# Data & Task Abstraction

**A practical framework for translating domain questions into defensible visual designs.**

**Marc Reyes**
Professional Lecturer · marc.reyes@dlsu.edu.ph
DATA101 — De La Salle University

# Today's Plan

01 · SETUP

## Why abstraction matters

Avoid the chart-first trap.

02 · DATA

## Dataset + attribute types

What you have, what it means.

03 · TASKS

## Goals + actions + targets

What your user needs to do.

04 · DESIGN

## From abstraction → charts

Views + interactions you can defend.

05 · PRACTICE

## Exercises + exit ticket + Python assignment

Write abstractions like a practitioner (then implement in pandas).

# Learning Outcomes

DATA

### Identify dataset structure

Table, time series, spatial, network, hybrid…

DATA

### Label attribute types

Categorical, ordinal, quantitative, temporal.

TASKS

### Write task statements

Action + Target + Constraints + Output.

DESIGN

### Justify chart + interaction

Design decisions that map to data + tasks.

# Warm-Up (3 minutes)

PROMPT

**“The Dean wants to know if students are struggling more this term.”**

METRIC

Scores? pass rate? attendance? drop rate?

BASELINE

Last term? last year? another section?

OUTPUT

Which groups? when? how big? how confident?

# Abstraction = translation

From domain language → to general structures that visualization methods can support.

# The Chart-First Trap (and How to Avoid It)

COMMON FAILURE MODE

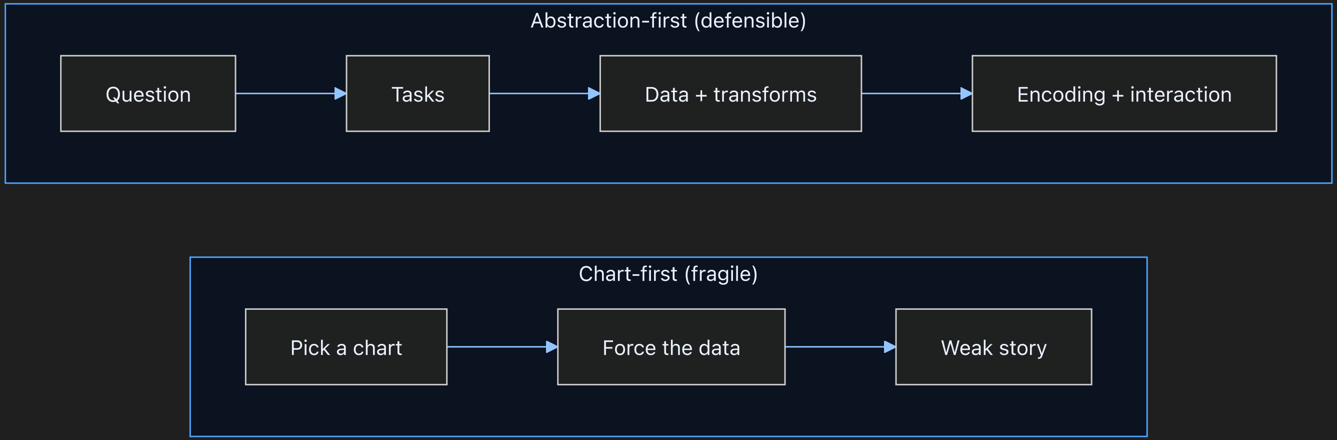
## Chart-first thinking

“Make a bar chart” is a solution, not a problem statement.

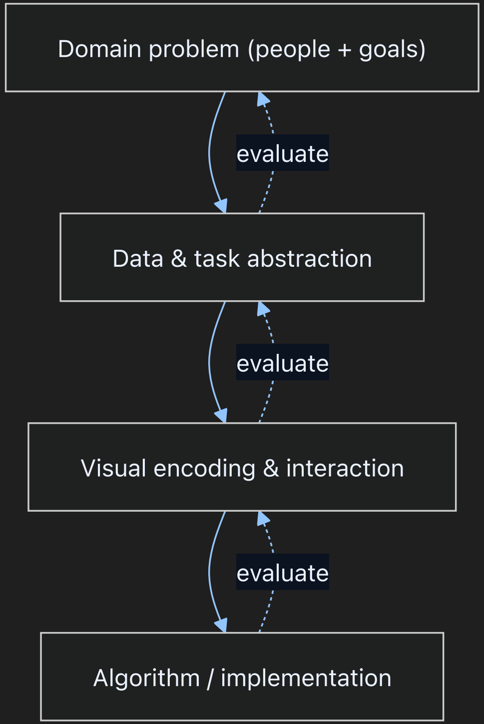
PROFESSIONAL WORKFLOW

## Abstraction-first thinking

Question → tasks → data needs → transforms → design.



