Class 3 – Data Visualization

Visual Perception & Cognitive Load

Data Types, Encodings & Grammar of Graphics

Python Visualization Fundamentals

Class Overview

Today's Learning Objectives

- Understand how humans perceive visual information
- Learn about cognitive load and its impact on visualization design
- Master data types and their valid visual encodings
- Explore the Grammar of Graphics framework
- Implement visualizations using Python (Matplotlib, Seaborn)
- Apply perceptual principles to create effective visualizations

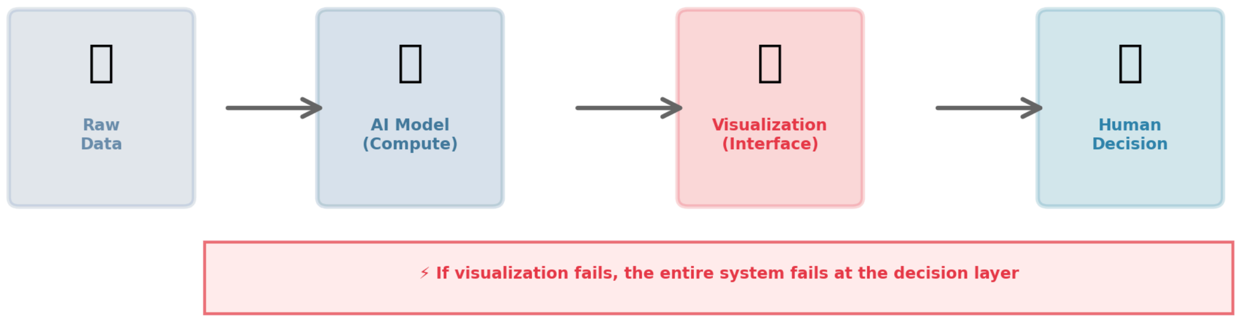
Course Context: Building on Week 2's Python introduction

Why Visualization Matters in Data Science

Visualization is not just presentation—it's cognition

- Data visualization is the interface between:
  - Computation (algorithms, models)
  - Human decision-making
- Every visualization choice affects:
  - ✅ Speed of insight
  - ✅ Accuracy of interpretation
  - ✅ Quality of decisions
- Poor visualization = Poor analytics outcomes

Data to Decision Pipeline: Visualization as Interface



⚡ If visualization fails, the entire system fails at the decision layer

Visualization as a Human–AI Interface

In modern analytics and AI systems:

```
┌──────────────┐       ┌───────────────┐       ┌─────────────┐
│   Raw Data   │  →    │  AI Model     │  →    │Visualization│  →  Human Decision
│              │       │  (Compute)    │       │  (Interface)│
└──────────────┘       └───────────────┘       └─────────────┘
```

- Models compute predictions
- Humans make decisions
- **Visualization is the critical translation layer**
- Human perceptual limits become system constraints

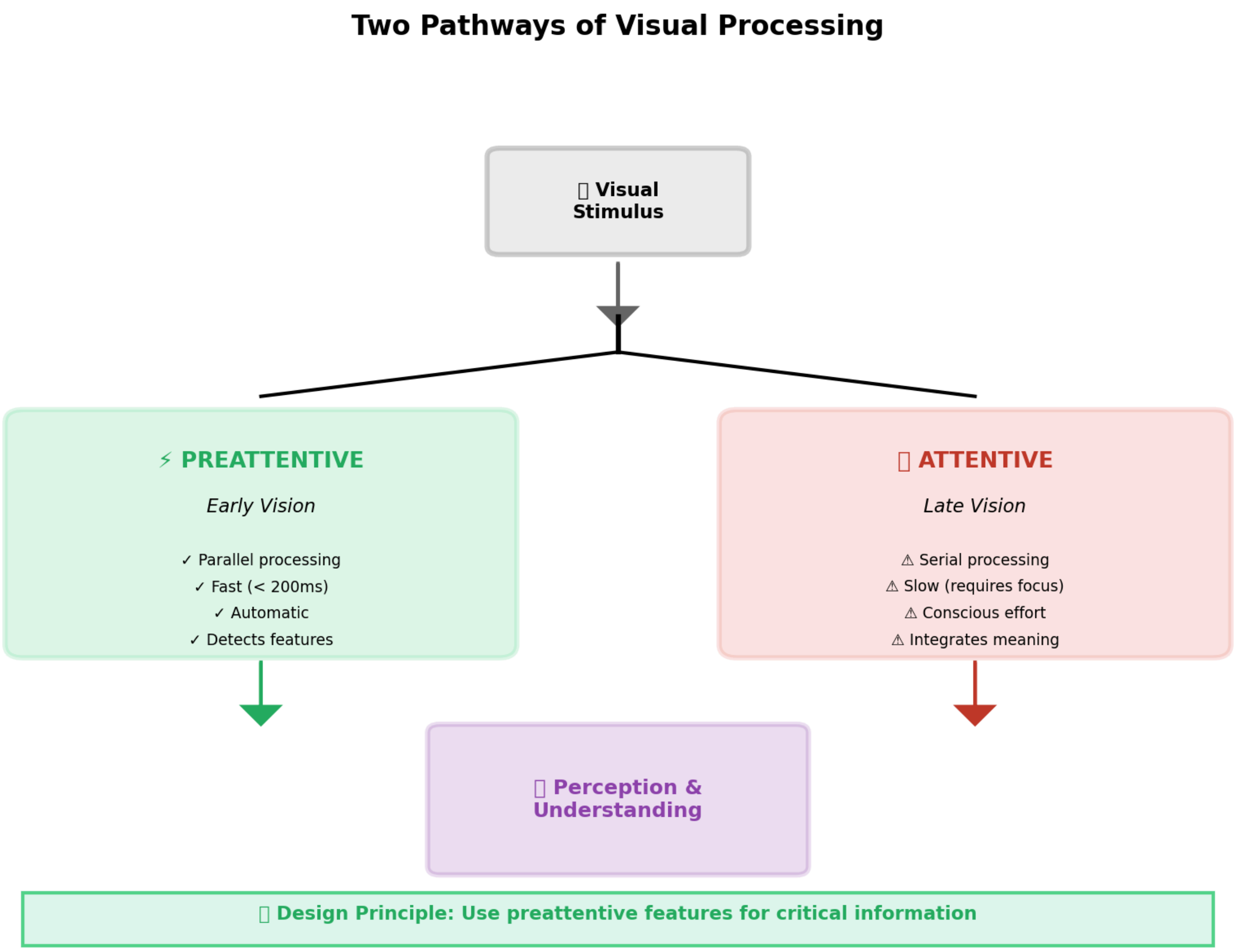
Key Insight: If the visualization fails, the entire system fails at the decision layer.

The Two Pathways of Visual Processing

Visual processing happens in two stages:

1. **Early Vision (Preattentive Processing)**
   - Parallel processing
   - Fast (< 200-250 milliseconds)
   - Automatic, no conscious effort
   - Detects basic features
2. **Late Vision (Attentive Processing)**
   - Serial processing
   - Slow (requires focus)
   - Conscious effort required
   - Integrates meaning and relationships

Design Principle: Leverage preattentive processing for critical information.



Preattentive Processing: The 200ms Window

Certain visual features are detected instantly

Preattentive features enable:

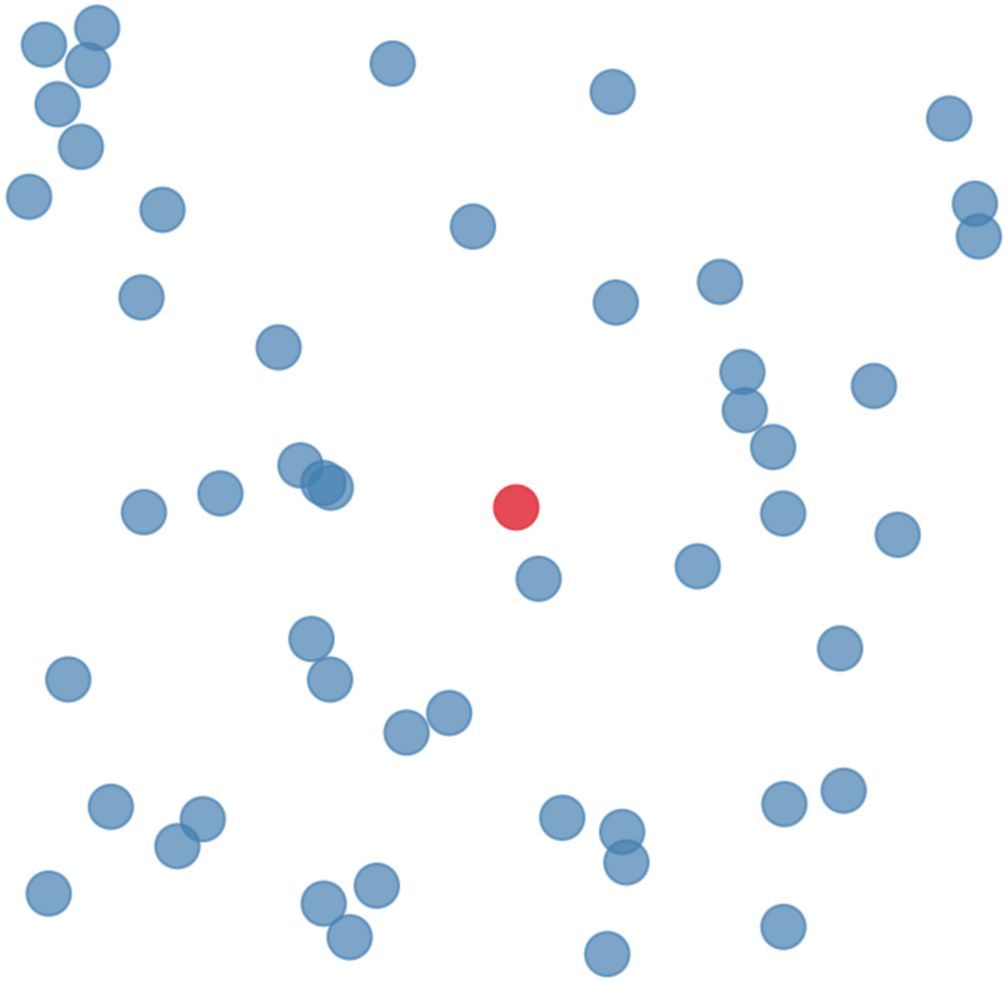
- ✨ Rapid detection
- ✨ Visual pop-out effect
- ✨ Fast filtering and scanning
- ✨ Parallel comparison

