Data Validation & Quality

Week 2 · CS 203: Software Tools and Techniques for AI

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Part 1: The Motivation

What did we actually collect?

Last Week: We Collected Data!

Remember our Netflix movie prediction project?

```python
# We wrote this beautiful code
movies = []
for title in movie_list:
    response = requests.get(OMDB_API, params={"t": title})
    movies.append(response.json())

df = pd.DataFrame(movies)
df.to_csv("netflix_movies.csv")
print(f"Collected {len(df)} movies!")
```

Output: `Collected 1000 movies!`

Feeling: Victory! Time to train models!

Reality Check: Let's Look at the Data

```python
import pandas as pd
df = pd.read_csv("lecture-demos/week02/data/movies.csv")
print(df.head())
```

```
   title          year    runtime    rating  boxoffice      genre                     rated
0  Inception      2010    148 min    8.8     $292576195  Action, Adventure, Sci-Fi   PG-13
1  Avatar         2009    162 min    7.9     $2923706026 Action, Adventure, Fantasy  PG-13
2  The Room       2003    99 min     3.9     N/A         Drama                       R
3  Inception      2010    148 min    8.8     $292576195  Action, Adventure, Sci-Fi   PG-13
4  Tenet          N/A     150 min    7.3     N/A         Action, Sci-Fi, Thriller    PG-13
```

Wait... something's wrong here.

The Problems Emerge

#	Issue	Example
1	DUPLICATES	Inception appears twice (rows 0 and 3)
2	MISSING	Year is "N/A" for Tenet (row 4)
3	WRONG TYPES	Runtime is "148 min" not integer 148
4	INCONSISTENT	BoxOffice has "$" and commas
5	N/A VALUES	Some BoxOffice entries are literally "N/A"

Let's Dig Deeper

```python
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Title       1000 non-null   object    <- All strings!
 1   Year        987 non-null    object    <- String, not int!
 2   Runtime     1000 non-null   object    <- "148 min" string
 3   imdbRating  892 non-null    object    <- String, not float!
 4   BoxOffice   634 non-null    object    <- "$292,576,195" string
```

Every column is a string (object)!

366 movies have no BoxOffice data!

What Happens If We Ignore This?

```
# Naive approach: just train the model!
from sklearn.linear_model import LinearRegression

X = df[['Year', 'Runtime', 'imdbRating']]
y = df['BoxOffice']

model = LinearRegression()
model.fit(X, y)
```

```
ValueError: could not convert string to float: '148 min'
```

The model refuses to train.

Or Worse: Silent Failures

```python
# "Fix" by forcing numeric conversion
df['Year'] = pd.to_numeric(df['Year'], errors='coerce')
df['Rating'] = pd.to_numeric(df['imdbRating'], errors='coerce')

# Now 13 movies have NaN year, 108 have NaN rating
# We lost data silently!

# Train anyway
model.fit(df[['Year', 'Rating']].dropna(), y.dropna())
# Model trains on 521 movies instead of 1000!
```

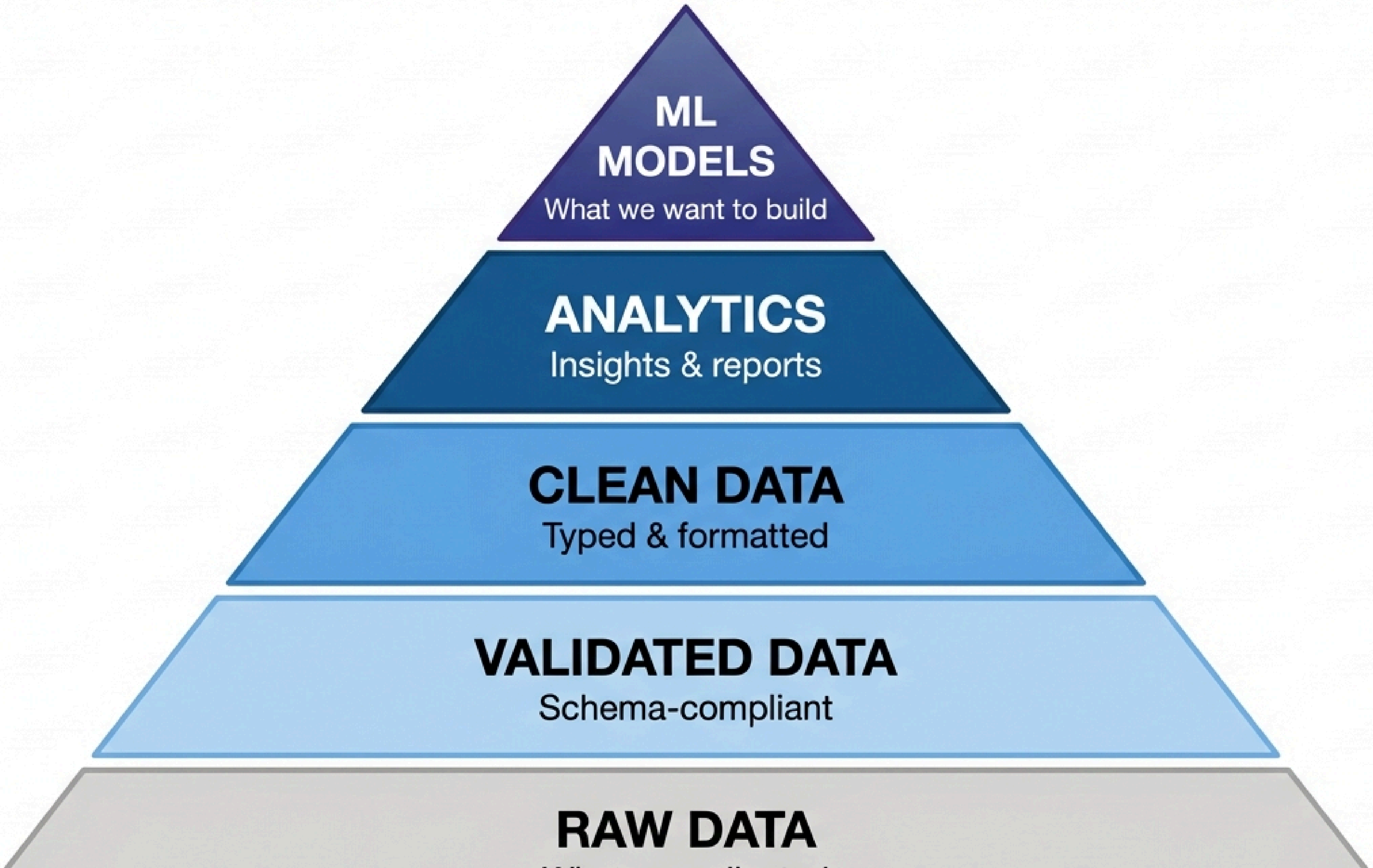
You trained on half your data without realizing.

Real-World Data Quality Disasters

Company	What Happened	Cost
NASA Mars Orbiter	Lockheed used pound-seconds, NASA expected newton-seconds	**$327 million** spacecraft lost
Knight Capital	Old code reactivated on 1 of 8 servers during deployment	**$440 million** in 45 minutes
UK COVID Stats	Excel .xls format limited to 65,536 rows	**16,000 cases** unreported
Zillow iBuying	Home price algorithm couldn't handle market volatility	**$500 million** loss, program shut down

Data quality is not optional. It's survival.

The Data Quality Pyramid



The Cost of Skipping Validation

The 1-10-100 Rule: It costs $1 to verify data at entry, $10 to fix it later, and $100 to recover from bad decisions made with bad data.

Where do problems get discovered?

Stage	Discovery Cost	Example
Data Entry	$1	Validation rejects bad input
Processing	$10	ETL* pipeline fails
Analysis	$50	Analyst spots anomaly in report
Production	$100+	Model makes bad predictions
Business Impact	$1000+	Wrong decisions based on flawed data

*ETL = Extract, Transform, Load - the process of moving data from sources to a destination (e.g., database or data warehouse)

Earlier is always cheaper.

Today's Mission

Transform messy raw data into clean, validated data.

Tools we'll learn:

- **Unix commands**: `head`, `tail`, `wc`, `file`, `sort`, `uniq`
- **jq**: JSON processing powerhouse
- **CSVkit**: CSV Swiss Army knife
- **JSON Schema**: Language-agnostic data contracts
- **Pydantic**: Pythonic data validation

Principle: Inspect before you trust. Validate before you use.

