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⚠️ Reminder to start the Zoom recording!

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💻 Lots of demo code today. Get ready to type!

LECTURE 5

# Data Wrangling and EDA

Exploratory Data Analysis and its role in the data science lifecycle.

**Data 100/Data 200, Spring 2025 @ UC Berkeley**

Narges Norouzi and Josh Grossman

Acknowledgments

# Plan for Next Few Weeks

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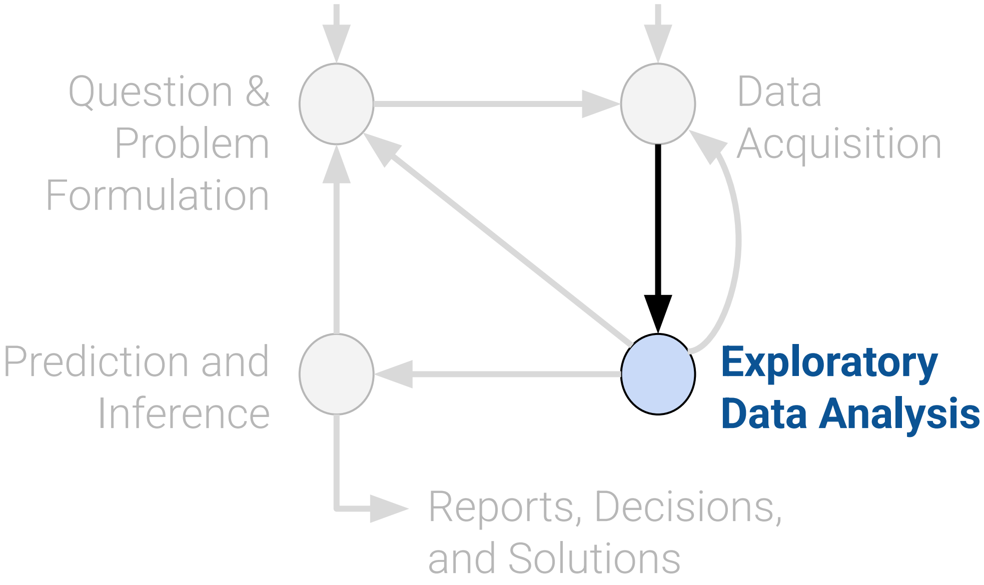

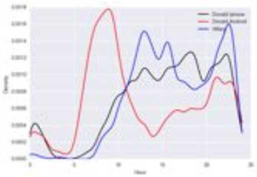

**(Weeks 1 and 2)**

Exploring and Cleaning Tabular Data
From `datascience` to `pandas`

**(Week 3)**

Data Science in Practice
**EDA, Data Cleaning**, Text processing (regular expressions)

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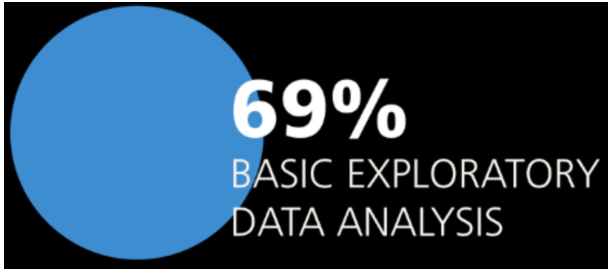
# Exploratory Data Analysis (EDA)