Examples of preattentive features:

- Position
- Color (hue)
- Intensity/brightness
- Size/length
- Orientation/angle
- Shape
- Motion
- Enclosure

Key Design Principle: Use preattentive features for what matters most in your visualization.

Preattentive Pop-Out: Find the Red Circle



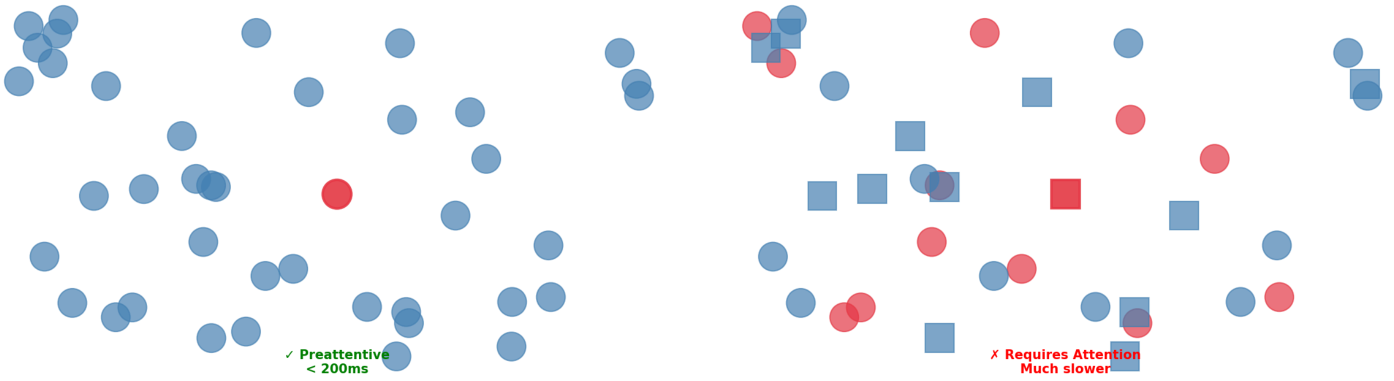
Demonstrating Preattentive Processing

Interactive Exercise: Compare these two search tasks

Why Preattentive Features Matter in Visualization

EASY: Feature Search
(Single feature - color)

DIFFICULT: Conjunction Search
(Multiple features - color AND shape)



Key Findings:

- **Left (Feature Search)**: Find the red circle
  - Uses only ONE attribute (color)
  - Found instantly (< 200ms)
  - **Preattentive** - no conscious effort required
- **Right (Conjunction Search)**: Find the red square
  - Requires TWO attributes (color AND shape)
  - Takes much longer (requires scanning)
  - **Attentive** - conscious effort required

Design Implication: Don't force users to search for multiple attributes simultaneously. In dashboards, make critical information stand out using a single preattentive feature (color, size, or position).

Visual Attention is Limited

The harsh reality of human attention:

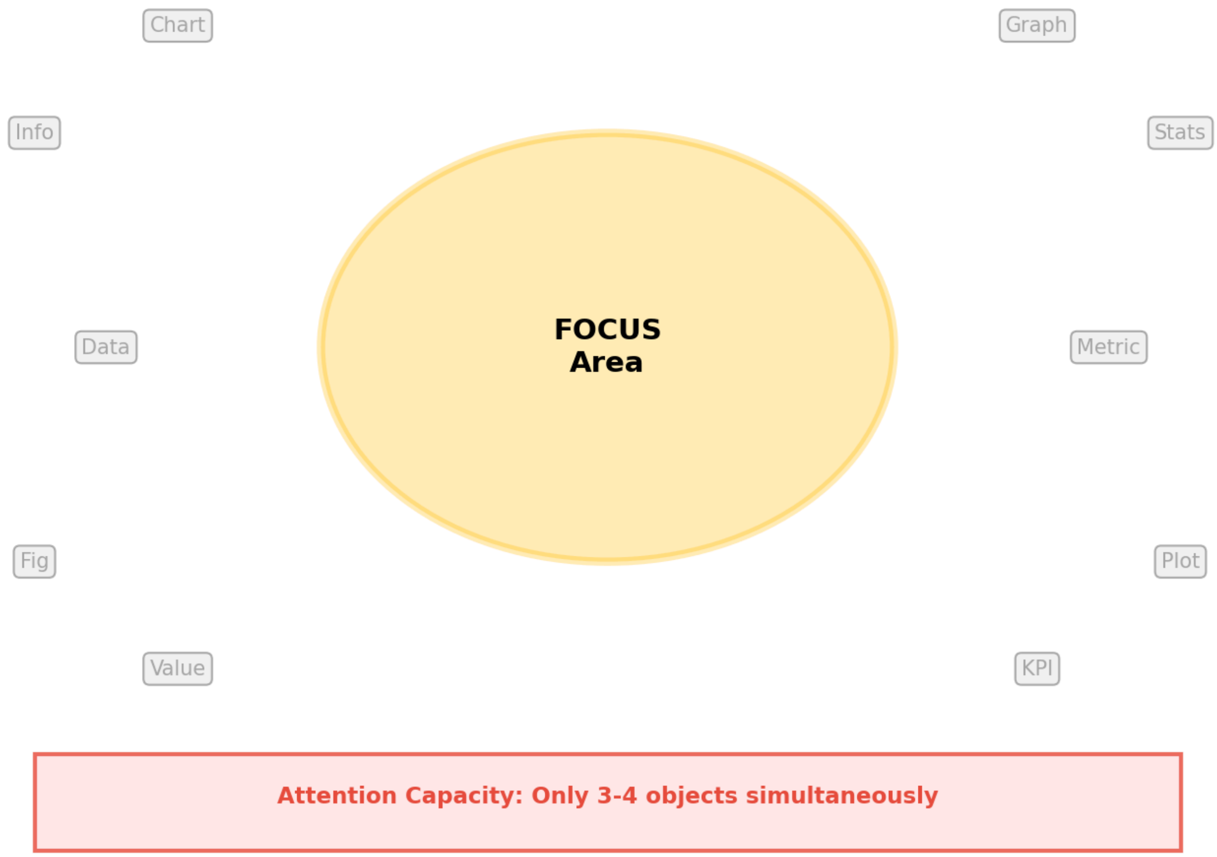
- ❌ Humans cannot attend to everything at once
- ❌ Attention is selective and focused
- ❌ Users must actively search, filter, and compare

Implications for dashboard design:

- If everything is highlighted, nothing is highlighted
- Overloading visual channels creates cognitive fatigue
- Priority must be encoded visually

Attention capacity: ~3-4 visual objects simultaneously

Visual Attention is Limited



Attention Capacity: Only 3-4 objects simultaneously

Change Blindness

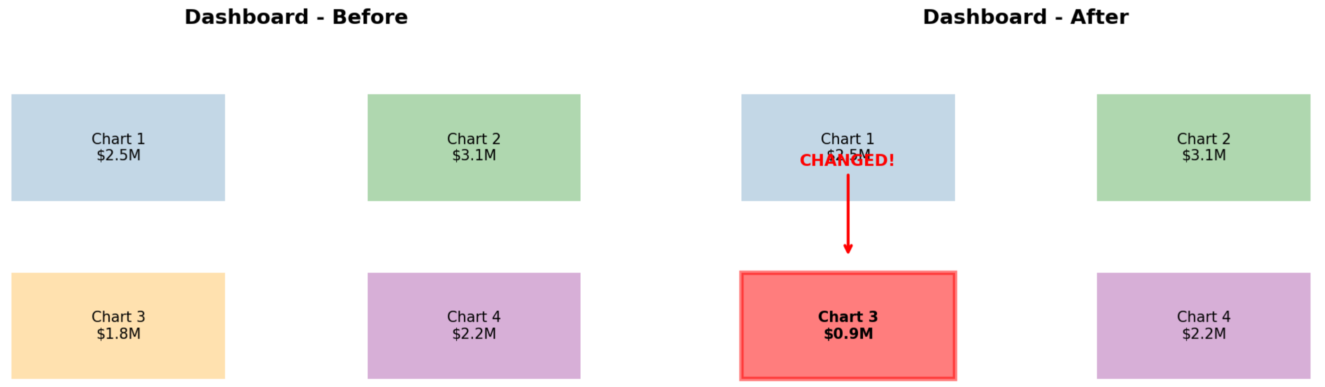
Large changes can go unnoticed if attention is not directed