Part 2: Types of Data Problems

Know your enemy

A Taxonomy of Data Problems

The Six Data Quality Dimensions

Dimension	Question	Example Problem
Completeness	Is all expected data present?	Missing ratings, null values
Accuracy	Is the data correct?	Year 2099 for a 1999 movie
Consistency	Does data agree across sources?	"USA" vs "United States"
Validity	Does data conform to rules?	Rating of 15.0 (max is 10)
Uniqueness	Are there duplicates?	Same movie appears 3 times
Timeliness	Is data up-to-date?	Using 2019 prices in 2024

Let's see examples of each...

Problem 1: Missing Values

The data simply isn't there.

```
title,year,rating,revenue
Inception,2010,8.8,292576195
Avatar,2009,7.9,2923706026
The Room,2003,3.9,
Tenet,,7.3,363656624
```

Types of missingness:

- **Empty string**: `""`
- **Null/None**: `null` in JSON
- **Sentinel value**: `"N/A"`, `"NULL"`, `-1`, `9999`
- **Missing key**: Key doesn't exist in JSON

Why it matters: ML models can't handle missing values directly.

Problem 2: Wrong Data Types

Data exists but in wrong format.

```
{
  "title": "Inception",
  "year": "2010",          // String, should be integer
  "rating": "8.8",         // String, should be float
  "runtime": "148 min",    // String with unit, should be integer
  "released": "16 Jul 2010" // String, should be date
}
```

Common type issues:

- Numbers stored as strings
- Dates in various string formats
- Booleans as "true"/"false"/"yes"/"no"/"1"/"0"
- Lists stored as comma-separated strings

Problem 3: Inconsistent Formats

Same concept, different representations.

```
# Date formats
2010-07-16
07/16/2010
16 Jul 2010
July 16, 2010

# Currency formats
$292,576,195
292576195
$292.5M
292,576,195 USD

# Boolean formats
true, True, TRUE, 1, yes, Yes, Y
```

Why it matters: Can't compare or aggregate inconsistent data.

Problem 4: Duplicates

Same record appears multiple times.

```
title,year,rating
Inception,2010,8.8
Avatar,2009,7.9
Inception,2010,8.8      <- Exact duplicate
The Matrix,1999,8.7
inception,2010,8.8      <- Case variation duplicate
Inception,2010,8.9      <- Near duplicate (different rating?)
```

Types of duplicates:

- **Exact**: Identical in every field
- **Partial**: Same key, different values (which is correct?)
- **Fuzzy**: Similar but not identical ("Spiderman" vs "Spider-Man")

Problem 5: Outliers and Anomalies

Values that are technically valid but suspicious.

```
title,year,rating,budget
Inception,2010,8.8,160000000
Avatar,2009,7.9,237000000
The Room,2003,3.9,6000000
Avengers,2012,8.0,-50000000     <- Negative budget?
Unknown,2025,9.9,999999999999   <- Future year, impossible rating
```

Questions to ask:

- Is this value within reasonable range?
- Is this value possible given business rules?
- Is this value consistent with other fields?

Problem 6: Encoding Issues

Text looks garbled or contains strange characters.

```
Expected: "Amelie"
Got:      "AmÃ©lie"      <- UTF-8 read as Latin-1

Expected: "Japanese text"
Got:      "æ¥æ¬èª"        <- Wrong encoding

Expected: "Zoe"
Got:      "Zo\xeb"        <- Raw bytes shown
```

Common encoding issues:

- UTF-8 vs Latin-1 (ISO-8859-1)
- Windows-1252 vs UTF-8
- BOM (Byte Order Mark) at file start

Problem 7: Schema Violations

Data structure doesn't match expectations.

```
// Expected schema
{"title": "string", "year": "integer", "genres": ["string"]}

// Actual data
{"title": "Inception", "year": 2010, "genres": ["Sci-Fi", "Action"]}  // OK
{"title": "Avatar", "year": "2009", "genres": "Action"}               // year is string, genres is string not array
{"Title": "Matrix", "Year": 1999}                                      // Wrong case, missing genres
{"title": null, "year": 2020, "genres": []}                           // Null title
```

Schema defines: Field names, types, required fields, constraints.

Summary: Data Problem Checklist

Problem	Question to Ask	Tool to Detect
Missing	Are there nulls/empty values?	`csvstat`, pandas
Types	Are numbers actually numbers?	`file`, schema validation
Format	Is date format consistent?	`grep`, regex
Duplicates	Are there repeated rows?	`sort`, `uniq`, `csvsql`
Outliers	Are values in valid range?	`csvstat`, histograms
Encoding	Is text readable?	`file`, `iconv`
Schema	Does structure match spec?	JSON Schema, Pydantic

Part 3: First Look at Your Data

Unix tools for initial inspection

Demo Files Location

All demos use data from:

```
lecture-demos/week02/
├── data/
│   ├── movies.csv        # 96 movies with quality issues
│   ├── movies.json       # 25 movies with issues (JSON)
│   ├── movie.json        # Single movie (OMDB format)
│   └── movie_schema.json # JSON Schema definition
├── 01_unix_inspection.sh # Unix CLI demos
├── 02_jq_basics.sh       # jq JSON processing
├── 03_csvkit_demo.sh     # CSVkit tools
├── 04_json_schema_validation.py
├── 05_pydantic_basics.py
├── 06_data_profiling.py
└── 07_validation_pipeline.py
```

Run demos from: `cd lecture-demos/week02/data`

Before You Do Anything: Look at the Data

Golden Rule: Never process data you haven't inspected.

```
# What kind of file is this?
file movies.csv

# How big is it?
ls -lh movies.csv
wc -l movies.csv

# What does it look like?
head movies.csv
tail movies.csv
```

These 5 commands should be muscle memory.

The `file` Command

Tells you what type of file you're dealing with.

```
# 01_unix_inspection.sh → PART 1
$ file movies.csv
movies.csv: UTF-8 Unicode text

$ file movies.json
movies.json: JSON text data

$ file movie.json
movie.json: JSON text data

# Check encoding specifically
$ file -i movies.csv
movies.csv: text/plain; charset=utf-8
```

Reveals: Text encoding, line endings, file format

The `wc` Command

Word count - but more useful for lines and characters.

```
# 01_unix_inspection.sh → PART 2
$ wc movies.csv
    97    496  6847 movies.csv
    |     |     |
    |     |     +-- bytes
    |     +-------- words
    +-------------- lines

# Just line count (most common)
$ wc -l movies.csv
97 movies.csv
# 97 lines = 1 header + 96 data rows

$ wc -l movies.json
27 movies.json
```

Quick sanity check: Does line count match expectations?

The `head` Command

See the first N lines of a file.

```
# 01_unix_inspection.sh → PART 3
$ head -5 movies.csv
title,year,runtime,rating,boxoffice,genre,rated
Inception,2010,148 min,8.8,$292576195,"Action, Adventure, Sci-Fi",PG-13
Avatar,2009,162 min,7.9,$2923706026,"Action, Adventure, Fantasy",PG-13
The Room,2003,99 min,3.9,N/A,Drama,R
Inception,2010,148 min,8.8,$292576195,"Action, Adventure, Sci-Fi",PG-13

$ head -3 movies.json
[
  {"Title": "Inception", "Year": "2010", ...},
  {"Title": "Avatar", "Year": "2009", ...},
```

Use case: Quickly see headers and sample data.

The `tail` Command

See the last N lines of a file.

```
# 01_unix_inspection.sh → PART 4
$ tail -5 movies.csv
Blackfish,2013,83 min,8.1,$2073582,"Documentary, Drama",PG-13
The Cove,2009,92 min,8.4,$864000,Documentary,PG-13
An Inconvenient Truth,2006,96 min,7.4,$50000000,Documentary,PG
March of the Penguins,2005,80 min,7.5,$127400000,"Documentary, Family",G
...

# Skip header (everything except first line)
$ tail -n +2 movies.csv | head -3
```

Use case: Check if file ends properly, skip headers.