## EDA is unboxing for data!



From Lecture 1

# The Data Science Lifecycle is a Cycle

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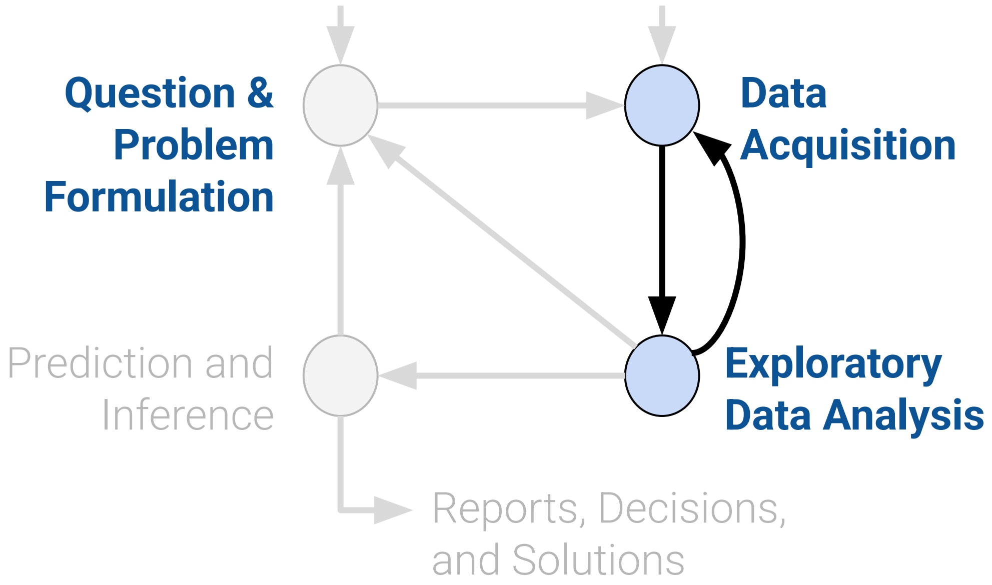
In practice, EDA informs whether you need more data to address your research question.


Question & Problem Formulation
Data Acquisition
Prediction and Inference
Exploratory Data Analysis
Reports, Decisions, and Solutions

# Key Data Properties to Consider in EDA

**Structure** -- the "shape" of a data file

**Granularity** -- how fine/coarse is each datum

**Temporality** -- how is the data situated in time

**Faithfulness** -- how well does the data capture "reality"

# Rectangular Data

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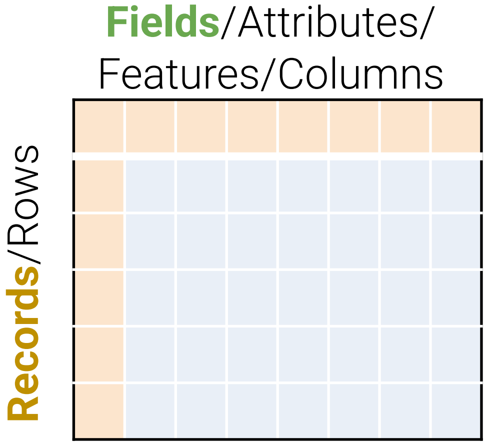
We often prefer **rectangular data** for data analysis

- Easy to manipulate and analyze
- Big part of **data cleaning**: Reshape to be more rectangular
- Example: dataset of spam emails → table of word counts



Two kinds of rectangular data: **Tables** and **Matrices**.

## **Tables** (`DataFrames` in R/Python)

- Named columns with **different** types
- Manipulated w/ data transformation functions (group by, join, filter …)

## Matrices

- **Numeric** data of the **same** type (float, int, etc.)
- Manipulated w/ linear algebra
- Faster computation, but less flexible