# Munzner’s Nested Model (Where Abstraction Lives)

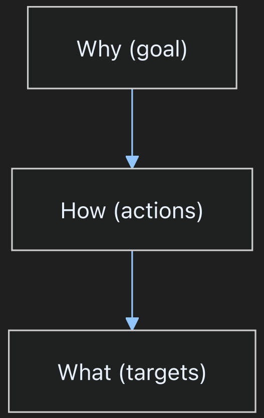


# Two Outputs You Should Be Able to Write

Before picking charts: write the **task spec** and **data spec**.

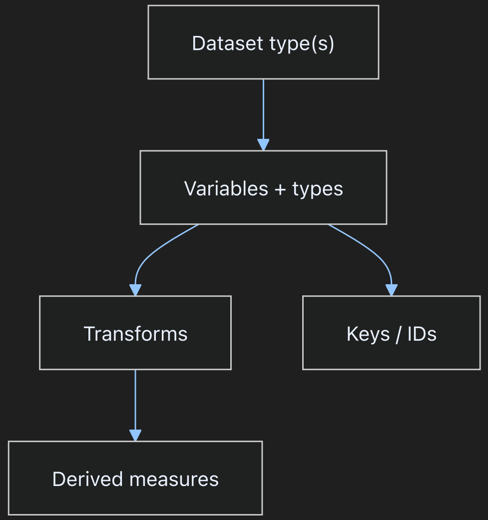
TASK ABSTRACTION

## Why → How → What




DATA ABSTRACTION

## Types → Variables → Transforms



# Running Example (We'll Use This All Lecture)

**Question:** "Are students struggling more this term?"

- Possible data sources: weekly quizzes, attendance logs, LMS activity, advising records
- Possible unit of analysis: student, section, program, college
- Possible time scale: week, month, midterms/finals phases

# What a “Good Answer” Looks Like

SUCCESS CRITERIA

TARGET

## Who?

Which sections/programs are struggling?

TIME

## When?

Which weeks; before/after which event?

MAGNITUDE

## How much?

Show distributions, not just averages.

BASELINE

## Compared to what?

Last term, target, or benchmark.

PART 1 · DATA

# Data Abstraction

From domain data → dataset types + attribute types + transformations

# Data Abstraction: What You Produce

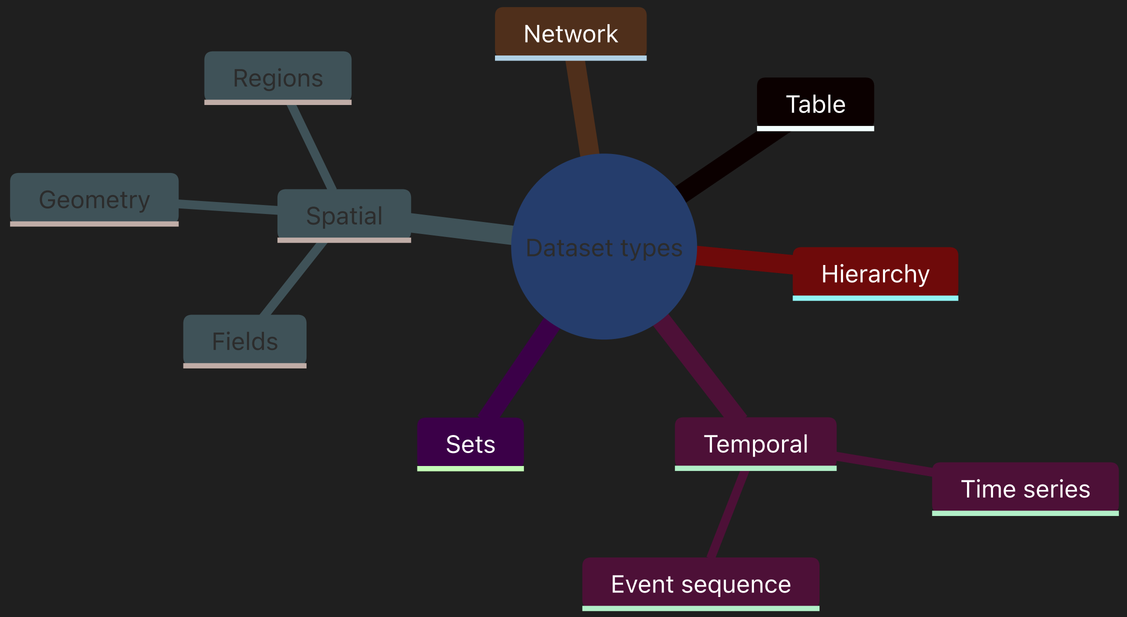
**Dataset type(s) + attribute types + required transforms**

- Dataset type(s): table, time series, spatial, hierarchy, network, field, sets
- “Items” vs “relationships” vs “positions”
- Variable list with attribute types + units
- Required transformations: cleaning, aggregation, binning, derived measures