Combining head and tail

See a slice of the file:

```
# Lines 100-110 (skip 99, take 11)
$ head -110 movies.csv | tail -11

# See header + specific row range
$ head -1 movies.csv && sed -n '500,510p' movies.csv
```

Practical example:

```
# File has 1 million rows, peek at middle
$ head -500000 huge.csv | tail -10
```

The `sort` Command

Sort lines alphabetically or numerically.

```
# 01_unix_inspection.sh → PART 5

# Sort by title (first 5)
$ tail -n +2 movies.csv | sort -t',' -k1 | head -5

# Sort by year descending (first 5)
$ tail -n +2 movies.csv | sort -t',' -k2 -nr | head -5
Tenet,N/A,150 min,7.3,N/A,...
Future Movie,2030,120 min,...
Unknown Movie,2025,90 min,...
```

`sort` Flags

Flag	Meaning
`-t','`	Field delimiter is comma
`-k3`	Sort by 3rd field
`-n`	Numeric sort
`-r`	Reverse (descending)
`-u`	Remove duplicates

```
# Combine flags: sort by rating, descending, unique
$ sort -t',' -k3 -nr -u movies.csv
```

The `uniq` Command

Find or remove duplicate lines.

```
# 01_unix_inspection.sh → PART 6

# Remove adjacent duplicates (MUST sort first!)
$ sort movies.csv | uniq

# Count occurrences of each line
$ sort movies.csv | uniq -c
```

Important: `uniq` only detects *adjacent* duplicates. Always `sort` first!

`uniq` Options

Option	What it shows
(none)	Deduplicated lines
`-c`	Count of each line
`-d`	Only duplicated lines
`-u`	Only unique lines (appear once)

```
# Show only duplicates
$ sort movies.csv | uniq -d
```

Finding Duplicates: Practical Example

```
# 01_unix_inspection.sh → PART 6

# Find duplicate titles
$ cut -d',' -f1 movies.csv | sort | uniq -d
Inception
Spider-Man
The Matrix
```

Counting Duplicates

```
# 01_unix_inspection.sh → PART 6

# How many times does each title appear?
$ cut -d',' -f1 movies.csv | sort | uniq -c | sort -rn | head -5
   3 Spider-Man
   2 The Matrix
   2 Inception
   1 Your Name
   1 WALL-E
```

Found 3 duplicate titles! (Spider-Man appears 3x, others 2x)

The `cut` Command

Extract columns from delimited data.

```
# 01_unix_inspection.sh → PART 7

# Get titles (first 5)
$ cut -d',' -f1 movies.csv | head -5
title
Inception
Avatar
The Room
Inception

# Get title and rating (columns 1 and 4)
$ cut -d',' -f1,4 movies.csv | head -5
title,rating
Inception,8.8
Avatar,7.9
The Room,3.9
Inception,8.8
```

The `grep` Command

Search for patterns in text.

```
# 01_unix_inspection.sh → PART 8

# Find rows containing "Inception"
$ grep "Inception" movies.csv
Inception,2010,148 min,8.8,$292576195,"Action, Adventure, Sci-Fi",PG-13
Inception,2010,148 min,8.8,$292576195,"Action, Adventure, Sci-Fi",PG-13

# Count N/A values
$ grep -c "N/A" movies.csv
15
```

`grep` Options

Option	Effect
`-c`	Count matches
`-n`	Show line numbers
`-v`	Invert (lines NOT matching)
`-i`	Case insensitive

```
# 01_unix_inspection.sh → PART 8

# N/A with line numbers (first 5)
$ grep -n "N/A" movies.csv | head -5

# Case insensitive search for "matrix"
$ grep -i "matrix" movies.csv
The Matrix,1999,136 min,8.7,$463517383,"Action, Sci-Fi",R
The Matrix,1999,136 min,8.7,$463517383,"Action, Sci-Fi",R
```

Putting It Together: Initial Inspection Script

```bash
#!/bin/bash
FILE=$1

echo "=== File Info ==="
file "$FILE"
ls -lh "$FILE"

echo -e "\n=== Line Count ==="
wc -l "$FILE"

echo -e "\n=== First 5 Lines ==="
head -5 "$FILE"

echo -e "\n=== Last 5 Lines ==="
tail -5 "$FILE"

echo -e "\n=== Potential Issues ==="
echo "N/A values: $(grep -c 'N/A' "$FILE")"
echo "Empty fields: $(grep -c ',,' "$FILE")"
echo "Duplicate lines: \
$(sort "$FILE" | uniq -d | wc -l)"
```

Part 4: jq - JSON Processing

The Swiss Army knife for JSON

Why jq?

JSON is everywhere:

- API responses
- Configuration files
- Log files
- NoSQL databases

Problem: JSON is hard to read and process in shell.

```
# Raw JSON - unreadable mess
$ cat movies.json
{"Title":"Inception","Year":"2010","Rated":"PG-13","Released":"16 Jul 2010","Runtime":"148 min","Genre":"Action, Adventure, Sci-Fi"}
```

Solution: `jq` - a lightweight JSON processor.

The jq Mental Model

> **Think of jq as a pipeline**: Data flows in, gets transformed, flows out. Each filter transforms the data for the next filter.

```
   Input JSON   -->  Filter 1  -->  Filter 2  -->  Filter 3  -->  Output
       .             .movies         .[0]          .title         "Inception"
    (whole doc)    (get field)   (first elem)  (get title)
```

Key concepts:

- `.` = current data (identity)
- `|` = pipe to next filter
- `[]` = iterate over array
- `.field` = access object field

jq is like SQL for JSON - query and transform in one line.

jq Basics: Pretty Printing

```
# 02_jq_basics.sh → PART 1

$ cat movie.json | jq .
{
  "Title": "Inception",
  "Year": "2010",
  "Rated": "PG-13",
  "Runtime": "148 min",
  "Genre": "Action, Adventure, Sci-Fi",
  "Director": "Christopher Nolan",
  "imdbRating": "8.8",
  "BoxOffice": "$292,576,195"
}
```

The `.` is the identity filter - it means "the whole input".

jq: Extracting Fields

```
# 02_jq_basics.sh → PART 2

# Get a single field
$ cat movie.json | jq '.Title'
"Inception"

# Get multiple fields
$ cat movie.json | jq '.Title, .Year'
"Inception"
"2010"

# Get first Rating (nested array)
$ cat movie.json | jq '.Ratings[0]'
{"Source": "Internet Movie Database", "Value": "8.8/10"}
```

Syntax: `.fieldname` extracts that field.

jq: Working with Arrays

```
# 02_jq_basics.sh → PART 3 (movies.json has 25 movies with issues)

# Get number of movies
$ cat movies.json | jq 'length'
25

# Get first movie
$ cat movies.json | jq '.[0]'
{"Title": "Inception", "Year": "2010", "Runtime": "148 min", ...}

# Get all titles (first 5)
$ cat movies.json | jq '.[].Title' | head -5
"Inception"
"Avatar"
"The Room"
"Inception"
"Tenet"
```

jq: The Array Iterator `[]`

```
# .[] iterates over array elements
$ cat movies.json | jq '.[]'
{"Title": "Inception", "Year": "2010"}
{"Title": "Avatar", "Year": "2009"}
{"Title": "The Matrix", "Year": "1999"}

# Chain with field extraction
$ cat movies.json | jq '.[].Title'
"Inception"
"Avatar"
"The Matrix"

# Same as:
$ cat movies.json | jq '.[] | .Title'
```

The pipe `|` passes output to next filter.

jq: Building New Objects

```
# 02_jq_basics.sh → PART 4

# Transform structure (first 3)
$ cat movies.json | jq '.[:3] | .[] | {name: .Title, year: .Year, rating: .imdbRating}'
{"name": "Inception", "year": "2010", "rating": "8.8"}
{"name": "Avatar", "year": "2009", "rating": "7.9"}
{"name": "The Room", "year": "2003", "rating": "3.9"}

# Collect into array
$ cat movies.json | jq '[.[:3][] | {name: .Title, year: .Year}]'
[
  {"name": "Inception", "year": "2010"},
  {"name": "Avatar", "year": "2009"},
  {"name": "The Room", "year": "2003"}
]
```

jq: Filtering with `select()`

```
# 02_jq_basics.sh → PART 5

# Find movies with N/A year
$ cat movies.json | jq '.[] | select(.Year == "N/A") | .Title'
"Tenet"

# Find movies with N/A BoxOffice
$ cat movies.json | jq '.[] | select(.BoxOffice == "N/A") | .Title'
"The Room"
"Tenet"
"Old Silent Film"

# Find movies with null/empty title
$ cat movies.json | jq '.[] | select(.Title == null or .Title == "")'
```

jq: Type Conversion

Remember: API data often has numbers as strings!

```
# 02_jq_basics.sh → PART 6

# Convert string to number
$ echo '{"Year": "2010"}' | jq '.Year | tonumber'
2010

# Safe year extraction (first 5 valid)
$ cat movies.json | jq '[.[] | select(.Year != "N/A" and .Year != null) | {title: .Title, year: (.Year | tonumber)}] | .[:5]'
[
  {"title": "Inception", "year": 2010},
  {"title": "Avatar", "year": 2009},
  ...
]
```