Common in:

- 🖥️ Real-time dashboards (values update but users don't notice)
- 📊 Multi-panel layouts (change in one panel while viewing another)
- 🎬 Animated transitions (too fast or too subtle)
- 📱 Information-dense interfaces

Design Solutions:

- Use motion for important changes
- Add explicit alerts/notifications
- Use color + position changes together
- Minimize unnecessary animation



Without directed attention, users often miss significant changes

Inattentional Blindness: The Invisible Gorilla

Famous experiment: Watch a video of people passing basketballs

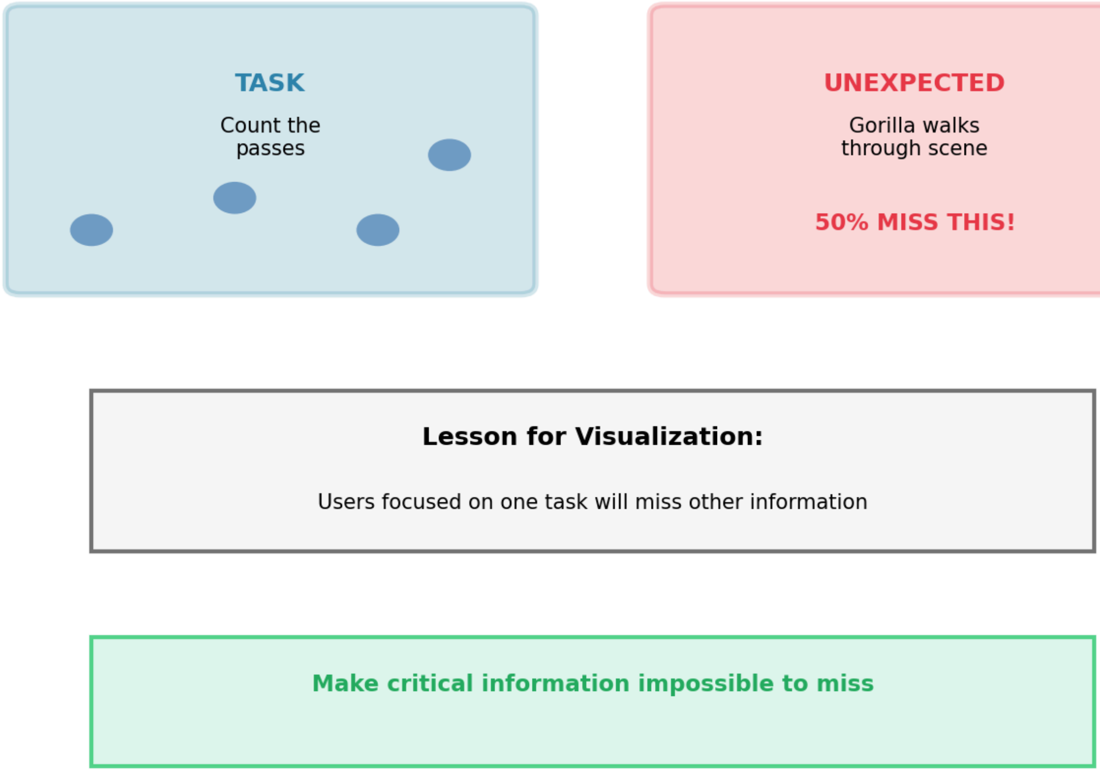
- Task: Count the passes
- Result: 50% of viewers miss a person in a gorilla suit walking through!

Lesson for visualization:

- Users focused on one task will miss other information
- Don't assume users will "just notice" important patterns
- **Make critical information impossible to miss**

Design Principle: If it's important, make it preattentive or explicitly direct attention to it.

Inattentional Blindness



TASK

Count the passes

UNEXPECTED

Gorilla walks through scene

50% MISS THIS!

Lesson for Visualization:

Users focused on one task will miss other information

Make critical information impossible to miss

Gestalt Principles: How We Group Information

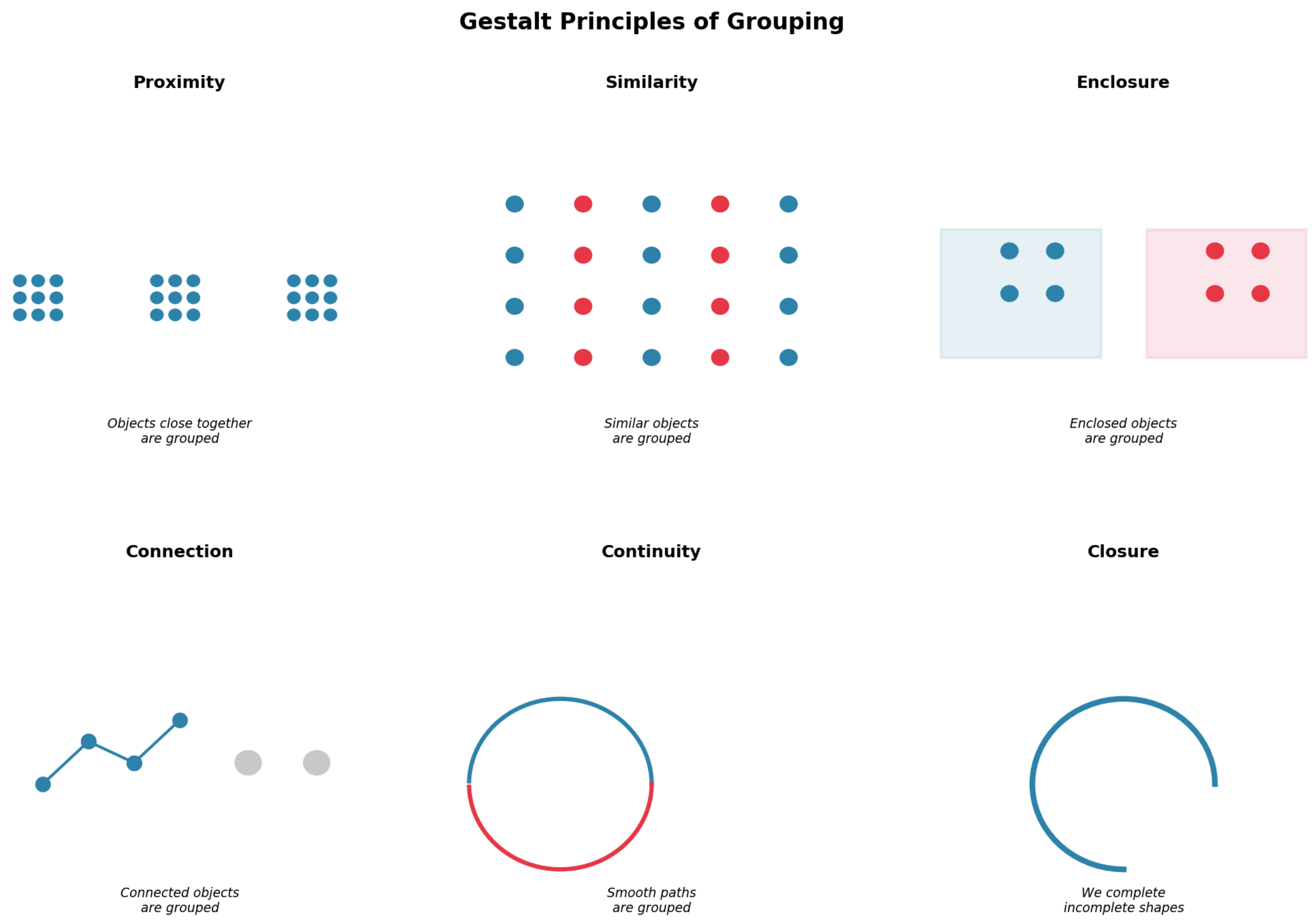
Gestalt Psychology: The whole is greater than the sum of its parts

Core principle: Our brains automatically organize visual elements into groups

Key Gestalt principles for visualization:

1. Proximity
2. Similarity
3. Enclosure/Common Region
4. Continuity
5. Connection
6. Closure

Why this matters: Perception overrides logic. Users will group elements based on visual properties, regardless of what your legend says.