# Start With an Inventory (Before Any Charts)

| Question | What you write down |
| --- | --- |
| What are the **items**? | rows / records (students, sessions, transactions) |
| What are the **variables**? | columns (program, score, week, minutes) |
| Are there **relationships**? | links (prerequisite, collaboration, referral) |
| Are there **positions**? | time order, coordinates, grid cells |

# Dataset Types (Visualization Lens)



# Dataset Type: Table (Items × Attributes)

**Example:** student records

- Items: students or section-week records
- Typical transforms: group-by, summarize, sort, filter
- Typical views: bar chart (compare), dot plot (rank), histogram/box plot (distribution)

# Dataset Type: Time Series (Ordered by Time)

**Common mistakes:** missing weeks, irregular sampling, mixing time zones.

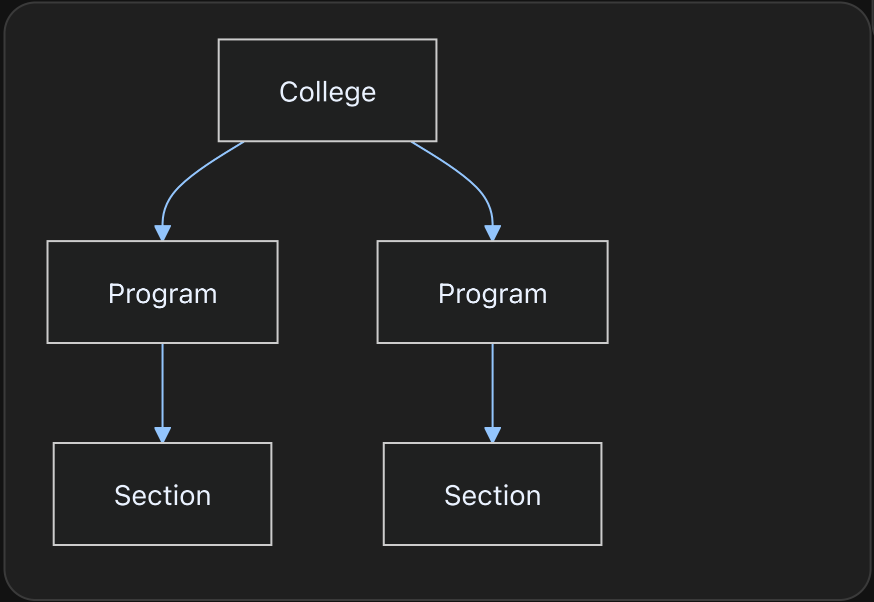
- Decide the time unit (day/week/month) and make it explicit
- Consider smoothing carefully (rolling mean can hide spikes)
- Baselines matter: compare to last term or target performance

# Spatial Data: Geometry vs Regions vs Fields

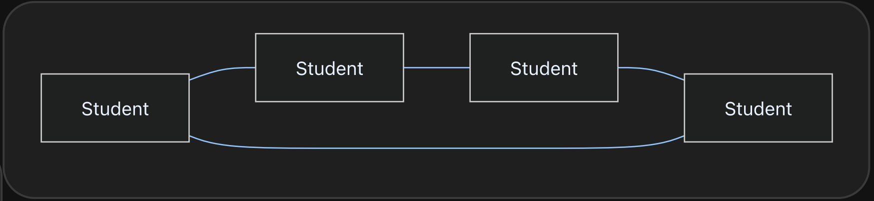
- **Geometry:** points/lines (GPS pings, routes) → proximity, clusters
- **Regions:** polygons (cities/barangays) → compare areas, choropleths (careful with population)
- **Fields:** values everywhere (density/temperature) → heatmaps, contours, binning choices

# Hierarchy vs Network (Know the Difference)

**Hierarchy** (parent → child)

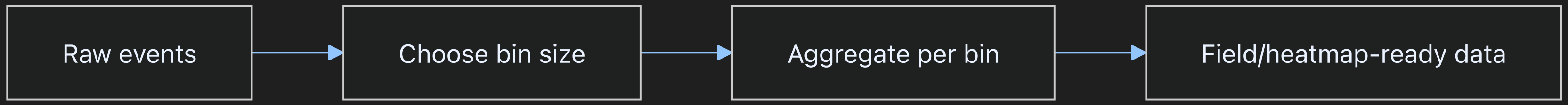



**Network** (links between peers)



# Fields & Density: Why Binning Is a Design Decision

- Raw events → bins (grid cells, time windows) → aggregated values
- Bigger bins: smoother but can hide local patterns
- Smaller bins: detailed but noisier; may exaggerate randomness