# Other Illnesses During the COVID-19 Pandemic

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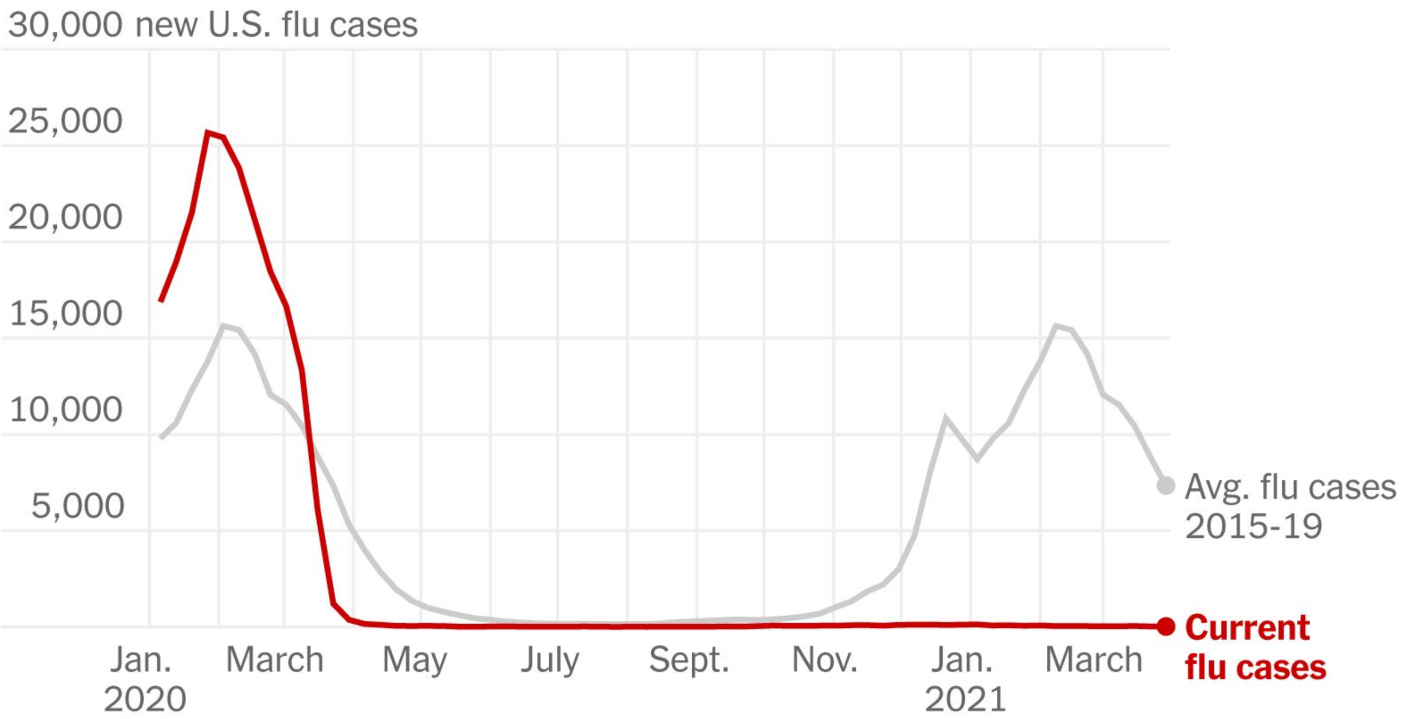
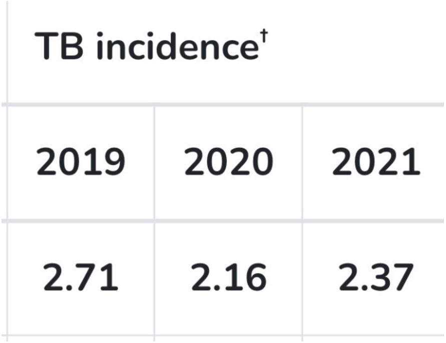


Source: New York Times

# Other Illnesses During the COVID-19 Pandemic



TB incidence[†]

| 2019 | 2020 | 2021 |
|---|---|---|
| 2.71 | 2.16 | 2.37 |

**TB**: Tuberculosis
**Incidence**: # cases per 100,000 people

Source: CDC (Centers for Disease Control and Prevention)

You're an analyst at the CDC.

How do you calculate these values?

U.S. TB incidence → Need U.S. TB case counts and U.S. population

U.S. TB case counts → **State-level TB case counts**

State-level TB case counts → Hospital-level TB case counts

# Demo Slides

lec05-part-1-eda-tuberculosis.ipynb

## CSV: Comma-Separated Values

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TB data from CDC (source)

CSV is a very common **tabular file format**.