jq: Handling Missing Data

```
# 02_jq_basics.sh → PART 7

# Default value with //
$ echo '{"title": "Test"}' | jq '.rating // "N/A"'
"N/A"

# Check if field exists
$ cat movie.json | jq 'has("BoxOffice")'
true
$ cat movie.json | jq 'has("Budget")'
false

# Count non-null ratings
$ cat movies.json | jq '[.[] | select(.imdbRating != null and .imdbRating != "N/A")] | length'
23
```

jq: Aggregation Functions

```
# 02_jq_basics.sh → PART 8

# Count elements
$ cat movies.json | jq 'length'
25

# Get unique Rated values
$ cat movies.json | jq '[.[].Rated] | unique'
["NR", "Not Rated", "PG", "PG-13", "R", "XX"]

# Count by Rated (simplified)
$ cat movies.json | jq 'group_by(.Rated) | map({rated: .[0].Rated, count: length})'
[
  {"rated": "NR", "count": 1},
  {"rated": "PG", "count": 2},
  {"rated": "PG-13", "count": 9},
  ...
]
```

jq: Sorting

```
# 02_jq_basics.sh → PART 9

# Sort by Year (first 5 titles)
$ cat movies.json | jq '[.[] | select(.Year != "N/A")] | sort_by(.Year) | .[:5] | .[].Title'
"The Matrix"
"Amelie"
"Spider-Man"
...

# Top 5 by Year (newest)
$ cat movies.json | jq '[.[] | select(.Year != "N/A")] | sort_by(.Year) | reverse | .[:5] | .[] | "\(.Title) (\(.Year))"'
"Unknown Movie (2025)"
"Avengers: Endgame (2019)"
"Parasite (2019)"
...
```

jq: Grouping

```
# Group movies by year
$ cat movies.json | jq 'group_by(.Year)'
[
  [{"Title": "The Matrix", "Year": "1999"}],
  [{"Title": "Avatar", "Year": "2009"}],
  [{"Title": "Inception", "Year": "2010"}, {"Title": "Toy Story 3", "Year": "2010"}]
]

# Count movies per year
$ cat movies.json | jq 'group_by(.Year) | map({year: .[0].Year, count: length})'
[
  {"year": "1999", "count": 1},
  {"year": "2009", "count": 1},
  {"year": "2010", "count": 2}
]
```

jq: Raw Output Mode

```
# 02_jq_basics.sh → PART 10

# Raw strings (without quotes)
$ cat movies.json | jq -r '.[0:3][].Title'
Inception
Avatar
The Room

# CSV output (first 5)
$ cat movies.json | jq -r '.[:5][] | [.Title, .Year, .imdbRating] | @csv'
"Inception","2010","8.8"
"Avatar","2009","7.9"
"The Room","2003","3.9"
...

# TSV output (first 3)
$ cat movies.json | jq -r '.[:3][] | [.Title, .Year] | @tsv'
Inception	2010
Avatar	2009
```

jq: Finding Data Issues

```
# 02_jq_basics.sh → PART 11

# Find movies with "N/A" years
$ cat movies.json | jq '[.[] | select(.Year == "N/A")] | length'
1

# Find movies with null/empty titles
$ cat movies.json | jq '.[] | select(.Title == null or .Title == "") | .Year'
"2020"
"2018"

# Find movies with invalid ratings (not a number)
$ cat movies.json | jq '.[] | select(.imdbRating == "invalid") | .Title'
"Joker"
```

jq: Data Quality Checks

```
# 02_jq_basics.sh → PART 11 (Data Summary)

# Full data quality summary
$ cat movies.json | jq '{
  total: length,
  null_titles: [.[] | select(.Title == null or .Title == "")] | length,
  na_years: [.[] | select(.Year == "N/A")] | length,
  na_boxoffice: [.[] | select(.BoxOffice == "N/A")] | length
}'
{
  "total": 25,
  "null_titles": 2,
  "na_years": 1,
  "na_boxoffice": 3
}
```

jq Cheat Sheet - Basics

Task	Command
Pretty print	`jq .`
Get field	`jq '.fieldname'`
Get nested	`jq '.a.b.c'`
Array element	`jq '.[0]'`
All elements	`jq '.[]'`
Filter	`jq '.[] | select(.x > 5)'`

jq Cheat Sheet - Advanced

Task	Command
Build object	`jq '{a: .x, b: .y}'`
Count	`jq 'length'`
Sort	`jq 'sort_by(.field)'`
Unique	`jq 'unique'`
Raw strings	`jq -r`

Part 5: CSVkit

The CSV Swiss Army Knife

Why CSVkit?

CSV looks simple but hides complexity:

- Quoted fields with commas inside
- Multiline values
- Different delimiters
- Inconsistent escaping

CSVkit: A suite of command-line tools for CSV files.

```
# Installation
pip install csvkit
```

Tools we'll cover:

`csvlook`, `csvstat`, `csvcut`, `csvgrep`, `csvsort`, `csvjson`, `csvsql`

csvlook: Pretty Print CSV

Makes CSV readable in terminal.

```
# 03_csvkit_demo.sh → PART 1

$ csvlook movies.csv | head -7
| title      | year | runtime  | rating | boxoffice    | genre                     | rated |
| ---------- | ---- | -------- | ------ | ------------ | ------------------------- | ----- |
| Inception  | 2010 | 148 min  |    8.8 | $292576195   | Action, Adventure, Sci-Fi | PG-13 |
| Avatar     | 2009 | 162 min  |    7.9 | $2923706026  | Action, Adventure, Fantasy| PG-13 |
| The Room   | 2003 | 99 min   |    3.9 | N/A          | Drama                     | R     |
| Inception  | 2010 | 148 min  |    8.8 | $292576195   | Action, Adventure, Sci-Fi | PG-13 |
| Tenet      | N/A  | 150 min  |    7.3 | N/A          | Action, Sci-Fi, Thriller  | PG-13 |
```

Compare to raw CSV - much easier to read!

csvstat: Data Profiling

Get statistics for every column automatically!

```
# 03_csvkit_demo.sh → PART 2

$ csvstat -c title movies.csv
  1. "title"
        Type of data:          Text
        Contains null values:  True
        Unique values:         92
        Longest value:         29 characters
        Most common values:    Spider-Man (3x)
                               The Matrix (2x)
                               Inception (2x)

# Just counts
$ csvstat --count movies.csv
96
```

csvstat: Specific Columns

```
# Stats for just one column
$ csvstat -c rating movies.csv
  3. "rating"
        Type of data:          Number
        Contains null values:  True (108 nulls)
        Smallest value:        1.2
        Largest value:         9.3
        Mean:                  6.84
        Median:                7.1
        StDev:                 1.23

# Stats for multiple columns
$ csvstat -c year,rating movies.csv

# Just show counts
$ csvstat --count movies.csv
1000
```

csvcut: Select Columns

```
# 03_csvkit_demo.sh → PART 3

# List column names
$ csvcut -n movies.csv
  1: title
  2: year
  3: runtime
  4: rating
  5: boxoffice
  6: genre
  7: rated

# Select by name (first 5)
$ csvcut -c title,year movies.csv | head -6
title,year
Inception,2010
Avatar,2009
The Room,2003
Inception,2010
Tenet,N/A
```

csvgrep: Filter Rows

```
# 03_csvkit_demo.sh → PART 4

# Exact match: Year = 2019
$ csvgrep -c year -m "2019" movies.csv | csvlook

# Titles starting with 'The'
$ csvgrep -c title -r "^The" movies.csv | csvcut -c title | head -10

# Rows without N/A in boxoffice (count)
$ csvgrep -c boxoffice -m "N/A" -i movies.csv | wc -l

# Rows with N/A rating
$ csvgrep -c rating -r "^N/A$" movies.csv | csvlook
```

csvsort: Sort Data

```
# 03_csvkit_demo.sh → PART 5

# Sort by year (first 5)
$ csvsort -c year movies.csv | head -6

# Sort by rating descending (first 5)
$ csvsort -c rating -r movies.csv | head -6

# Sort by multiple columns
$ csvsort -c year,rating movies.csv | head -10

# Numeric sort happens automatically for number columns!
```

csvjson: Convert to JSON

```
# 03_csvkit_demo.sh → PART 6

# First 3 rows as JSON
$ head -4 movies.csv | csvjson | jq '.'
[
  {"title": "Inception", "year": "2010", "runtime": "148 min", ...},
  {"title": "Avatar", "year": "2009", "runtime": "162 min", ...},
  {"title": "The Room", "year": "2003", "runtime": "99 min", ...}
]

# Indented output
$ head -3 movies.csv | csvjson -i 2
```

Great for converting between formats!

csvsql: Query CSV with SQL!