# Sets & Membership Data

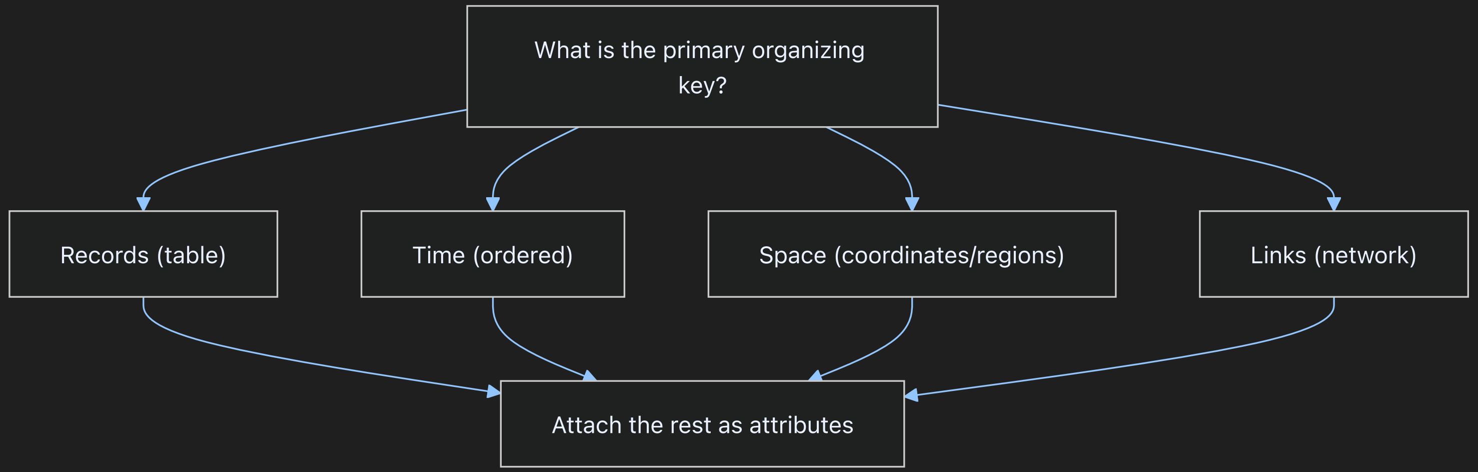
When items belong to multiple groups (e.g., students in orgs + electives).

- Dataset structure: items + membership lists
- Typical tasks: overlap, exclusive groups, coverage
- Warning: Venn diagrams don’t scale; consider tables or UpSet-style views

# Hybrid Datasets (Most Real Problems)

Many datasets are **table + time + category** (and sometimes spatial).

- Choose a primary structure (often a table of records)
- Decide whether time/space are axes or attributes; keep stable IDs (student_id, section_id)



# Attribute Types (Semantics of Variables)

## Categorical
different kinds

Examples: program, device_type

Channels: color hue, shape, grouping

## Ordinal
ranked kinds

Examples: Likert 1–5, grade bands

Channels: position, ordered color

## Quantitative
magnitude

Examples: score, minutes, count

Channels: position, length, size

## Temporal
time

Examples: week, timestamp

Channels: position (x), ordering

# Measurement Scales (What Math Is Valid?)

| Scale | Example | You can do… | Don't… |
|---|---|---|---|
| Nominal | program | count, mode | average it |
| Ordinal | rank, Likert | median, order | assume equal gaps |
| Interval | °C | differences | claim "twice as hot" |
| Ratio | counts, ₱ | ratios, % change | ignore units |

# Identifiers vs Measures vs Categories

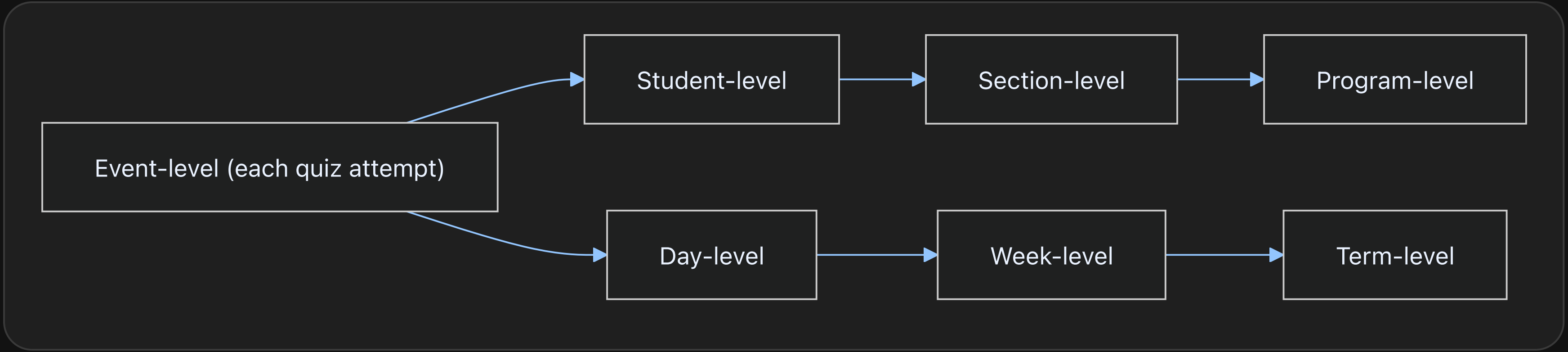
- **Identifier:** labels one item (StudentID, SectionCode) → use for joins, not charts
- **Measure:** numeric value with meaning (score, minutes, count) → plot/analyze
- **Category code:** looks numeric but is categorical (1=CS, 2=IT) → treat as categorical

Quick test: “If I average this, does the result mean anything?”