- **Records** (rows) are delimited by a newline: `'\n'`
- **Fields** (columns) are delimited by commas: `','`

Pandas: `pd.read_csv(header=...)`

**Fields**/Attributes/Features/Columns

**Records**/Rows

| | U.S. jurisdiction | TB cases 2019 | ... |
|---|---|---|---|
| 0 | Total | 8,900 | ... |
| 1 | Alabama | 87 | ... |

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# Key Data Properties to Consider in EDA

(we'll come back to this!)

**Structure** -- the "shape" of a data file

**Granularity** -- how fine/coarse is each datum → a single "piece" of data

**Temporality** -- how is the data situated in time

**Faithfulness** -- how well does the data capture "reality"

# An Important Conundrum in Data Science

| | |
|---|---|
| **Singular "data"** | "The data show**s** …" |
| **Plural "data" (~~datums~~)** | "The data show …" |

Either is fine 🙂

# Granularity: How Fine/Coarse Is Each Datum?

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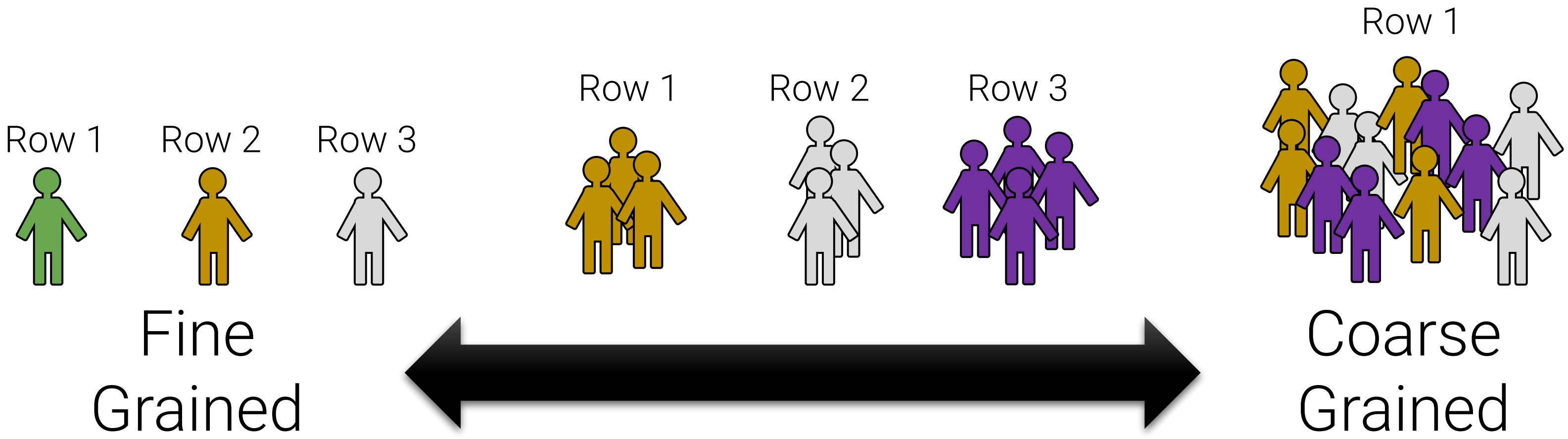

Row 1 Row 2 Row 3

Fine Grained

Row 1 Row 2 Row 3

Row 1

Coarse Grained

What does each **record** (row) represent?

- Examples: a single purchase, a single person, a group of users
- Some data will include summaries (aka **rollups**) as records.

If the data are **coarse**, how were the records aggregated?

- Summing, averaging, or something else?

# Demo Slides

lec05-part-1-eda-tuberculosis.ipynb

## Granularity of TB data

What does each row of the TB data represent?

Do all rows have the same granularity?