Yes, you can run SQL on CSV files.

```
# 03_csvkit_demo.sh → PART 7

# Basic select
$ csvsql --query "SELECT title, rating FROM movies WHERE rating > 8.5 ORDER BY rating DESC" movies.csv | csvlook

# Find duplicates
$ csvsql --query "SELECT title, COUNT(*) as count FROM movies GROUP BY title HAVING count > 1" movies.csv | csvlook
| title      | count |
| ---------- | ----- |
| Inception  |     2 |
| Spider-Man |     3 |
| The Matrix |     2 |
```

csvsql: Data Validation Queries

```
# 03_csvkit_demo.sh → PART 7

# Movies per year (sample)
$ csvsql --query "SELECT year, COUNT(*) as count FROM movies GROUP BY year ORDER BY count DESC LIMIT 5" movies.csv | csvlook

# Count N/A boxoffice by year
$ csvsql --query "SELECT year, COUNT(*) as missing FROM movies WHERE boxoffice = 'N/A' GROUP BY year ORDER BY missing DESC LIMIT 5" movies.csv | csvlook
```

csvclean: Fix Common Issues

```
# 03_csvkit_demo.sh → PART 8

# Check for structural issues (dry run)
$ csvclean -n movies.csv
(no issues found)

# If issues existed, it would create:
# - movies_out.csv (cleaned)
# - movies_err.csv (errors with line numbers)

# Common fixes:
# - Removes rows with wrong column count
# - Normalizes quoting
# - Reports line numbers of errors
```

CSVkit Pipeline Example

```
# 03_csvkit_demo.sh → PART 9

# Top rated movies by genre (sample)
$ csvcut -c title,rating,genre movies.csv \
  | csvgrep -c rating -r "^[0-9]" \
  | csvsort -c rating -r \
  | head -10 \
  | csvlook

# Data quality summary
$ echo "Total rows: $(csvstat --count movies.csv)"
$ echo "Unique titles: $(csvcut -c title movies.csv | tail -n +2 | sort -u | wc -l)"
$ echo "N/A in boxoffice: $(csvgrep -c boxoffice -m 'N/A' movies.csv | wc -l)"
$ echo "N/A in rating: $(csvgrep -c rating -m 'N/A' movies.csv | wc -l)"
```

CSVkit Cheat Sheet - Core Tools

Tool	Purpose	Example
`csvlook`	Pretty print	`csvlook data.csv`
`csvstat`	Statistics	`csvstat -c column data.csv`
`csvcut`	Select columns	`csvcut -c col1,col2 data.csv`
`csvgrep`	Filter rows	`csvgrep -c col -m "value"`
`csvsort`	Sort	`csvsort -c col -r data.csv`

CSVkit Cheat Sheet - Advanced Tools

Tool	Purpose	Example
`csvjson`	To JSON	`csvjson data.csv`
`csvsql`	SQL queries	`csvsql --query "..."`
`csvclean`	Fix issues	`csvclean data.csv`
`csvjoin`	Join files	`csvjoin -c id a.csv b.csv`
`csvstack`	Concatenate	`csvstack a.csv b.csv`

Part 6: Data Profiling

Understanding your data before using it

What is Data Profiling?

Data profiling = Analyzing data to understand its structure, content, and quality.

Aspect	Questions to Ask
Structure	How many rows? Columns? What types?
Completeness	How many nulls per column?
Uniqueness	How many distinct values? Duplicates?
Distribution	Min, max, mean, median? Outliers?
Patterns	What formats are used? Any anomalies?

Profiling Step 1: Basic Shape

```
# 03_csvkit_demo.sh → PART 2 (csvstat)

# How many rows and columns?
$ head -1 movies.csv | tr ',' '\n' | wc -l      # columns
7

$ wc -l movies.csv                              # rows (including header)
97

# Or with csvstat
$ csvstat --count movies.csv
96
```

First sanity check: Does shape match expectations?

Profiling Step 2: Column Types

```
$ csvstat movies.csv 2>&1 | grep "Type of data"
        Type of data:          Text
        Type of data:          Number
        Type of data:          Number
        Type of data:          Number
        Type of data:          Text

# Expected: title(text), year(int), rating(float), revenue(int), genre(text)
# Actual: Matches! But let's verify...
```

Profiling Step 3: Null Analysis

```
# Count nulls per column
$ csvstat movies.csv 2>&1 | grep -A1 "Contains null"

-- Contains null values:  False

-- Contains null values:  True (13 nulls)

-- Contains null values:  True (108 nulls)

-- Contains null values:  True (366 nulls)
```

Results:

- Title: 0 nulls (good!)
- Year: 13 nulls (1.3%)
- Rating: 108 nulls (10.8%)
- Revenue: 366 nulls (36.6%) - **problem!**

Profiling Step 4: Unique Values

```
# How many distinct values?
$ csvstat movies.csv 2>&1 | grep "Unique values"
        Unique values:          987      # title - expect 1000, so ~13 duplicates
        Unique values:          85       # year - reasonable range
        Unique values:          78       # rating - 1.0 to 10.0 scale
        Unique values:          634      # revenue - 634 non-null values

# Most common values (find duplicates, common patterns)
$ csvstat movies.csv 2>&1 | grep -A5 "Most common values"
```

Profiling Step 5: Value Ranges

```
$ csvstat -c year movies.csv
        Smallest value:        1920
        Largest value:         2024
        Mean:                  2005.3
        Median:                2010
        StDev:                 15.2

# Check for suspicious outliers
# 1920 seems old - is it valid?
# 2024 is current year - any future years?
```

```
# Find extremes
$ csvsort -c year movies.csv | head -5      # oldest
$ csvsort -c year -r movies.csv | head -5   # newest
```

Profiling Step 6: Pattern Detection

```
# What values does 'rating' column have?
$ csvcut -c rating movies.csv | sort | uniq -c | sort -rn | head
    892 (valid numbers 1.0-10.0)
     47 N/A
     38
     23 Not Rated

# Aha! Three types of "missing":
# 1. Empty string
# 2. "N/A" string
# 3. "Not Rated" string
```

This is why automated profiling misses things!

Profiling Summary: Movies Dataset

Column	Type	Nulls	Unique	Issues
title	Text	0	987	13 duplicates
year	Int	13	85	1920-2024 range
rating	Float	108	78	"N/A", empty, "Not Rated"
revenue	Int	366	634	36% missing!
genre	Text	0	23	Multi-value ("Action, Drama")

Key findings:

1. Revenue is missing for 1/3 of movies
2. Rating has multiple representations of "missing"
3. There are 13 duplicate titles
4. Genre contains multiple values in one field

Part 7: Schema Validation

Contracts for your data

What is a Schema?

Schema = A formal description of expected data structure.

Schema Defines	Examples
Field names	What columns/keys should exist?
Data types	String, integer, float, boolean, array?
Constraints	Required? Min/max? Pattern? Enum?
Relationships	References to other data?

Analogy: A schema is like a contract between data producer and consumer.

Schema: The Blueprint Analogy

Think of a schema like a building blueprint: Before construction begins, everyone agrees on what the building should look like. The blueprint defines rooms, dimensions, materials - and the building must match.