# Derived Measures (Often the Real KPI)

- Rates: pass_rate = passes / enrolled
- Normalization: incidents per 1,000 students (not raw counts)
- Change: week-over-week difference or percent change
- Composite indices: only if components and weights are justified

# Granularity & Aggregation (Choose With Tasks)




Aggregation hides variance; keep distributions when decisions affect individuals.

# Reshaping for Visualization

**Wide** (one row per student)

| student | quiz1 | quiz2 | quiz3 |
|---|---:|---:|---:|
| A | 7 | 8 | 6 |

**Long / tidy** (one row per observation)

| student | quiz | score |
|---|---|---:|
| A | quiz1 | 7 |
| A | quiz2 | 8 |
| A | quiz3 | 6 |

# Data Quality & Bias (A Fast Checklist)

- Missingness: random or systematic? (e.g., absent students)
- Outliers: errors or rare events?
- Units: consistent? (minutes vs hours; ₱ vs $)
- Denominators: use rates when group sizes differ
- Coverage: who is excluded by the data collection process?

# Practice 1 (5 minutes): Abstract This Dataset

## Wi-Fi session log

Columns: `timestamp`, `student_program`, `access_point`, `session_minutes`, `device_type`

- Dataset type(s)?
- Attribute type of each variable?
- One derived measure you might need (rate/ratio/change)?

PART 2 · TASKS

# Task Abstraction

From domain questions → actions + targets + constraints

# Task Abstraction: What You Produce

## Action + Target + Constraints + Output

- Action: compare, rank, summarize, detect, locate, filter
- Target: items, groups, attributes, time ranges, links
- Constraints: “this term only”, “by program”, “top 5 sections”
- Output: “a ranked list”, “a time window”, “a set of flagged outliers”

## Chart Request → Task Statement (Rewrite)

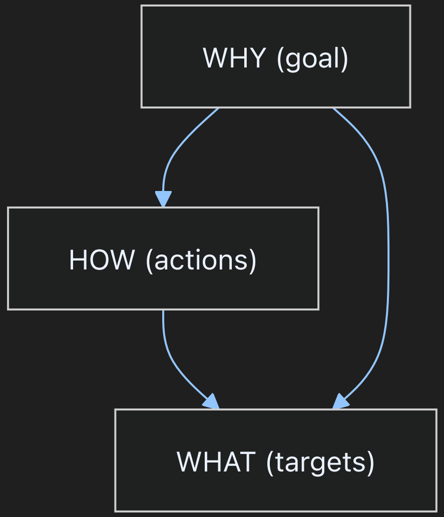
- ❌ “Make a bar chart of programs”

  ✅ “Compare programs by **pass rate** this term”
- ❌ “Use a line chart for quizzes”

  ✅ “Detect **when** quiz performance drops and **which sections** drop the most”
- ❌ “Create a dashboard with filters”

  ✅ “Enable **browsing** by program and **drill-down** to student-level details on demand”

# A Strong Framework: WHY / HOW / WHAT



# WHY / HOW / WHAT Vocabulary

WHY (GOAL)

## Motivation

- Discover: find unknown patterns
- Present: communicate clearly
- Monitor: track known metrics
- Lookup: answer a specific question

HOW (ACTIONS)