Image source: NPR

# Key Data Properties to Consider in EDA

**Multiple Files**

File Format

Variable Type

**Structure** -- the "shape" of a data file

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## Demo Slides

lec05-part-1-eda-tuberculosis.ipynb

## Joining Multiple Files

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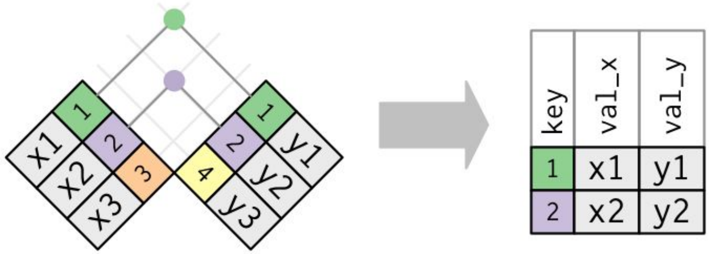
Incidence = Case Count / Population

TB case counts → CDC data

U.S. population → Census data

It's time to merge!



| key | val_x | val_y |
|---|---|---|
| 1 | x1 | y1 |
| 2 | x2 | y2 |

Image source: R4DS

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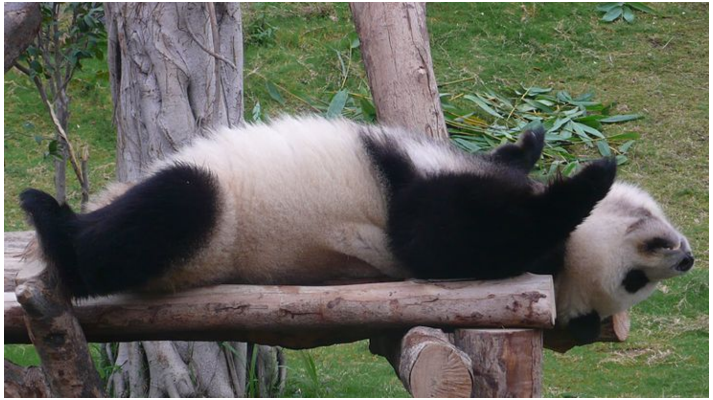
# 2-minute stretch break!



Multiple Files

**File Format**

Variable Type

# Key Data Properties to Consider in EDA

**Structure** -- the "shape" of a data file

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## Demo Slides

lec05-part-2-eda-structure.ipynb

## TSV: Tab Separated Values

Another common table file format.

- **Fields** are delimited by `'\t'` (tab)
- Like a CSV with tabs instead of commas

`pd.read_csv`: Need to specify

```
    delimiter='\t'
```

TaB soda: Precursor to Diet Coke

## Demo Slides

lec05-part-2-eda-structure.ipynb

# JSON: JavaScript Object Notation

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CA Senators+Reps data (congress.gov API)

Very similar to Python dictionaries

- **Self-documenting**: Metadata (data about the data) + records in the same file

`pd.read_json()`

`pd.DataFrame(json_dict)`

JSON is **non-rectangular**, so good to inspect the file before importing.

