Statistics and Data Analysis
Unit 01 – Lecture 01 Notes
Data Types, Sources, and Cleaning Basics

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February 17, 2026

Why This Lecture Exists

Before we compute statistics or build models, we must ensure the data is:

- correctly **typed** (numbers are numbers, dates are dates),
- correctly **formatted** (consistent schema and representation),
- and reasonably **clean** (no obvious errors, duplicates, or impossible values).

Otherwise, we can get very convincing but completely wrong conclusions.

1. Dataset Basics

1.1 Observation vs variable

- An **observation** is one record/row (e.g., one student).
- A **variable** (or feature/attribute) is one column (e.g., attendance%).
- A **dataset** is a table of observations and variables.

1.2 Why type matters

If a numeric column is stored as text, then:

- sorting can become wrong ("100" comes before "20" in string order),
- mean/median cannot be computed correctly,
- plots may fail or mislead.

So the first step in almost every analysis is: **inspect data types**.

2. Data Types and Formats

2.1 Common data types (practical)

- **Numeric**: integers (count) and real values (measurement).
- **Categorical**:
  - **Nominal**: no natural order (branch = CSE/ECE).
  - **Ordinal**: ordered categories (rating = low/medium/high).
- **Binary**: yes/no, 0/1, pass/fail.
- **Datetime**: dates and timestamps.
- **Text**: comments, feedback (often unstructured).

2.2 Data formats

- **Structured**: fixed schema, tabular (CSV, SQL tables).
- **Semi-structured**: key-value or tagged (JSON, XML).
- **Unstructured**: free form (text documents, images, audio).

Why formats matter. Structured data is easiest to analyze directly. Semi-structured data needs parsing and may have missing keys. Unstructured data typically needs **feature extraction** (e.g., word counts from text, embeddings, image features).

Exercise 1 (solution)

Classify:

- Age: numeric (integer)
- Program/Branch: categorical (nominal)
- Attendance (%): numeric (real)
- Join date: datetime
- Feedback comment: text

3. Data Sources and Acquisition

3.1 Common sources

- **Surveys/forms**: can have missing fields and user entry errors.
- **Databases**: usually structured but can include stale/inconsistent codes.
- **Logs**: large volume, semi/unstructured, need parsing.
- **Sensors**: frequent readings, can have noise and missing intervals.
- **APIs**: provide JSON/XML, rate limits, schema changes.

3.2 Acquisition methods

- file import (CSV/Excel)
- database query (SQL)
- API requests (JSON)
- manual entry (small datasets only; double-check)

Exercise 2 (solution)

- Daily attendance: database export (or CSV export)
- Platform clicks: logs
- Feedback comments: survey + text field (unstructured text)
- Weather readings: sensors or API

4. Data Cleaning Basics

4.1 What is "dirty" data?

Dirty data commonly includes:

- Missing values (blank, NaN, NULL)
- Duplicate records
- Inconsistent categories (`cse`, `CSE`, `CSE`)
- Out-of-range values (attendance 105%, CGPA 12)
- Wrong type ("nine" in a numeric column)

4.2 Missing values

Missing values occur for many reasons: non-response in surveys, sensor failure, system bugs, etc.

Basic options.

1. **Drop rows/columns**: only if missingness is small and not biased.
2. **Impute**: fill missing values using a rule.
3. **Flag**: create a new column indicating missingness.

Mean vs median imputation (why median is common). The mean is sensitive to outliers. The median is more robust. So for a numeric column like income or CGPA, median is often a safer default imputation.

Exercise 3 (solution)

If 2 values are missing out of 20:

$$\text{missing } \% = \frac{2}{20} \times 100\% = 10\%$$

A reasonable action: **median imputation** for CGPA and optionally add a flag column `cgpa_was_missing`.

4.3 Outliers

An outlier is a value that looks unusually far from the rest. Important: outliers can be **errors** or **true extremes**. So the goal is not to automatically delete outliers; the goal is to **detect and investigate**.

IQR rule (fences). Compute:

$$\text{IQR} = Q_3 - Q_1$$

Then:

$$\text{Lower fence} = Q_1 - 1.5 \times \text{IQR}, \quad \text{Upper fence} = Q_3 + 1.5 \times \text{IQR}$$

Values outside fences are flagged as possible outliers.

Exercise 4 (solution)

Attendance (%): 70, 75, 80, 85, 90, 95, 150. Median is 85.

