early (missingness, strange values)

EDA Checklist (Minimum)

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- **Group summaries:** mean/median/std by program or gender

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- Numeric vs numeric: scatter plot
- Numeric vs categorical: boxplot (numeric grouped by category)
- Many numeric features: correlation heatmap

Exercise 2: Choose the Plot

Pick a good plot for each:

1. Distribution of `final_marks` (numeric)
2. Compare `final_marks` across `program` (categorical)
3. Relationship between `study_hours_week` and `final_marks`

Solution 2

- (1) Histogram or boxplot
- (2) Boxplot of marks grouped by program
- (3) Scatter plot (hours vs marks)

Exercise 3: Spot Data Leakage

A student computes mean/std for scaling using the **entire dataset**, then splits into train/test and trains a model.

Question: Is this correct? If not, what should be done instead?

Solution 3

Not correct: it uses test information during training (**leakage**).
Correct approach:

- split into train/test first
- compute scaling parameters on **train only**
- apply the same parameters to test

Mini Demo (Python)

Run from the lecture folder:

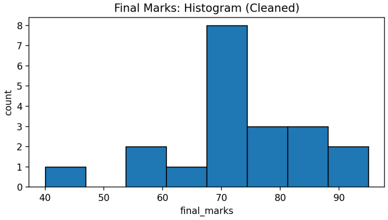
```
python demo/pipeline_eda_demo.py
```

Outputs:

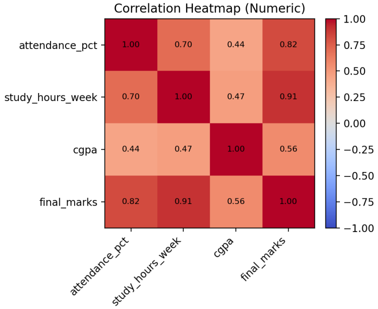
- `data/case_study_clean.csv`
- `data/summary_by_program.csv`
- `data/corr_matrix.csv`
- plots in `images/` (histogram, boxplot, scatter, heatmap)

Demo Output (Example)

Histogram



Correlation Heatmap



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- Pipelines make preprocessing repeatable and reduce mistakes
- EDA is about understanding quality, distributions, and relationships
- Pick plots based on variable types (numeric vs categorical)
- Save cleaned data, plots, and summary tables as reusable artifacts

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