Schema: The Blueprint Analogy

Without blueprint (schema):

- Builder guesses what's needed
- Inspector can't verify if it's correct
- Different workers make inconsistent decisions
- Problems discovered when building collapses

With blueprint (schema):

- Clear expectations documented upfront
- Automatic verification at each step
- Everyone builds the same thing
- Problems caught before they become disasters

Why Schemas Matter

Without schema:

```python
# What is this?
data = {"yr": 2010, "rt": "8.8", "ttl": "Inception"}
# Who knows what yr means? Is rt a string or should it be float?
```

With schema:

```python
# Clear expectations
schema = {
    "title": {"type": "string", "required": True},
    "year": {"type": "integer", "minimum": 1880, "maximum": 2030},
    "rating": {"type": "number", "minimum": 0, "maximum": 10}
}
```

Why Schemas Matter

Schemas enable:

- Automatic validation
- Documentation
- Code generation
- Early error detection

JSON Schema: The Standard

JSON Schema is a vocabulary for validating JSON data.

```json
{
  "$schema": "https://json-schema.org/draft/2020-12/schema",
  "type": "object",
  "properties": {
    "title": {
      "type": "string",
      "minLength": 1
    },
    "year": {
      "type": "integer",
      "minimum": 1880,
      "maximum": 2030
    },
    "rating": {
      "type": "number",
      "minimum": 0,
      "maximum": 10
    }
  },
  "required": ["title", "year"]
}
```

JSON Schema: Type Keywords

Keyword	Valid Values
`"type": "string"`	`"hello"`, `""`
`"type": "integer"`	`42`, `-1`, `0`
`"type": "number"`	`3.14`, `42`, `-1.5`
`"type": "boolean"`	`true`, `false`
`"type": "null"`	`null`
`"type": "array"`	`[1, 2, 3]`, `[]`
`"type": "object"`	`{"a": 1}`, `{}`

Multiple types:

```
{"type": ["string", "null"]}    // String or null
```

JSON Schema: String Constraints

```
{
  "type": "string",
  "minLength": 1,              // At least 1 character
  "maxLength": 100,            // At most 100 characters
  "pattern": "^[A-Z].*$",      // Must start with uppercase
  "format": "email"            // Must be valid email
}
```

Common formats:

- `"email"` - Email address
- `"date"` - ISO 8601 date (2010-07-16)
- `"date-time"` - ISO 8601 datetime
- `"uri"` - Valid URI
- `"uuid"` - UUID format

JSON Schema: Number Constraints

```
{
  "type": "number",
  "minimum": 0,              // >= 0
  "maximum": 10,             // <= 10
  "exclusiveMinimum": 0,     // > 0
  "exclusiveMaximum": 10,    // < 10
  "multipleOf": 0.1          // Must be multiple of 0.1
}
```

Example for rating:

```
{
  "type": "number",
  "minimum": 0,
  "maximum": 10,
  "multipleOf": 0.1
}
```

JSON Schema: Arrays

```
{
  "type": "array",
  "items": {
    "type": "string"          // All items must be strings
  },
  "minItems": 1,              // At least 1 item
  "maxItems": 10,             // At most 10 items
  "uniqueItems": true         // No duplicates
}
```

Example for genres:

```
{
  "genres": {
    "type": "array",
    "items": {"type": "string"},
    "minItems": 1
  }
}
```

JSON Schema: Enums

Restrict to specific values:

```json
{
  "rated": {
    "type": "string",
    "enum": ["G", "PG", "PG-13", "R", "NC-17", "Not Rated"]
  }
}
```

Validation result:

- `"PG-13"` - Valid
- `"PG13"` - Invalid (not in enum)
- `"M"` - Invalid (not in enum)

JSON Schema: Required Fields

```
{
  "type": "object",
  "properties": {
    "title": {"type": "string"},
    "year": {"type": "integer"},
    "rating": {"type": "number"},
    "revenue": {"type": "integer"}
  },
  "required": ["title", "year"]    // Only title and year are required
}
```

Validation:

- `{"title": "X", "year": 2010}` - Valid (rating, revenue optional)
- `{"title": "X"}` - Invalid (missing required field: year)

Complete Movie Schema Example

```json
{
  "$schema": "https://json-schema.org/draft/2020-12/schema",
  "type": "object",
  "properties": {
    "title": {"type": "string", "minLength": 1},
    "year": {"type": "integer", "minimum": 1880, "maximum": 2030},
    "rating": {"type": ["number", "null"], "minimum": 0, "maximum": 10},
    "revenue": {"type": ["integer", "null"], "minimum": 0},
    "genres": {
      "type": "array",
      "items": {"type": "string"},
      "minItems": 1
    },
    "rated": {
      "type": "string",
      "enum": ["G", "PG", "PG-13", "R", "NC-17", "Not Rated"]
    }
  },
  "required": ["title", "year", "genres"]
}
```

Validating with Python

```python
# 04_json_schema_validation.py

from jsonschema import validate, ValidationError

schema = {
    "type": "object",
    "properties": {
        "title": {"type": "string"},
        "year": {"type": "integer", "minimum": 1880}
    },
    "required": ["title", "year"]
}

movie = {"title": "Inception", "year": 2010}

try:
    validate(instance=movie, schema=schema)
    print("Valid!")
except ValidationError as e:
    print(f"Invalid: {e.message}")
```

Schema-First Development

Traditional approach:

1. Collect data
2. Write code to process it
3. Discover problems in production

Schema-first approach:

1. Define schema (contract)
2. Validate data against schema on ingestion
3. Reject invalid data early
4. Process only valid data

Part 8: Pydantic

Pythonic data validation

Why Pydantic?

JSON Schema limitations:

- Separate from your Python code
- No IDE autocompletion
- Manual validation calls
- Verbose error handling

Pydantic advantages:

- Uses Python type hints (you already know this!)
- Automatic validation on object creation
- IDE support (autocomplete, type checking)
- Clear, readable error messages
- Used by FastAPI, LangChain, and many modern libraries

Pydantic: Basic Model

```python
# 05_pydantic_basics.py

from pydantic import BaseModel

class Movie(BaseModel):
    title: str
    year: int
    rating: float

# Valid data - works!
movie = Movie(title="Inception", year=2010, rating=8.8)
print(movie.title)  # "Inception"
print(movie.year)   # 2010 (as int, not string!)
```

Key insight: Just define a class with type hints. Pydantic does the rest.

Pydantic: The Immigration Officer Analogy

Think of Pydantic like an immigration officer: Before entering the country (your code), your documents (data) are checked. Wrong passport type? Rejected. Missing visa? Rejected. Once you're through, everyone inside is guaranteed to have valid documents.

```python
class Movie(BaseModel):  # <- The document checklist
    title: str           # Must have a title (like name on passport)
    year: int            # Must be a valid year (like birth date)
    rating: float        # Must have a rating (like visa number)

# Immigration check happens at entry (object creation)
movie = Movie(**raw_data)  # <- Validation happens HERE

# Once inside, you're guaranteed valid
print(movie.year + 1)  # Safe - year is definitely an int
```

No more "is this a string or int?" questions inside your code.

Pydantic: Automatic Type Coercion

```
# Pydantic converts types automatically when possible
movie = Movie(title="Inception", year="2010", rating="8.8")
print(movie.year)    # 2010 (converted from string to int)
print(movie.rating)  # 8.8 (converted from string to float)

# But invalid conversions fail
movie = Movie(title="Inception", year="not a year", rating=8.8)
# ValidationError: Input should be a valid integer
```

Principle: Be strict about structure, flexible about representation.

Pydantic: Validation Errors

```python
from pydantic import ValidationError

try:
    movie = Movie(title="", year=2010, rating=8.8)
except ValidationError as e:
    print(e)
```

```
1 validation error for Movie
title
  String should have at least 1 character [type=string_too_short]
```

Errors are clear: Field name, what's wrong, and why.

Pydantic: Field Constraints

```python
# 05_pydantic_basics.py

from pydantic import BaseModel, Field

class Movie(BaseModel):
    title: str = Field(min_length=1)
    year: int = Field(ge=1880, le=2030)  # ge = greater or equal
    rating: float = Field(ge=0, le=10)
    revenue: int | None = None  # Optional field

Movie(title="X", year=1850, rating=8.0)
# ValidationError: year - Input should be >= 1880
```

Pydantic: Optional and Default Values

```python
from pydantic import BaseModel
from typing import Optional

class Movie(BaseModel):
    title: str
    year: int
    rating: Optional[float] = None      # Can be None
    genres: list[str] = []              # Default empty list
    is_released: bool = True            # Default value
```

```python
movie = Movie(title="Tenet", year=2020)
print(movie.rating)      # None
print(movie.genres)      # []
print(movie.is_released) # True
```

Pydantic vs JSON Schema

Aspect	JSON Schema	Pydantic
Language	JSON (separate file)	Python (in your code)
Type hints	No	Yes
IDE support	Limited	Full autocomplete
Validation	Manual call	Automatic on create
Error messages	Technical	Human-readable
Learning curve	New syntax	Just Python

Recommendation: Use Pydantic for Python projects, JSON Schema for APIs/cross-language.