- $Q_1 = 75$ (median of 70,75,80)
- $Q_3 = 95$ (median of 90,95,150)
- IQR $= 95 - 75 = 20$
- Fences: $75 - 30 = 45$ and $95 + 30 = 125$
- Since $150 > 125$, 150 is an outlier (by IQR rule).

4.4 Duplicates and inconsistent categories

Duplicates can happen due to repeated exports, multiple submissions, or system errors. Always check duplicates using a sensible key (e.g., `student_id`).

Inconsistent categories occur due to case and whitespace differences. Common fixes:

- strip whitespace
- convert to a standard case (e.g., uppercase)
- map synonyms (e.g., “Male” and “M” to “M”)

5. Mini Demo (Python)

Run this from the lecture folder:

```
python demo/cleaning_demo.py
```

The demo performs these steps:

- prints shape, head, and dtypes of `data/messy_students.csv`
- reports missingness and duplicates
- trims and standardizes categorical values (program, gender, city)
- converts numeric columns, parses dates
- flags out-of-range values and imputes numeric missing values using median
- removes duplicate `student_id` rows
- saves `data/students_clean.csv`
- saves plots in `images/` (missingness and outlier visualization)

References

- Wickham, H. *Tidy Data.* Journal of Statistical Software, 2014.
- McKinney, W. *Python for Data Analysis.* O'Reilly, 2022.
- Montgomery, D. C., & Runger, G. C. *Applied Statistics and Probability for Engineers.* Wiley, 7th ed., 2020.

Appendix: Slide Deck Content (Reference)

The material below is a reference copy of the slide deck content. Exercise solutions are explained in the main notes where applicable.

Title Slide

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

Quick Links

Types & Formats Sources Cleaning Demo Summary

Agenda

- Overview
- Data Types and Formats
- Data Sources and Acquisition
- Data Cleaning
- Demo
- Summary

Learning Outcomes

- Identify common data types and formats used in analytics
- List common data sources and acquisition methods
- Detect typical data quality issues (missing values, duplicates, outliers)
- Apply basic cleaning steps in Python and save a cleaned dataset

Dataset, Observation, Variable

- **Dataset:** a collection of observations (rows) and variables (columns)
- **Observation:** one record (e.g., one student)
- **Variable/Feature:** one attribute (e.g., attendance, CGPA)

Goal: convert raw data into a form suitable for analysis and modeling.

Common Data Types (Practical View)

- **Numeric:** integers (count), real values (measurements)
- **Categorical:** nominal (branch), ordinal (rating: low/med/high)
- **Binary:** yes/no, pass/fail
- **Date/Time:** join date, timestamp
- **Text:** feedback, comments

Exercise 1: Classify Variable Types

For each variable, write the type (numeric/categorical/binary/datetime/text):

1. Age
2. Program/Branch (CSE, ECE, ...)
3. Attendance (%)
4. Join date
5. Feedback comment

Solution 1

- Age: numeric (integer)
- Program/Branch: categorical (nominal)
- Attendance (%): numeric (real)
- Join date: datetime
- Feedback: text (unstructured)

Data Formats

- **Structured:** fixed schema (tables)
  Examples: CSV, SQL tables
- **Semi-structured:** flexible schema with tags/keys
  Examples: JSON, XML
- **Unstructured:** free-form content
  Examples: text documents, images, audio

Structured Example (Table)

student_id	program	attendance_pct	cgpa
1001	CSE	92	8.2
1002	CSE	85	7.5
1003	ECE	105	8.9

Note: 105% attendance is an example of an out-of-range value.

Semi-structured Example (JSON)

```
{
  "student_id": 1001,
  "program": "CSE",
  "attendance_pct": 92,
  "courses": ["Math", "DSA", "Stats"]
}
```

Keys may vary from record to record (flexible schema).

Unstructured Example (Text/Log)

```
2026-02-08 10:02:11 INFO login user=1007 device=android city=Delhi
```

Useful information exists, but it requires parsing and feature extraction.