Gestalt Principles of Grouping
Proximity
Objects close together are grouped
Similarity
Similar objects are grouped
Enclosure
Enclosed objects are grouped
Connection
Connected objects are grouped
Continuity
Smooth paths are grouped
Closure
We complete incomplete shapes

Gestalt Principle: Proximity

Objects close together are perceived as related

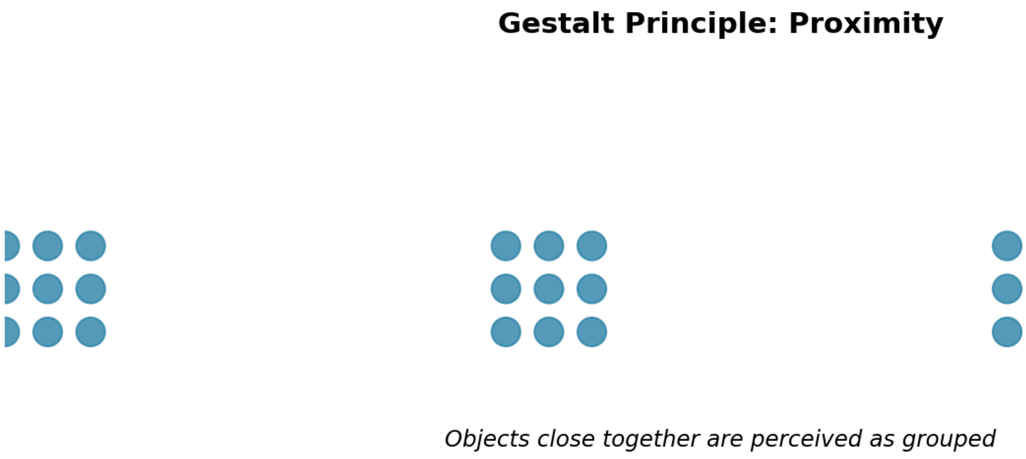
```
A A A    B B B    C C C
A A A    B B B    C C C
A A A    B B B    C C C
```

Users will see 3 groups, not 27 individual items.

In visualization:

- ✅ Place related charts near each other
- ✅ Use whitespace to separate unrelated elements
- ❌ Don't rely only on color to show groups
- ❌ Accidental proximity creates false relationships

Real-world mistake: Dashboard elements randomly placed create confusing relationships.


Gestalt Principle: Proximity
Objects close together are perceived as grouped

Gestalt Principle: Similarity

Objects that look similar are perceived as related

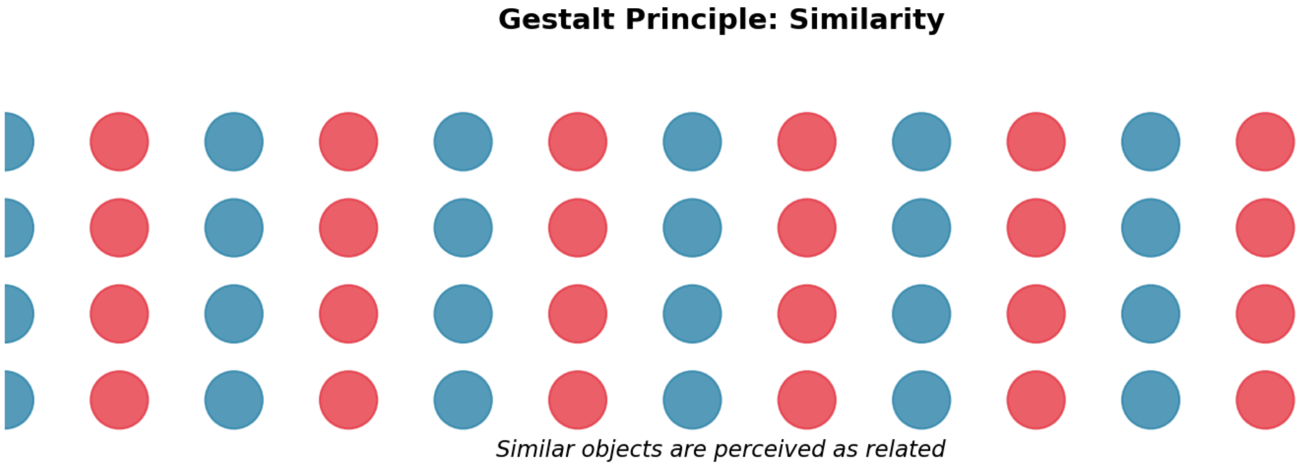
Similar:

- Color
- Shape
- Size
- Orientation
- Texture

In visualization:

- ✅ Use consistent encoding within a group
- ✅ Use distinct styles for different data types
- ❌ Don't reuse visual encodings inconsistently
- ❌ Don't use similar colors for unrelated data

Example: All sales data in blue shades, all costs in red shades.


Gestalt Principle: Similarity
Similar objects are perceived as related

Gestalt Principle: Enclosure & Common Region

Objects within a boundary are perceived as grouped

```
┌──────────┐  ┌──────────┐
│ Group A  │  │ Group B  │
│ ● ● ●    │  │ ■ ■ ■    │
│ ● ● ●      │    │ ■ ■ ■      │
└────────────┘    └────────────┘
```

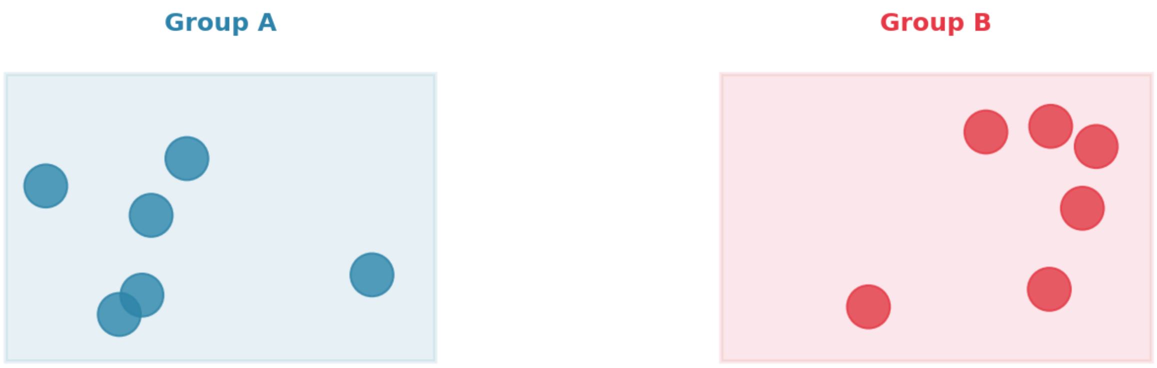
Power of enclosure:

- Stronger than color alone
- Stronger than proximity
- Creates clear visual hierarchy

In dashboards:

- Use cards/panels for related metrics
- Use background shading for grouped sections
- Be careful with nested enclosures (can create confusion)

Gestalt Principle: Enclosure & Common Region



Enclosure creates strong grouping

Gestalt Principle: Connection

Physically connected elements are perceived as related

```
A ── B      C    D

E           F ── G
```

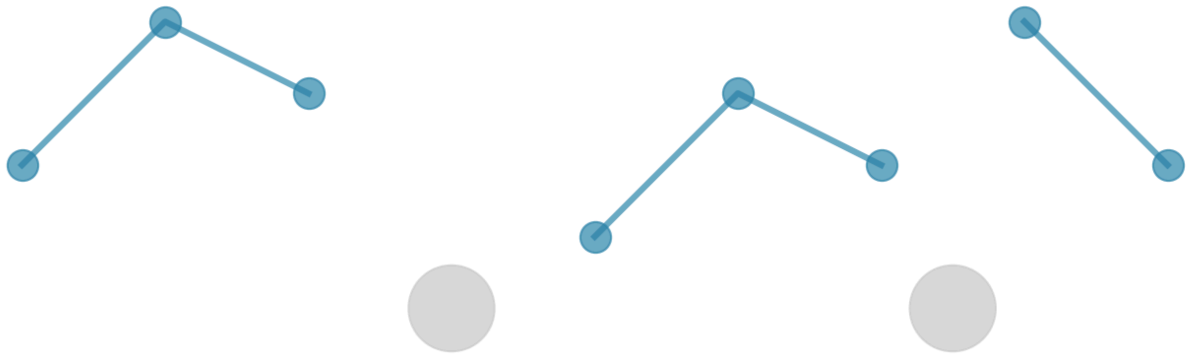
We see: (A-B), C, D, E, (F-G)

In visualization:

- Line charts naturally show relationships
- Connected scatter plots show sequences
- Network diagrams use this principle fundamentally

Design tip: Connection is one of the strongest grouping cues.