Pydantic: The Mental Model

The Three-Step Workflow

Step	Code	What Happens
1. DEFINE	`class Movie(BaseModel): ...`	Declare your schema with type hints
2. CREATE	`movie = Movie(**raw_data)`	Validation happens automatically
3. USE	`movie.title`, `movie.year + 1`	Data is guaranteed valid

At step 2, one of two things happens:

- **Valid data** → Object created, ready to use
- **Invalid data** → `ValidationError` raised immediately

Pydantic: Practical Example

```python
# 05_pydantic_basics.py - MovieFromAPI class

from pydantic import BaseModel, Field
from typing import Optional

class MovieFromAPI(BaseModel):
    """Validates movie data from OMDB API."""
    Title: str = Field(min_length=1)
    Year: str  # API returns string, we'll convert later
    imdbRating: Optional[str] = None
    BoxOffice: Optional[str] = None

# Parse API response - validation happens automatically
raw = {"Title": "Inception", "Year": "2010", "imdbRating": "8.8"}
movie = MovieFromAPI(**raw)  # Works!

raw_bad = {"Title": "", "Year": "2010"}
movie = MovieFromAPI(**raw_bad)  # ValidationError!
```

What We'll Cover in Lab

Pydantic deep dive:

- Nested models (Movie with Director, Actors)
- Custom validators (`@validator` decorator)
- Parsing JSON files with Pydantic
- Model serialization (`.model_dump()`, `.model_dump_json()`)
- Strict mode vs coercion mode

The lab is where you'll get hands-on practice!

Part 9: Encoding & Edge Cases

When text isn't just text

The Encoding Problem

Computers store text as numbers. But which numbers?

```
Character 'A' = 65 (ASCII)
Character 'e' with accent = ??? (depends on encoding!)
```

Encoding = The mapping between characters and bytes.

Encoding	Characters	Use Case
ASCII	128	English only
Latin-1	256	Western European
UTF-8	1,112,064	Everything (modern standard)
UTF-16	Same as UTF-8	Different byte format
Windows-1252	256	Microsoft's Latin-1 variant

UTF-8: The Modern Standard

UTF-8 is the dominant encoding for the web and modern systems.

Why UTF-8?

- Backwards compatible with ASCII
- Supports all languages
- Variable length (1-4 bytes per character)
- Self-synchronizing

```
# Check file encoding
$ file movies.csv
movies.csv: UTF-8 Unicode text

$ file old_data.csv
old_data.csv: ISO-8859-1 text
```

Encoding Problems in Practice

What you expect:

```
Amelie (with accent)
Crouching Tiger, Hidden Dragon (Chinese title)
```

What you get:

```
AmÃ©lie                    <- UTF-8 decoded as Latin-1
Crouching Tiger (????????)   <- Wrong encoding
```

Common scenarios:

1. File saved in one encoding, read in another
2. Copy-paste from web with different encoding
3. Database with mixed encodings
4. Legacy systems using old encodings

Detecting Encoding

```
# The file command guesses encoding
$ file -i movies.csv
movies.csv: text/plain; charset=utf-8

# For more accuracy, use chardet (Python)
$ pip install chardet
$ chardetect movies.csv
movies.csv: utf-8 with confidence 0.99

# Or with Python
$ python -c "import chardet; print(chardet.detect(open('movies.csv','rb').read()))"
{'encoding': 'utf-8', 'confidence': 0.99}
```

Converting Encodings

```
# Convert from Latin-1 to UTF-8
$ iconv -f ISO-8859-1 -t UTF-8 old_file.csv > new_file.csv

# Convert from Windows-1252 to UTF-8
$ iconv -f WINDOWS-1252 -t UTF-8 windows_file.csv > utf8_file.csv

# List available encodings
$ iconv -l
```

Python approach:

```python
# Read with specific encoding
with open('file.csv', encoding='latin-1') as f:
    content = f.read()

# Write as UTF-8
with open('file_utf8.csv', 'w', encoding='utf-8') as f:
    f.write(content)
```

CSV Edge Cases: Quoting

What if your data contains commas?

```
title,year,description
Inception,2010,A mind-bending, complex thriller    <- WRONG! Extra column
"Inception",2010,"A mind-bending, complex thriller" <- Correct: quoted
```

What if your data contains quotes?

```
title,year,tagline
Say "Hello",2020,A movie about "greetings"   <- WRONG!
"Say ""Hello""",2020,"A movie about ""greetings""" <- Correct: escaped
```

Rule: Fields with commas, quotes, or newlines must be quoted.

CSV Edge Cases: Line Endings

Different systems use different line endings:

System	Line Ending	Bytes
Unix/Linux/Mac	LF	`\n` (0x0A)
Windows	CRLF	`\r\n` (0x0D 0x0A)
Old Mac	CR	`\r` (0x0D)

Problems occur when mixing:

```
# Detect line endings
$ file data.csv
data.csv: ASCII text, with CRLF line terminators

# Convert Windows to Unix
$ sed -i 's/\r$//' data.csv
# Or
$ dos2unix data.csv
```

CSV Edge Cases: Multiline Values

Values can contain newlines (if quoted):

```
title,year,plot
"Inception",2010,"A thief who steals corporate secrets through dream-sharing
technology is given the inverse task of planting an idea into the mind
of a C.E.O."
"Avatar",2009,"A paraplegic Marine..."
```

This is valid CSV! But many simple parsers break.

Solution: Use proper CSV parsers (pandas, csvkit), not line-by-line reading.

CSV Edge Cases: Empty vs Null

What does this mean?

```
title,year,rating
Inception,2010,8.8
Avatar,2009,
The Room,2003,""
```

Row	rating value	Interpretation
1	`8.8`	Rating is 8.8
2	(nothing)	Rating is null/missing
3	`""`	Rating is empty string

Is empty string the same as null? Depends on your interpretation!

Handling Edge Cases: Best Practices

1. Always specify encoding explicitly:

```
pd.read_csv('file.csv', encoding='utf-8')
```

2. Use proper CSV parsers:

```
# Good
import csv
with open('file.csv') as f:
    reader = csv.reader(f)

# Bad
with open('file.csv') as f:
    for line in f:
        fields = line.split(',')  # Breaks on quoted commas!
```

3. Validate after reading:

```
assert df['year'].dtype == 'int64', "Year should be integer"
```

Part 10: Validation Principles

Best practices for data quality

Principle 1: Validate at the Boundary

Check data when it enters your system, not later.

External Data → Validation Layer → Your System

↓

Invalid data rejected

Why?

- Invalid data doesn't spread through your system
- Easier to debug (you know exactly where it failed)
- Clear separation of concerns

Principle 2: Fail Fast

Stop immediately when you find invalid data.

```python
# Bad: Continue and hope for the best
for movie in movies:
    try:
        process(movie)
    except:
        pass  # Silent failure!

# Good: Fail fast and loud
for movie in movies:
    validate(movie)  # Raises exception if invalid
    process(movie)
```

Benefits:

- Find problems early
- Don't waste time processing bad data
- Easier debugging

Principle 3: Be Explicit About Missing Data

Don't guess. Document and handle explicitly.

```python
# Bad: Implicit handling
rating = movie.get('rating', 0)  # Is 0 a valid rating or missing?

# Good: Explicit handling
rating = movie.get('rating')
if rating is None:
    raise ValidationError("Rating is required")
# Or
if rating is None:
    rating = DEFAULT_RATING  # Explicitly documented default
```

Principle 4: Validate Types AND Values

Type checking isn't enough.

```python
# Type is correct (integer), but value is invalid
year = -500     # Negative year
year = 9999     # Far future
year = 1066     # Before cinema existed

# Need both type AND range validation
def validate_year(year):
    if not isinstance(year, int):
        raise TypeError("Year must be integer")
    if year < 1880 or year > 2030:
        raise ValueError(f"Year {year} out of valid range")
```

Principle 5: Log Validation Failures

Keep records of what failed and why.

```python
import logging

def validate_movies(movies):
    valid = []
    for i, movie in enumerate(movies):
        try:
            validate(movie)
            valid.append(movie)
        except ValidationError as e:
            logging.warning(f"Row {i}: {e.message} - {movie}")

    logging.info(f"Validated {len(valid)}/{len(movies)} movies")
    return valid
```

Principle 5: Log Validation Failures

Why?

- Understand data quality trends
- Debug upstream issues
- Audit trail

Principle 6: Separate Validation from Cleaning

Two different operations:

Validation	Cleaning
Checks if data is valid	Fixes invalid data
Returns true/false	Modifies data
Should not modify	Requires decisions
Objective	Subjective

```python
# Validation: Does it pass?
def is_valid_year(year):
    return isinstance(year, int) and 1880 <= year <= 2030

# Cleaning: Make it pass
def clean_year(year_str):
    return int(year_str.strip())
```

Principle 7: Test Your Validation

Validation code needs tests too!

```python
def test_year_validation():
    # Valid cases
    assert validate_year(2010) == True
    assert validate_year(1880) == True  # Boundary
    assert validate_year(2030) == True  # Boundary

    # Invalid cases
    assert validate_year(1879) == False  # Just below
    assert validate_year(2031) == False  # Just above
    assert validate_year("2010") == False  # Wrong type
    assert validate_year(None) == False   # Null
```

Edge cases are where bugs hide!