## Verbs

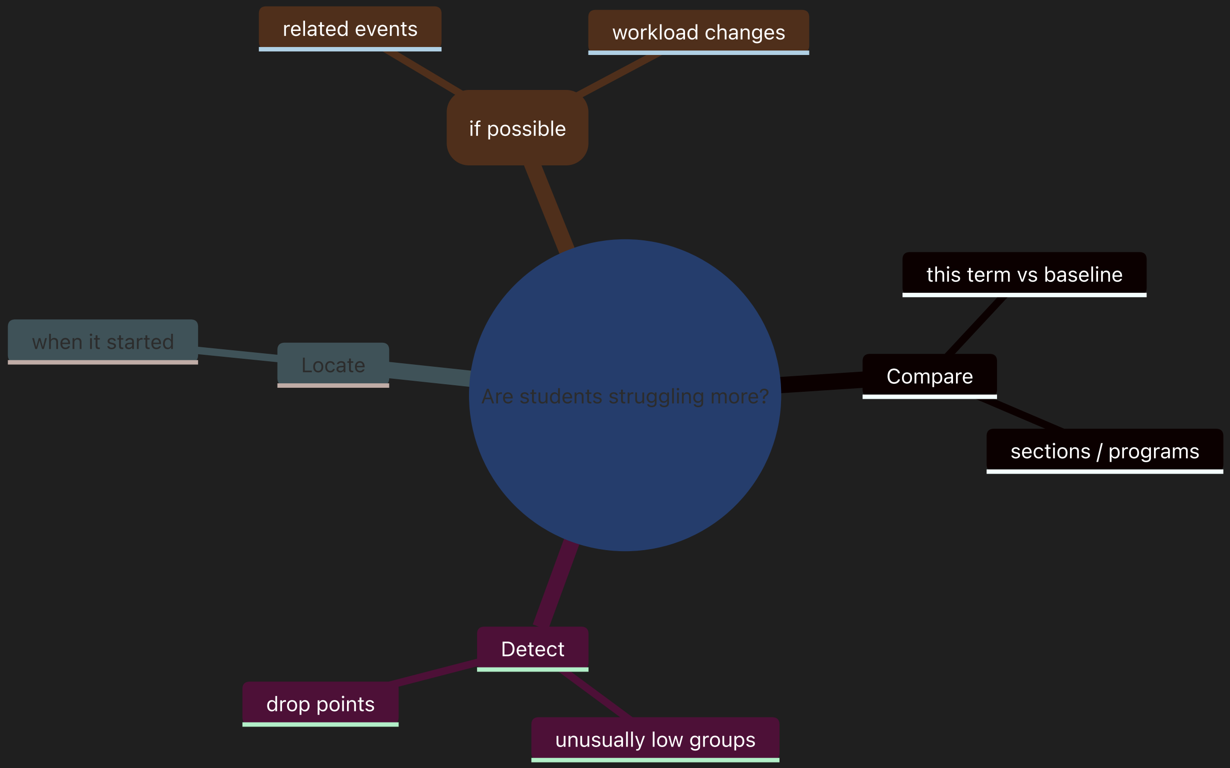
- Search: lookup · locate · browse · explore
- Query: filter · sort · group
- Compare: rank · contrast · benchmark
- Detect: outliers · change points

WHAT (TARGETS)

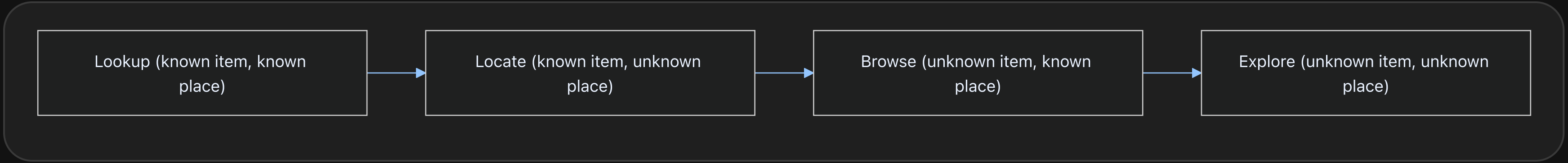
## Objects

- Items: student, section, record
- Groups: program, cohort
- Attributes: score, pass_rate, minutes
- Ranges: week 3–6, pre/post event
- Links: prereq, collaboration, referral

# Decompose the Running Example Into Subtasks



# Search Tasks: Lookup → Explore




- Shneiderman: overview first → zoom/filter → details on demand

# Compare Tasks: Three Common Patterns

- **Compare categories:** section A vs B (use aligned scales; sort when needed)
- **Rank:** top/bottom N (make ordering explicit; show ties)
- **Benchmark:** compare to a target (add reference lines/bands)

If comparison is the task, design for *alignment* and *readable differences*.

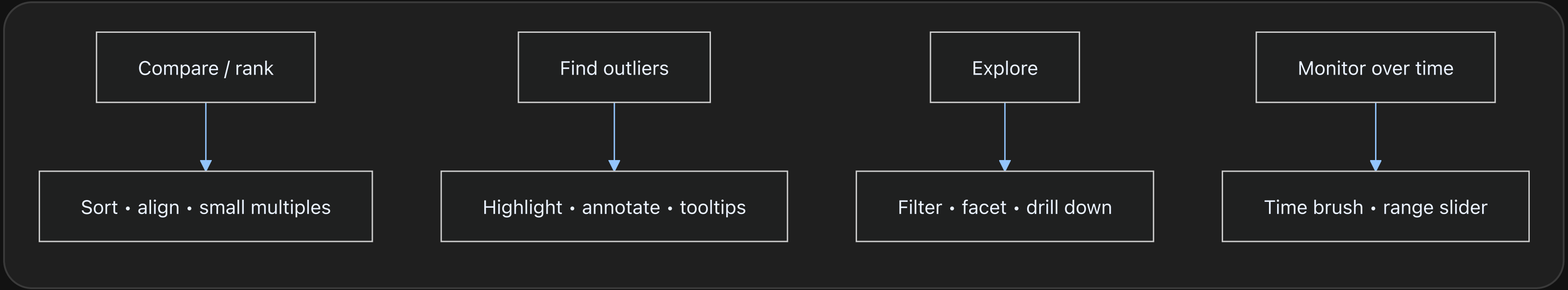
# Distribution Tasks: “What’s Typical?” + “Who Is Different?”