Common Data Sources

- Surveys and forms (Google Forms, LMS exports)
- Databases (student records, attendance systems)
- Web and app logs (clickstream)
- Sensors/IoT (temperature, GPS)
- Public datasets (government portals, research repositories)

Acquisition Methods

- Files: CSV/Excel export → `read_csv`, `read_excel`
- Database query: SQL → extract tables
- API calls: JSON responses → parse and store
- Manual entry: small datasets (careful with errors)

Exercise 2: Choose a Source

For each case, suggest a likely source (survey/database/log/API):

1. Daily attendance of students
2. Online learning platform clicks
3. Student feedback comments
4. Weather readings every minute

Solution 2

- Attendance: database export (or CSV from attendance system)
- Clicks: logs (web/app logs)
- Feedback: survey + text field (unstructured text)
- Weather readings: sensors/IoT or API

Why Cleaning Matters

- Models and statistics assume data is meaningful and consistent
- "Garbage in, garbage out" → wrong conclusions
- Cleaning improves: accuracy, fairness, and reproducibility

Common Data Quality Issues

- Missing values (blank, NaN, NULL)
- Duplicates (same record repeated)
- Inconsistent categories (`cse`, `CSE`, `CSE`)
- Out-of-range values (attendance 105%, CGPA 12)
- Wrong data type ("nine" instead of 9.0)

Handling Missing Values (Basic Options)

- **Drop:** remove rows/columns (only if few missing and safe)
- **Impute:** fill with mean/median/mode (simple baseline)
- **Domain rule:** fill with a meaningful default (carefully)
- **Flag:** create an indicator feature "was_missing"

Exercise 3: Missingness Decision

In a dataset of 20 students, the column `cgpa` has 2 missing values.

- What is the missingness percentage?
- Suggest one reasonable action for this column.

Solution 3

- Missingness $= 2/20 \times 100\% = 10\%$
- Action: impute using **median** CGPA (robust) and optionally add a flag

Outliers (Basic Idea)

An outlier is a value that is unusually far from typical values.

- Outliers can be **errors** (wrong entry) or **real extremes**
- They can strongly affect mean, variance, and some models
- Use rules like IQR fences as a **screening** step

IQR Rule (Fences)

$$\text{Lower fence} = Q_1 - 1.5 \times \text{IQR}, \quad \text{Upper fence} = Q_3 + 1.5 \times \text{IQR}$$

$$\text{IQR} = Q_3 - Q_1$$

Values outside fences are *possible* outliers.

Exercise 4: IQR Outlier Check

Attendance (%): 70, 75, 80, 85, 90, 95, 150

Task: Compute Q_1, Q_3, IQR, fences, and decide if 150 is an outlier.

Solution 4

Sorted data: 70, 75, 80, 85, 90, 95, 150 (n=7). Median = 85.
Lower half: 70, 75, 80 $\Rightarrow Q_1 = 75$
Upper half: 90, 95, 150 $\Rightarrow Q_3 = 95$
IQR $= 95 - 75 = 20$
Fences: $75 - 30 = 45$ and $95 + 30 = 125$
Conclusion: $150 > 125 \Rightarrow$ outlier (by IQR rule).

Cleaning Checklist (Fast)

- Check shape, column names, and data types
- Check missingness and duplicates
- Standardize categories (trim whitespace, normalize case)
- Check ranges and impossible values
- Save a cleaned version (do not overwrite raw file)

Mini Demo (Python)

Run from the lecture folder:

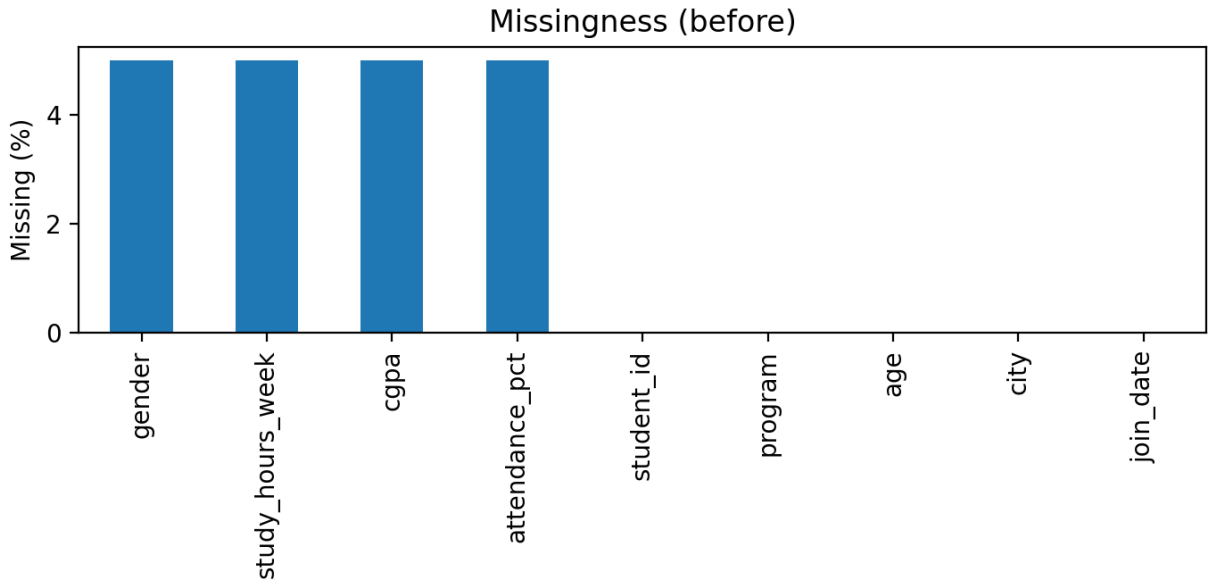
```
python demo/cleaning_demo.py
```

Outputs:

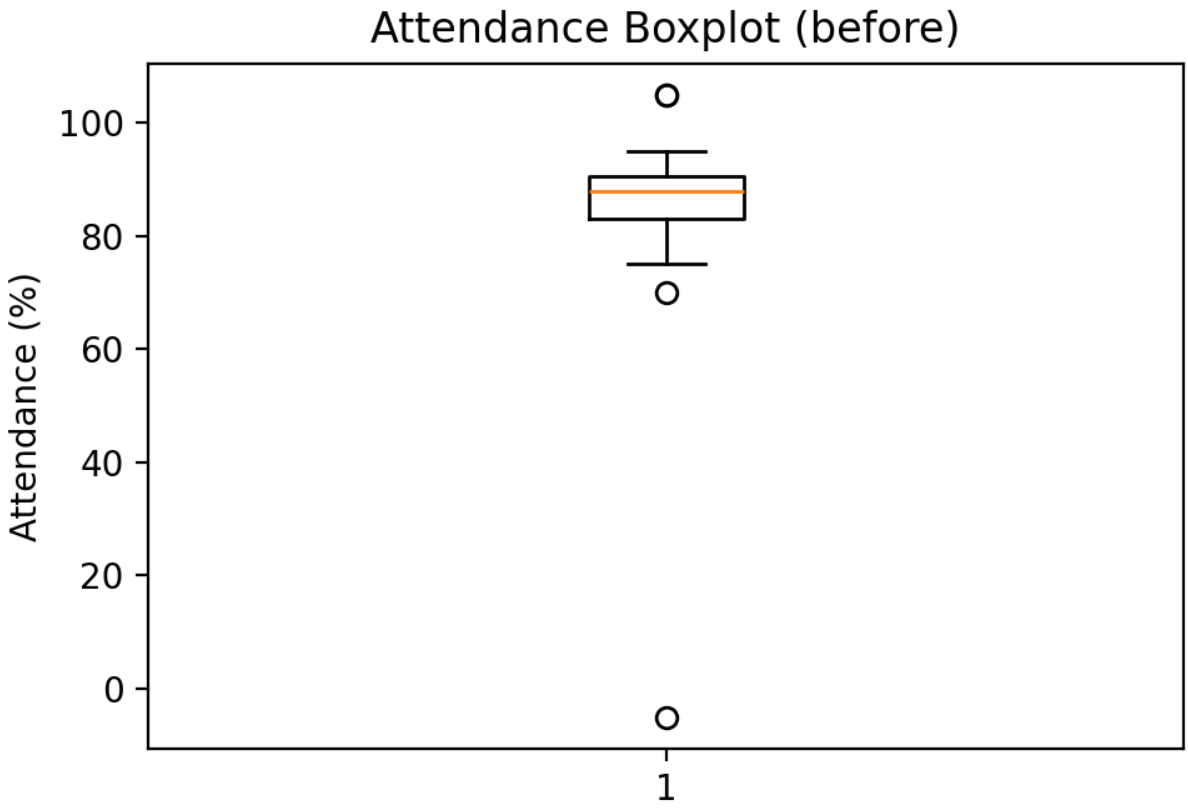
- `data/students_clean.csv`
- plots in `images/` (missingness and outlier visual)

Demo Output (Example)

Missingness



Attendance Outliers



Summary

- Data types and formats determine how we store and process data
- Different sources require different acquisition and validation steps
- Cleaning deals with missing values, duplicates, inconsistencies, and outliers
- Always save a cleaned dataset and document the rules you applied

Exit question: In one sentence, why can "attendance 105%" be dangerous in analysis?