Common Validation Mistakes

Mistakes that let bad data slip through:

Mistake	Example	Better Approach
Only checking type	`isinstance(x, int)`	Also check range: `0 < x < 1000`
Trusting "not None"	`if value:`	Empty string `""` is falsy but not None
Case sensitivity	`if status == "active"`	`if status.lower() == "active"`
Whitespace	`if name == "John"`	`if name.strip() == "John"`
Encoding	Reading UTF-8 as ASCII	Always specify encoding
Off-by-one	`year < 2024`	Should it be `<= 2024`?

Rule of thumb: If something CAN go wrong, it WILL. Validate defensively.

Part 11: Building a Validation Pipeline

Putting it all together

The Validation Pipeline

Ingest → **Inspect** → **Validate** → **Clean**
↓
Reject invalid records

Stage	Action	Tools
1. Ingest	Load raw data	`curl`, `requests`
2. Inspect	Profile and understand	`jq`, `csvstat`, pandas
3. Validate	Check against rules	JSON Schema, Pydantic
4. Clean	Fix and transform	pandas, custom functions

Stage 1: Ingest

```bash
# Download or receive data
curl -o movies_raw.json "$API_URL"

# Check what we got
file movies_raw.json
wc -l movies_raw.json
head movies_raw.json | jq .
```

```python
# Load with explicit encoding
import json
with open('movies_raw.json', encoding='utf-8') as f:
    movies = json.load(f)
print(f"Loaded {len(movies)} movies")
```

Stage 2: Inspect and Profile

```bash
# Quick profile with jq
cat movies.json | jq 'length'                                    # Count
cat movies.json | jq '[.[].year] | unique | sort'        # Year range
cat movies.json | jq '[.[].rating | select(. == null)] | length'  # Null ratings
```

```python
# Or with Python/pandas
df = pd.DataFrame(movies)
print(df.info())
print(df.describe())
print(df.isnull().sum())
```

Stage 3: Validate - Define Schema

```python
# 07_validation_pipeline.py - CleanMovie schema

from pydantic import BaseModel, Field
from typing import Optional, List

class CleanMovie(BaseModel):
    title: str = Field(..., min_length=1)
    year: int = Field(..., ge=1888, le=2030)
    rating: Optional[float] = Field(None, ge=0, le=10)
    revenue: Optional[int] = Field(None, ge=0)
    runtime_minutes: Optional[int] = None
    genres: List[str] = []
```

Stage 3: Validate - Run Validation

```python
# 07_validation_pipeline.py - validate_batch method

valid_movies = []
invalid_movies = []

for i, raw in enumerate(data):
    try:
        cleaned = transform_movie(raw)  # Transform first
        movie = CleanMovie(**cleaned)   # Validate with Pydantic
        valid_movies.append(movie)
    except (ValidationError, ValueError) as e:
        invalid_movies.append({'index': i, 'raw_data': raw, 'error': str(e)})

print(f"Valid: {len(valid_movies)}, Invalid: {len(invalid_movies)}")
```

Stage 4: Clean and Transform

```python
# 07_validation_pipeline.py - transform_movie function

def transform_movie(raw: dict) -> dict:
    """Transform raw API data to clean format."""
    return {
        'title': raw.get('Title', raw.get('title', '')),
        'year': clean_year(raw.get('Year', raw.get('year'))),
        'rating': clean_rating(raw.get('imdbRating', raw.get('rating'))),
        'revenue': clean_revenue(raw.get('BoxOffice')),
        'runtime_minutes': clean_runtime(raw.get('Runtime')),
        'genres': clean_genres(raw.get('Genre')),
    }
```

Stage 4: Helper Functions

```python
# 07_validation_pipeline.py - cleaning functions

def clean_revenue(value):
    """Convert '$292,576,195' to 292576195"""
    if value is None or value == '' or value == 'N/A':
        return None
    cleaned = str(value).replace('$', '').replace(',', '')
    return int(cleaned) if int(cleaned) >= 0 else None

def clean_runtime(value):
    """Convert '148 min' to 148"""
    if value is None or value == '' or value == 'N/A':
        return None
    match = re.search(r'(\d+)', str(value))
    return int(match.group(1)) if match else None
```

Complete Pipeline Script (Part 1)

```bash
#!/bin/bash
# validate_movies.sh

INPUT=$1
OUTPUT_VALID="movies_valid.json"
OUTPUT_INVALID="movies_invalid.json"

echo "=== Stage 1: Ingest ==="
echo "Input file: $INPUT"
file "$INPUT"
cat "$INPUT" | jq 'length'
```

Complete Pipeline Script (Part 2)

```
echo -e "\n=== Stage 2: Profile ==="
cat "$INPUT" | jq '[.[].year | select(. == null)] | length'
cat "$INPUT" | jq '[.[].rating | select(. == null)] | length'

echo -e "\n=== Stage 3: Validate ==="
python validate.py "$INPUT" "$OUTPUT_VALID" "$OUTPUT_INVALID"

echo -e "\n=== Stage 4: Summary ==="
echo "Valid records: $(cat $OUTPUT_VALID | jq 'length')"
echo "Invalid records: $(cat $OUTPUT_INVALID | jq 'length')"
```

Pipeline Output

```
=== Stage 1: Ingest ===
Input file: movies_raw.json
movies_raw.json: JSON data, UTF-8 Unicode text
1000

=== Stage 2: Profile ===
Null years: 13
Null ratings: 108

=== Stage 3: Validate ===
Processing 1000 movies...
Valid: 879, Invalid: 121

=== Stage 4: Summary ===
Valid records: 879
Invalid records: 121

Validation complete. Check movies_invalid.json for details.
```

Back to Netflix: Cleaned Data

```
# Before cleaning
{"Title": "Inception", "Year": "2010", "imdbRating": "8.8",
 "BoxOffice": "$292,576,195", "Genre": "Action, Adventure, Sci-Fi"}

# After pipeline
{"title": "Inception", "year": 2010, "rating": 8.8,
 "revenue": 292576195, "genres": ["Action", "Adventure", "Sci-Fi"]}
```

Now we can train our model!

```
df = pd.DataFrame(cleaned_movies)
X = df[['year', 'rating']]  # Numeric columns
y = df['revenue']
model.fit(X, y)  # Works!
```

Part 12: Looking Ahead

Lab preview and next week

This Week's Lab

Hands-on Practice:

1. **Unix inspection** - `head`, `tail`, `wc`, `file`, `sort`, `uniq`
2. **jq exercises** - JSON querying and transformation
3. **CSVkit** - Profile and query CSV files
4. **Pydantic deep dive** - Nested models, custom validators
5. **Build a pipeline** - End-to-end validation of messy data

Goal: Take raw messy data and produce clean validated dataset.

Lab Dataset

You'll receive:

- `movies_raw.json` - 1000 movies with various quality issues
- `schema.json` - Partial schema (you'll complete it)

Issues to find and fix:

- Missing values (null, "N/A", empty string)
- Wrong types (numbers as strings)
- Duplicates
- Inconsistent formats
- Outliers

Next Week Preview

Week 3: Data Labeling

- Why labeling is the bottleneck
- Labeling tools and platforms
- Quality control for labels
- Inter-annotator agreement
- Managing labeling projects

The data we cleaned now needs labels for ML!

Interview Questions

Common interview questions on data validation:

1. **"How would you handle missing values in a dataset?"**
   - Identify types of missingness (MCAR, MAR, MNAR)
   - Strategies: deletion, imputation, flagging
   - Context matters: dropping vs filling depends on data and use case
2. **"What's the difference between validation and cleaning?"**
   - Validation: checking if data meets rules (returns true/false)
   - Cleaning: transforming data to meet rules (modifies data)
   - Validation should come first to understand the problems

Key Takeaways

1. **Look before you process** - Never trust raw data
2. **Know your enemy** - Understand types of data problems
3. **Tools matter** - jq, CSVkit, Pydantic save hours
4. **Schema-first** - Define expectations before processing
5. **Validate at the boundary** - Catch problems early
6. **Fail fast** - Don't propagate bad data
7. **Use Pydantic** - Pythonic validation with type hints

Resources

Tools:

- jq: https://stedolan.github.io/jq/manual/
- CSVkit: https://csvkit.readthedocs.io/
- Pydantic: https://docs.pydantic.dev/
- JSON Schema: https://json-schema.org/

Practice:

- jq playground: https://jqplay.org/

Questions?

Thank You!

See you in the lab!