- Ask for: center, spread, skew, outliers
- Use: histogram (shape), box plot (summary), violin (density)
- Don’t hide the distribution behind a single average when decisions affect people

# Relationship Tasks: Correlate, Cluster, or Explain?

- **Correlate:** do two measures move together?
- **Cluster:** do groups form naturally (segments)?
- **Explain:** what factors predict an outcome? (needs modeling + careful claims)
- Reminder: correlation ≠ causation; check confounders and sampling bias

# Tasks ↔ Interactions (Design on Purpose)



# Task Quality Rubric (For Reports and Projects)

- Uses a clear **action verb** (compare/rank/detect…)
- Names an explicit **target** (items/groups/attributes/time range)
- States constraints (population/timeframe/baseline)
- Produces an **output** that someone can verify (ranked list, flagged cases, chosen window)

# Practice 2 (7 minutes): Write Two Task Statements

Pick one dataset from Practice 1 and write:

- One **monitoring** task (ongoing tracking)
- One **discovery** task (exploration)

Use: **Action + Target + Constraints + Output**

PART 3 · DESIGN

# Putting It Together

From abstractions → justified visualization designs

# The 4-Step Abstraction Worksheet (Use This Every Time)

# Channel Effectiveness

RULE OF THUMB

Most precise → least precise

Position (common scale)
↓
Length
↓
Angle / Area
↓
Color / Shape

DESIGN IMPLICATIONS

How this changes chart choices

- **Ranking / comparison** → dot plots, sorted bars, small multiples
- **Magnitude** → avoid area-only encodings for precision
- **Categories** → use hue for grouping, not “how much”
- **Many groups** → sort + label; reduce legend hunting

If the task is comparison, prioritize **position** and **alignment**.

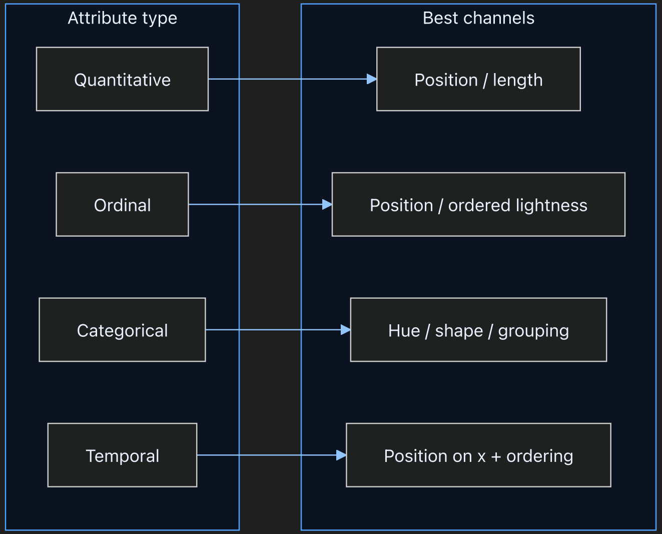
# Match Encoding to Type

ABSTRACTION → SAFE CHANNELS

Attribute types constrain what encodings mean.

- **Quantitative** → position / length for comparison
- **Ordinal** → position or ordered lightness
- **Categorical** → hue, shape, grouping
- **Temporal** → position on x + ordering

If the type is wrong, the chart is wrong—even if it looks polished.



# Evaluation Checklist (Before You Submit a Viz)

## TASKS

- Action verb is explicit (compare/rank/detect...)
- Target + baseline are named
- Output is verifiable (top-5 list, flagged weeks...)