Gestalt Principle: Connection



Connected elements are perceived as groups

Gestalt and Dashboard Design Mistakes

Common failures when Gestalt principles are ignored:

❌ **Random layout**: Elements scattered without visual hierarchy
❌ **Inconsistent spacing**: Creates accidental groups
❌ **Color chaos**: Similar colors used for unrelated data
❌ **Over-boxing**: Everything has a border, nothing stands out
❌ **No whitespace**: Cognitive overload

✅ **Good dashboard design:**

- Clear visual hierarchy through proximity and enclosure
- Consistent use of similarity within groups
- Strategic whitespace guides attention
- Visual grouping matches logical relationships

Introduction to Cognitive Load Theory

Core Concept: Working memory has limited capacity

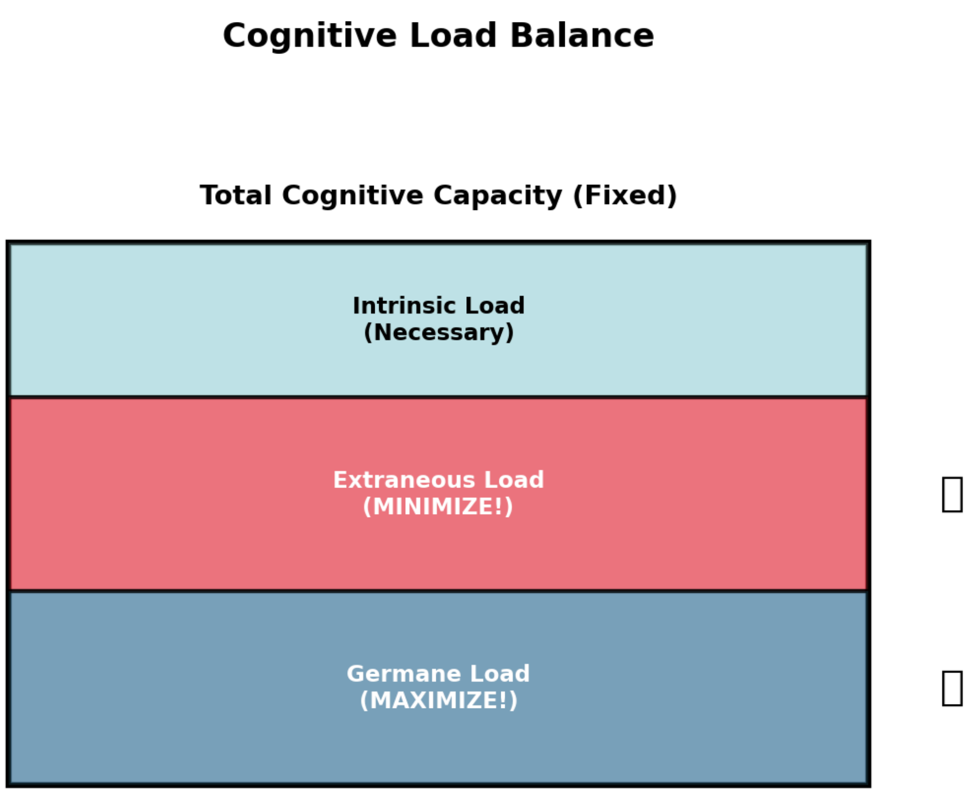
Cognitive Load Theory (Sweller, 1988):

- Human working memory can hold ~7±2 chunks of information
- Processing capacity is limited
- Overload leads to errors and decision fatigue

Three types of cognitive load:

1. **Intrinsic Load** - inherent complexity of the task
2. **Extraneous Load** - unnecessary complexity from poor design
3. **Germane Load** - productive mental effort toward learning/insight

Goal in visualization: Minimize extraneous load, manage intrinsic load, maximize germane load.



Intrinsic Load: Inherent Complexity

Intrinsic load comes from:

- Data complexity (volume, dimensionality)
- Task complexity (comparison, correlation, prediction)
- Domain complexity (specialized knowledge required)

You cannot eliminate intrinsic load, but you can manage it:

✅ **Staging**: Break complex tasks into steps
✅ **Scaffolding**: Provide context and guides
✅ **Progressive disclosure**: Show detail on demand
✅ **Hierarchy**: Present overview first, details later

Example:

- ❌ Showing 50 variables at once → overwhelming
- ✅ Showing top 10, with option to explore more → manageable

Extraneous Load: Unnecessary Complexity

Extraneous load comes from poor design choices:

❌ Chart junk (decorative elements)
❌ 3D effects with no purpose
❌ Cluttered layouts
❌ Inconsistent encodings
❌ Poor color choices
❌ Missing labels or legends
❌ Excessive animation

These add NO value but consume cognitive resources

The solution: Ruthlessly eliminate extraneous load

> "Perfection is achieved not when there is nothing more to add, but when there is nothing left to take away." — Antoine de Saint-Exupéry

Germane Load: Productive Mental Effort

Germane load supports:

- Understanding patterns
- Making comparisons
- Drawing insights
- Building mental models
- Learning relationships

How to maximize germane load:

✅ Clear visual hierarchy guides thinking
✅ Comparisons are easy (aligned scales)
✅ Patterns pop out (preattentive features)
✅ Context is provided (annotations, benchmarks)
✅ User can explore (interactive elements)

The goal: All cognitive effort goes toward insight, not decoding the chart.

The Cognitive Load Balance

Visualization design as optimization:

```
Total Cognitive Capacity (Fixed)
┌─────────────────────────────┐
│ Intrinsic Load (Necessary)  │
├─────────────────────────────┤
│ Extraneous Load (MINIMIZE THIS!)  │ ← Bad design
├─────────────────────────────┤
│ Germane Load (MAXIMIZE THIS!)  │ ← Insight generation
└─────────────────────────────┘
```

Design principle:

- Every design choice should either reduce extraneous load or increase germane load
- If it does neither, remove it

Real-world impact: Reducing cognitive load = faster decisions = better outcomes

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PART 2: DATA TYPES & VISUAL ENCODINGS

Slides 22-33

Cognitive Load in Dashboard Design

Scenario: Executive dashboard with 20 KPIs

❌ **High Extraneous Load Approach:**

- All metrics same size and color

- No hierarchy
- 3D pie charts and gratuitous gradients
- Cluttered legends
- Inconsistent time periods

✅ **Low Extraneous Load Approach:**

- Top 3-5 metrics prominently displayed
- Clear visual hierarchy
- Simple, clean charts
- Direct labeling (no legend hunting)
- Consistent time periods and scales

Result: Same data, drastically different cognitive load and decision quality.

Exercise: Cognitive Load Analysis

Look at two versions of the same dashboard (provided)

For each, identify:

1. Sources of **extraneous load** (what can be removed?)
2. Ways to reduce **intrinsic load** (how to simplify?)
3. Opportunities for **germane load** (what supports insight?)

Discussion: How would redesigning reduce decision time and errors?

Data Types: The Foundation of Encoding

Understanding data types is critical because:

- Data type determines valid encodings
- Violating data type rules creates confusion
- Different data types support different tasks

Four fundamental data types:

1. **Nominal** (Categorical)
2. **Ordinal** (Ordered categories)
3. **Quantitative** (Numerical)
4. **Temporal** (Time-based)

Rule: Data type restricts which visual encodings are appropriate.

Nominal (Categorical) Data

Characteristics:

- Discrete categories
- No inherent order
- Identity and difference matter

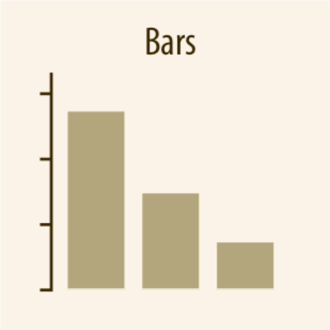
Examples:

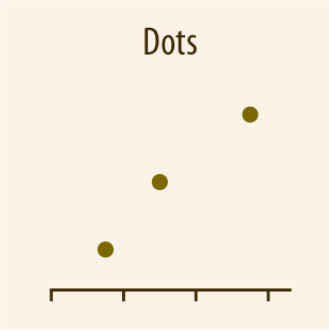
- Product categories (Electronics, Clothing, Food)
- Geographic regions (North, South, East, West)
- Customer segments (A, B, C)
- Business units

Valid encodings:

- ✅ Hue (color)
- ✅ Shape
- ✅ Position (grouped)
- ❌ NOT size, intensity, or ordering

Common mistake: Using a gradient color scale for categories (e.g., red→yellow→green for product types)





Ordinal Data

Characteristics:

- Discrete categories with order
- Rank matters
- Intervals may not be equal

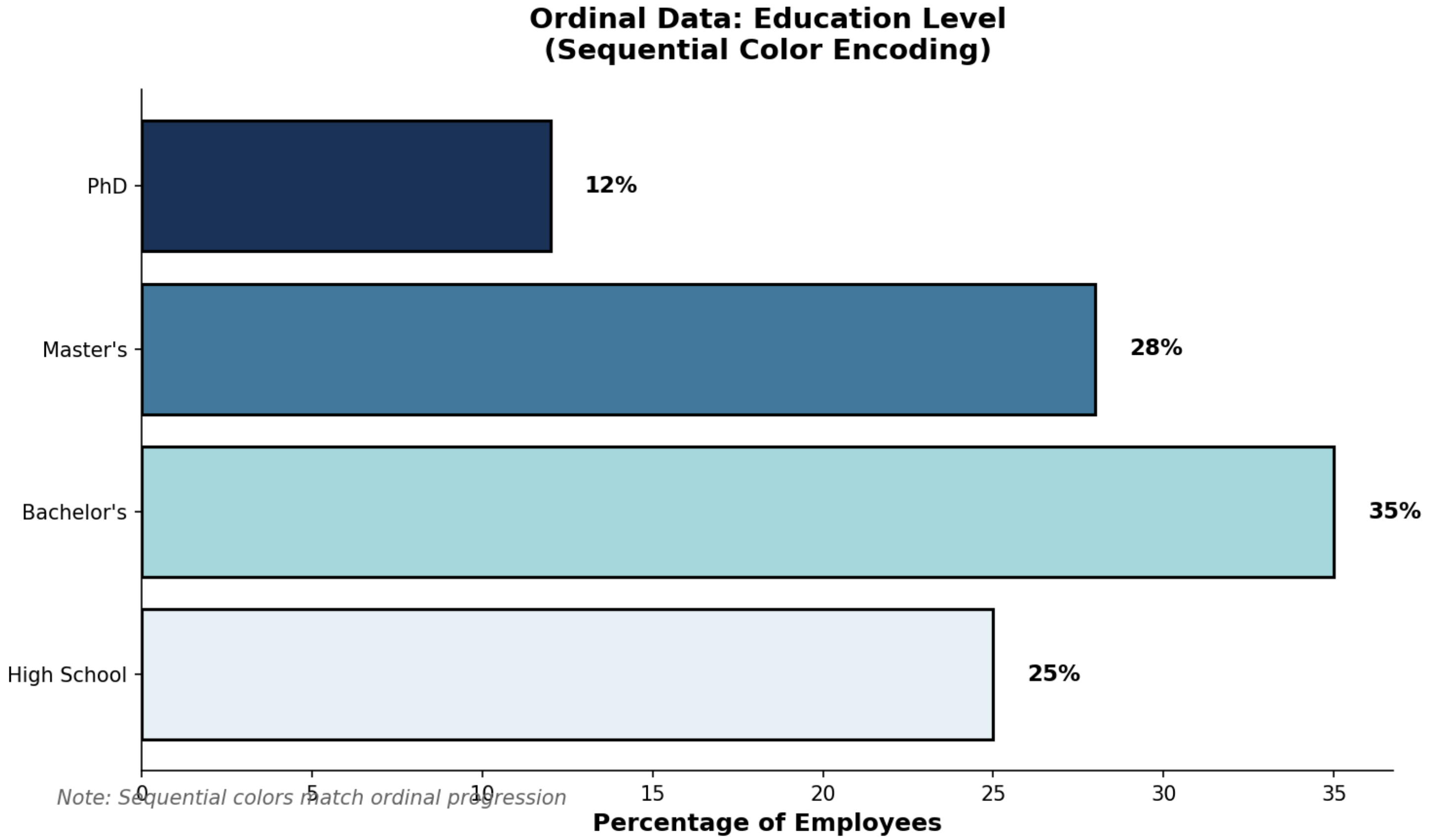
Examples:

- Education level (High School < Bachelor's < Master's < PhD)
- Customer satisfaction (Poor < Fair < Good < Excellent)
- Priority (Low < Medium < High)
- Size categories (S < M < L < XL)

Valid encodings:

- ✅ Sequential color scale (light to dark)
- ✅ Position (ordered)
- ✅ Size (with caution)
- ❌ NOT random colors or shapes

Common mistake: Using arbitrary colors (red, blue, green) for ordered categories.



Quantitative Data

Characteristics:

- Continuous numerical values
- Magnitude and precise differences matter
- Supports arithmetic operations

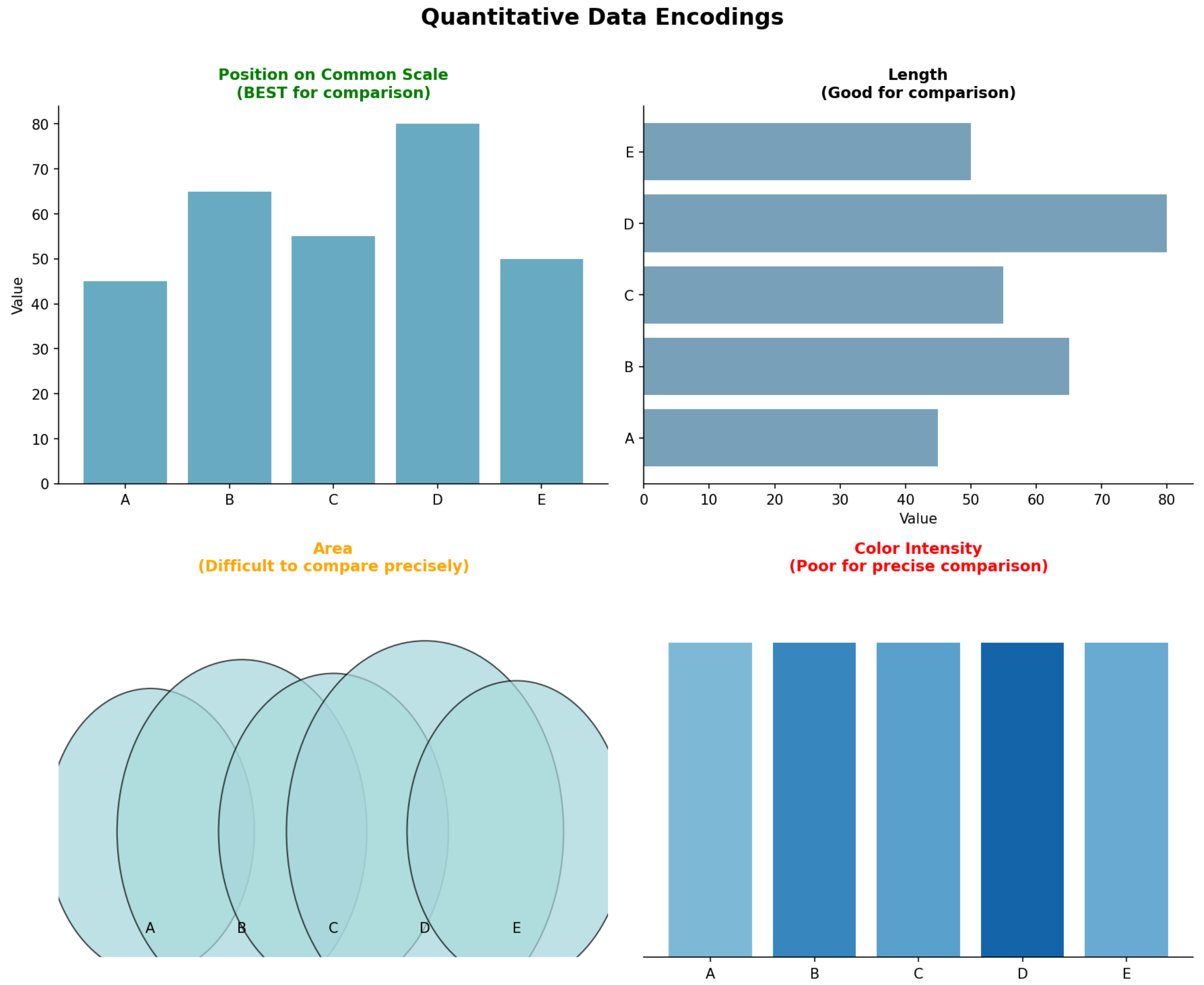
Examples:

- Revenue ($1M, $2.5M, $3M)
- Temperature (72°F, 85°F)
- Count of customers (100, 250, 500)
- Percentage growth (5%, 12%, -3%)

Valid encodings (ordered by effectiveness):

- ✅ Position on common scale (BEST)
- ✅ Length
- ✅ Area (with caution)
- ⚠️ Color intensity (for heatmaps, not precise comparison)
- ❌ NOT angle alone, NOT arbitrary hue

Key principle: For precise comparison, use position or length.



Temporal (Time-Series) Data

Characteristics:

- Ordered by time
- Sequential dependency matters
- Trends, cycles, and patterns

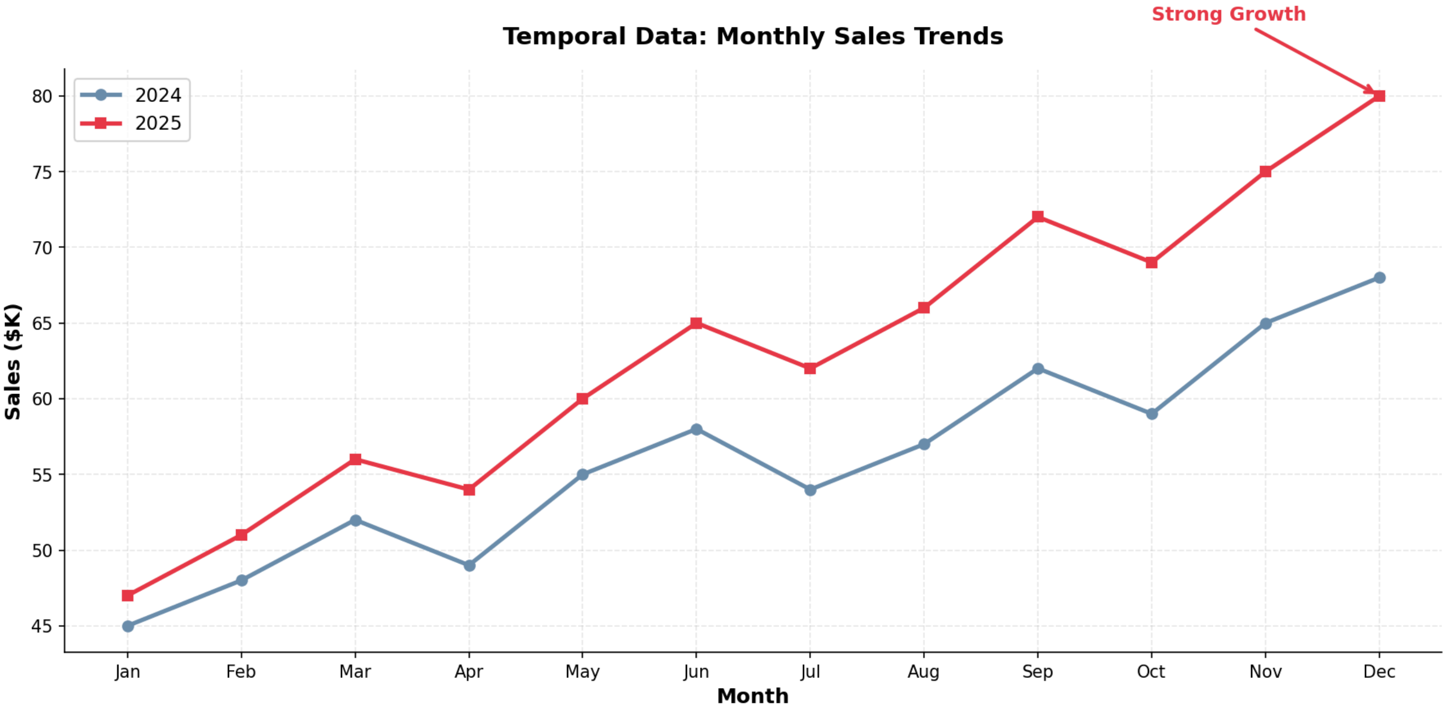
Examples:

- Daily stock prices
- Monthly sales
- Hourly website traffic
- Quarterly earnings

Best practices:

- ✅ Time typically on x-axis (horizontal)
- ✅ Use line charts for continuous trends
- ✅ Maintain consistent time intervals
- ✅ Show context (reference periods, benchmarks)
- ❌ Don't break time axis arbitrarily

Note: Temporal data is a special case—always respect chronological order!



Visual Variables (Bertin, 1967)

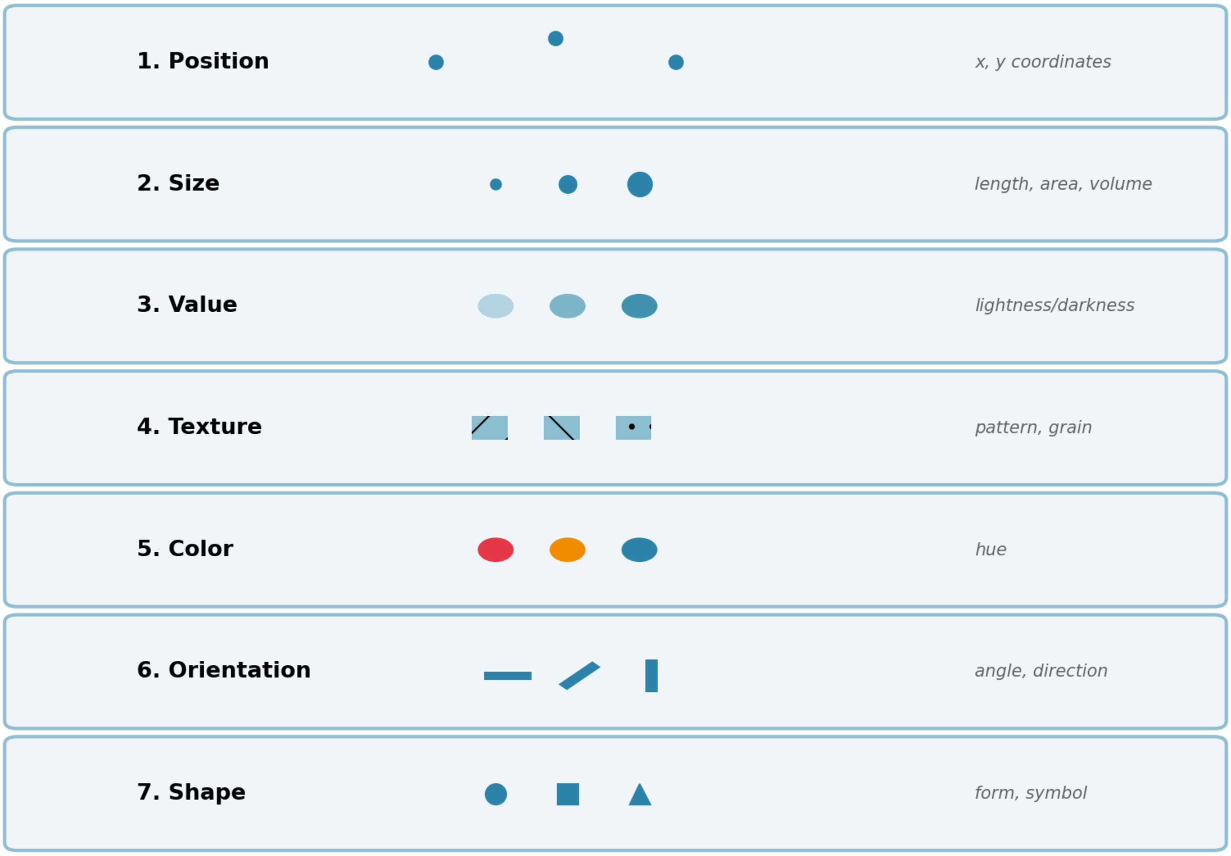
Jacques Bertin identified fundamental visual variables:

1. **Position** (x, y coordinates)
2. **Size** (length, area, volume)
3. **Value** (lightness/darkness)
4. **Texture** (pattern)
5. **Color** (hue)
6. **Orientation** (angle)
7. **Shape** (form)

Not all variables are equal!

- Some support quantitative judgments (position, size)
- Others support categorical distinctions (hue, shape)
- Some are perceptually weaker (texture, orientation)

Bertin's Visual Variables (1967)



1. Position — *x, y coordinates*

2. Size — *length, area, volume*

3. Value — *lightness/darkness*

4. Texture — *pattern, grain*

5. Color — *hue*

6. Orientation — *angle, direction*

7. Shape — *form, symbol*

Not all variables are equally effective for all data types

Graphical Perception Research (Cleveland & McGill)

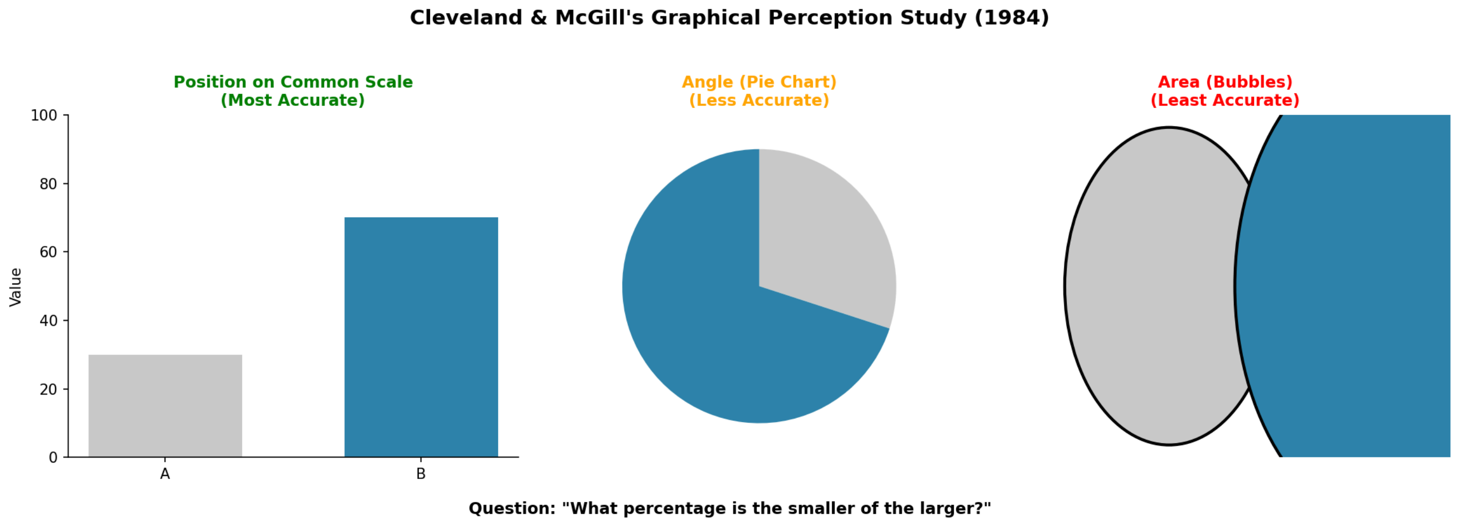
Landmark study (1984): Empirically tested how accurately people decode visual encodings

The experiment:

- Show two bars/wedges/circles
- Ask: "What percentage is the smaller of the larger?"
- Measure accuracy and speed