- Nested tables
- Inconsistent fields across records

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Multiple Files

File Format

**Variable Type**

# Key Data Properties to Consider in EDA

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# Variable Feature Types

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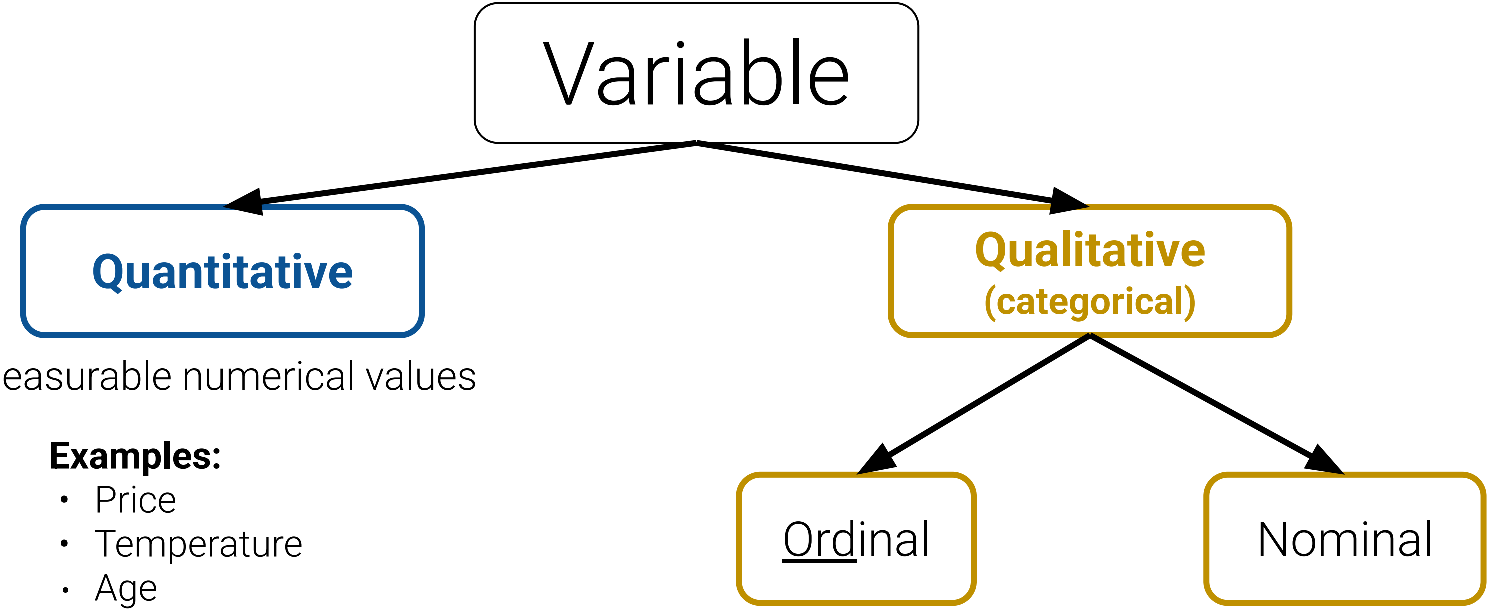

Variable

**Quantitative**

Measurable numerical values

**Examples:**

- Price
- Temperature
- Age

**Qualitative (categorical)**

Ordinal

Ordered categories

**Examples:**

- Grade level
- Age group

Nominal

Unordered categories

**Examples:**

- Phone brand
- Cal ID number (assigned, not measured!)

**A safe default: Store qualitative data as strings!**

# Variable Types

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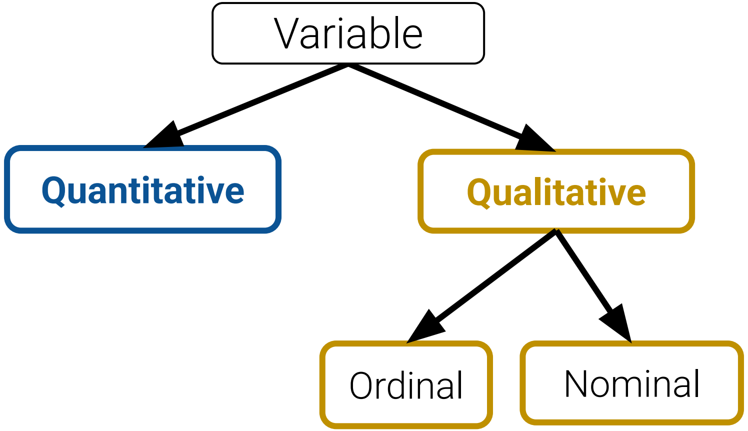
What is the feature type of each variable?

| Q | Variable | Feature Type |
|---|---|---|
| 1 | $CO_2$ level (ppm) | **Quantitative** |
| 2 | Income bracket (low, med, high) | **Qualitative Ordinal** |
| 3 | Race/Ethnicity | **Qualitative Nominal** |
| 4 | Political party | **Qualitative Ordinal / Nominal** |
| 5 | Year | **Quantitative / Qualitative Ordinal** |
| 6 | GPA | **Quantitative / Qualitative Ordinal** |
| 7 | Date and time | **Slido!** |



The distinction between categories is sometimes murky. Context matters!