## DATA

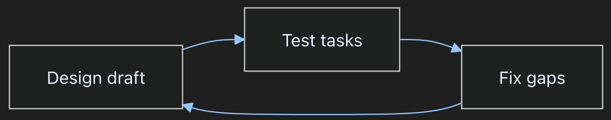
- Types + units are correct
- IDs are stable; joins are valid
- Denominators are handled (rates vs counts)

## DESIGN

- Aligned scales for comparisons
- Legible labels, annotations, and legends
- Uncertainty + missingness are disclosed

## ITERATION

- Test with 2–3 real task questions
- Revise at the abstraction level first
- Then adjust encodings/interactions



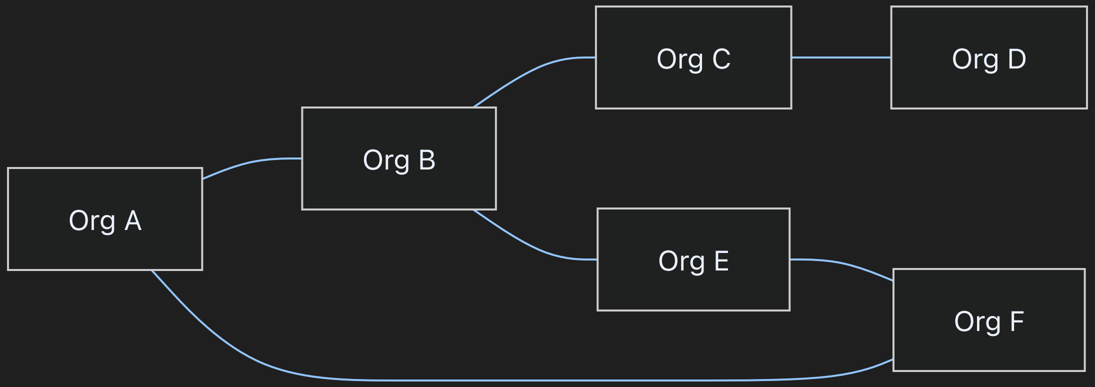
# Case Study: Student Performance (A Task-Driven Design)

- **Data abstraction:** table of section-week records

  Variables: section (cat), week (temp), avg_score (quant), pass_rate (quant), n_students (quant)
- **Key tasks:** compare sections, detect drops, locate weeks, drill down to details

# Case Study: Collaboration Network (Different Data, Different Tasks)

- **Data abstraction:** network (nodes=orgs, links=collaborations), link weight=quant
- **Tasks:** find hubs, bridge orgs, communities; compare before/after an event
- **Design hint:** combine network view with a sortable table for reliable ranking



# Key Takeaways

- Abstraction is the bridge from **domain** to **design**
- Data abstraction: dataset types + attribute types + transformations
- Task abstraction: goals + actions + targets (+ constraints + output)
- Good charts are **defensible** because they directly support tasks
- Avoid common failures: type mixing, raw counts without denominators, over-aggregation, vague tasks

# Exit Ticket + References

## Exit ticket (answer in 2–3 sentences each)

What is the dataset type and attribute types for your chosen example?

Write one task as **Action + Target + Constraints + Output**

What interaction would most help that task, and why?

## References


- Munzner, *Visualization Analysis & Design*
- Brehmer & Munzner (2013), abstract task typology
- Wickham (2014), tidy data



Marc Reyes · `marc.reyes@dlsu.edu.ph`

# Python Assignment (Take-Home): Abstraction → Design

GOAL

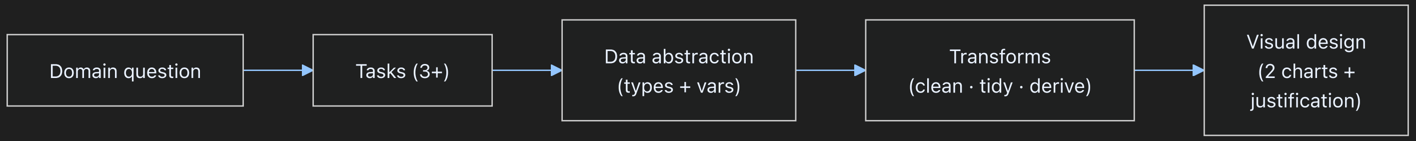
**Turn a domain question into a defendable visualization workflow.**

WRITE

- **1 domain question** (one sentence)
- **Data abstraction**: dataset type(s) + variable types
- **Task abstraction**: 3 tasks (Action + Target + Constraints + Output)

BUILD (PYTHON)

- **Transforms**: clean, tidy/reshape, derive measures
- **2 charts** that directly support your tasks
- **Justification**: 4–6 sentences mapping choices to tasks



# Starter Code + Deliverables

```python
import pandas as pd

df = pd.read_csv("your_data.csv")

# 1) Data abstraction: fix types (example)
# df["date"] = pd.to_datetime(df["date"])

# 2) Transforms: tidy + aggregate for a task
result = (
    df.dropna()
      .groupby(["group", "time"], as_index=False)
      .agg(value=("value", "mean"), n=("value", "size"))
)
```

SUBMIT

- `abstraction.md` (data spec + task statements)
- `analysis.ipynb` (transforms + charts)
- Export charts as `.png` or `.svg`

RUBRIC (SIMPLE)

- Correct types + meaningful derived measures
- Tasks are specific and verifiable
- Charts clearly support tasks (not “favorite charts”)