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# What type of variable is a datetime (e.g., 01/01/2025 3:30pm)?

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# Key Data Properties to Consider in EDA

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# Efficiently Storing Datetimes

As humans, we write datetimes as strings: **01/01/2025 3:30pm**

There are 13 characters in the string **010120250330p**

Datetime column with 1 billion entries → ~13 billion characters → 13 GB column 😱

What if we stored datetimes as **integers**?

1 billion integers → ~4 billion bytes → 4 GB column 😎

# Temporality: Unix / POSIX Time

**Datetimes** measured in **seconds** since **January 1st 1970 UTC** (Coordinated Universal Time)

Feb 4, 2025 5:00pm PDT → **`1738674000`** (1,738,674,000 seconds)

Feb 4, 1950 5:00pm PDT → **`-628167600`** (-628,167,600 seconds)

Another bonus of numeric representation: We can do math!

For example, we can calculate # days between dates using subtraction and division.

# Demo Slides

lec05-part-2-eda-structure.ipynb

## Unix / POSIX Time

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Berkeley PD calls for service data

`pd.to_datetime()`

`pd.series.dt.date()`

`pd.series.dt.dayofweek()`

`pd.series.dt.hour()`

...

# Lecture 5 ended here!

We will cover the rest in Lecture 6

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# Key Data Properties to Consider in EDA

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# What are some potential issues with this dataset?

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# What are Some Potential Issues with this Dataset?

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| ID | Category | State | Location | Device | Purchased | ... |
|---|---|---|---|---|---|---|
| 0 | Shoes | CA | CA | 1 | 1 | ... |
| 1 | Socks | NM | NM | 1 | 0 | ... |
| 2 | Socks | XY | XY | 1 | 0 | ... |
| 3 | Shirts | NY | NY | 1 | NA | ... |
| 4 | Shoes | FL | FL | 1 | 0 | ... |
| 4 | Shoes | FL | FL | 1 | 0 | ... |
| 5 | Shirts | CA | CA | 1 | 0 | ... |
| 6 | Pnts | TX | TX | 1 | 1 | ... |
| 7 | Hats | CA | CA | 1 | -1 | ... |
| ... | ... | ... | ... | ... | ... | ... |

# Faithfulness: Do I trust this data?

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### Fully Duplicated Records or Fields

Identify and ignore/drop.

### Labeling or Spelling Errors

Apply corrections. Only ignore if you have to.

### Missing data

Need to think carefully about **why** the data is missing.

Examples

```
"  "            1970, 2000
0, -1           NaN
999, 12345      Null
```

NaN: "Not a Number"

Real zero or NaN placeholder? Sometimes both!

See footnote 12 in onlinelibrary.wiley.com/doi/abs/10.1111/jels.12343

# Missing Data: Approaches

## A. Keep as NaN

- A good default.
- If qualitative/categorical → Create a "Missing" category.

## B. Drop records with missing values

- Typically a bad default!
- Temperature probe went offline for a minute → Likely **missing at random** → OK to drop
- Police officer never records outcomes of vehicle stops → Likely not missing at random

## C. Imputation/Interpolation: Infer missing values

- **Mean/median imputation:** replace NaN with mean/median
- **Hot deck imputation:** use a random non-NaN value
- **Regression imputation:** use a model to predict value
- **Multiple imputation:** multiple random values + check sensitivity

(beyond this course)

## Demo Slides

lec05-part-2-eda-structure.ipynb

## Missing Values

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Berkeley PD calls for service data

Approaches:

- Keep missing values as NaN
- Drop missing values
- Impute

`pd.series.isna()`

`pd.DataFrame.info()`

# We did it!

**Structure** -- the "shape" of a data file

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LECTURE 5

# Data Wrangling and EDA

Content credit: Acknowledgments