Key finding: Position is dramatically more accurate than angle or area

This research transformed visualization from art to science



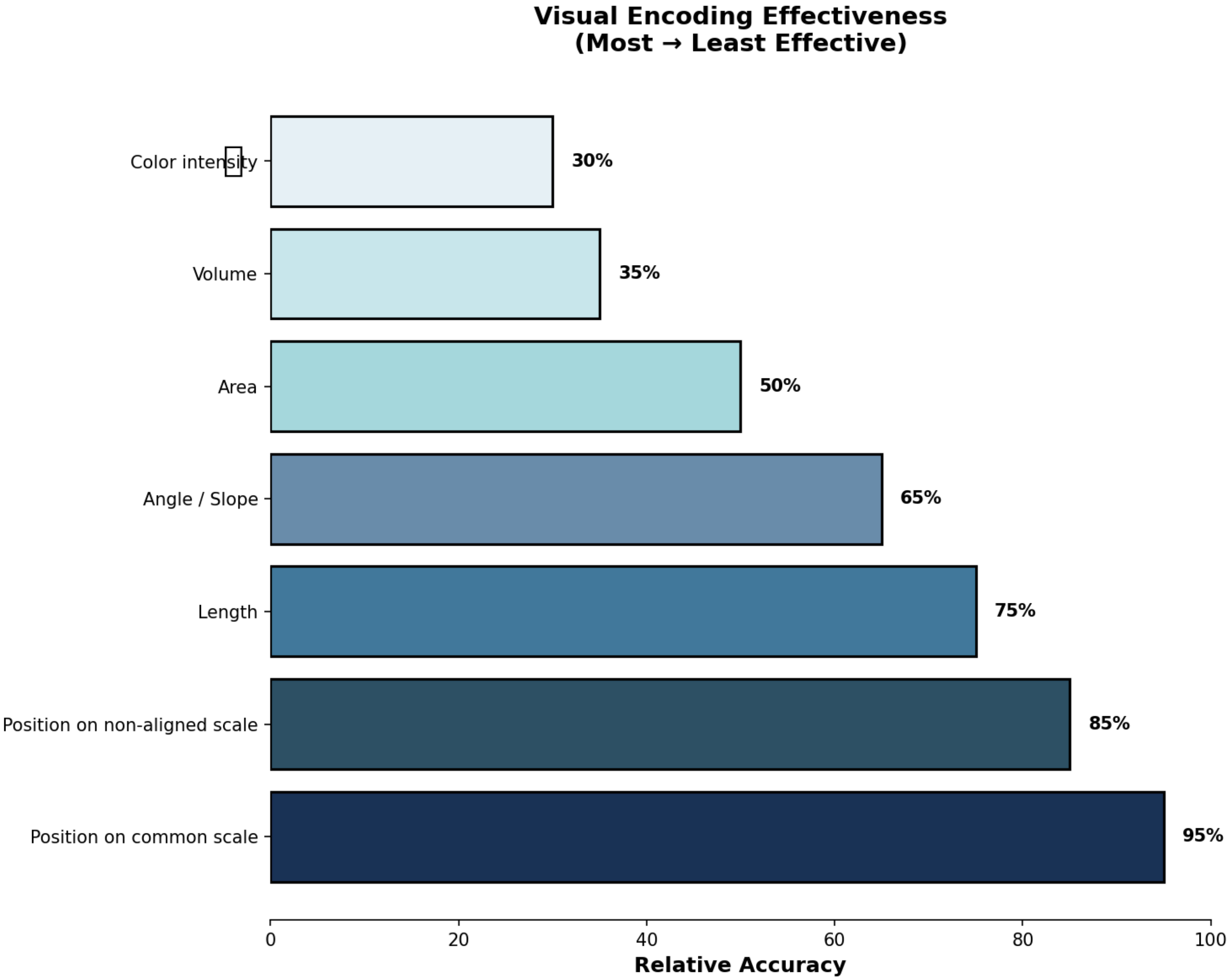
Ranking of Visual Encodings (Most→Least Effective)

For Quantitative Data:

1. ⭐ **Position on common scale** (scatter plots, aligned bars)
2. **Position on non-aligned scale** (small multiples with different scales)
3. **Length, direction, angle**
4. **Area**
5. **Volume, curvature**
6. **Shading, color saturation**

Implications:

- Bar charts > Pie charts for comparison
- Dot plots > Bubble charts for precision
- Heatmaps good for patterns, not precise values



Why Color Is Weak for Quantitative Data

Color perception challenges:

- Non-linear perception (perceptual vs. actual lightness)
- Context-dependent (surrounding colors affect perception)
- Individual variation (color blindness affects ~8% of males)
- Poor for precise comparison

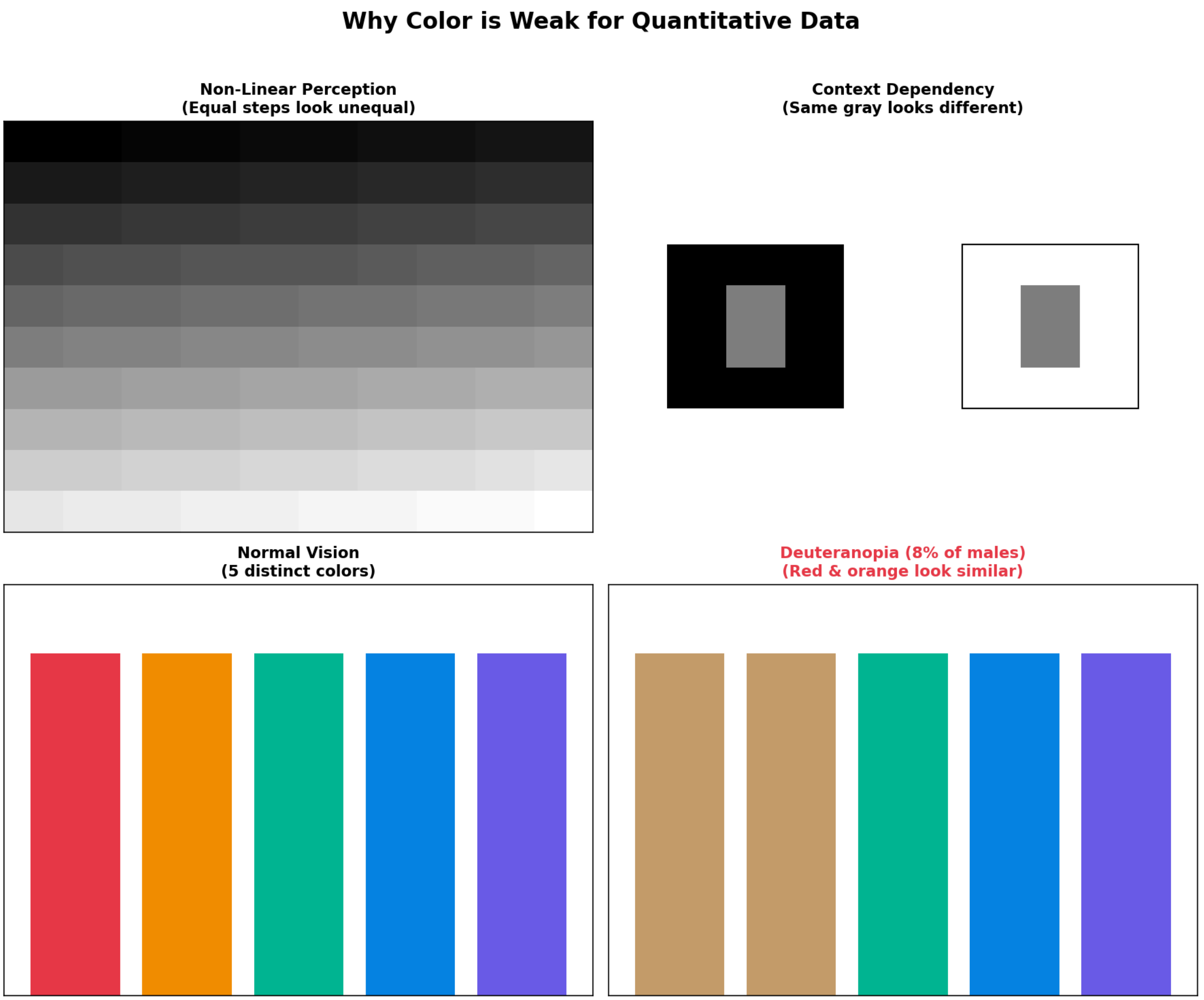
When to use color for quantitative data:

- ✅ Heatmaps (patterns, not precise values)
- ✅ Choropleth maps (general magnitude)
- ✅ Diverging scales (positive vs. negative)

When NOT to use color:

- ❌ Precise comparisons
- ❌ As the only encoding for critical information

Best practice: Use color for categories or as a secondary encoding, not primary for quantities.



Why Color is Weak for Quantitative Data

Non-Linear Perception (Equal steps look unequal)

Context Dependency (Same gray looks different)

Normal Vision (5 distinct colors)

Deuteranopia (8% of males) (Red & orange look similar)

Data × Task × Encoding Framework

Effective visualization requires matching all three:

```
┌──────────┐     ┌──────────┐     ┌──────────┐
│   Data   │  +  │   Task   │  =  │ Encoding │
│   Type   │     │          │     │  Choice  │
└──────────┘     └──────────┘     └──────────┘
```

Always ask:

1. **What is the data type?** (Nominal, Ordinal, Quantitative, Temporal)
2. **What is the task?** (Compare, Identify trend, Find outliers, etc.)
3. **Which encoding best supports this?**

Example:

- Data: Quarterly revenue (Quantitative + Temporal)
- Task: Show trend over time
- Encoding: Line chart with position on aligned scales ✅

PART 3: GRAMMAR OF GRAPHICS FRAMEWORK

Slides 34-44

Common Encoding Violations

Mistakes that violate perception principles:

❌ **Pie charts with too many slices** (angle is hard to compare)
❌ **3D charts** (perspective distorts perception)
❌ **Dual-axis charts** (misleading scale comparison)
❌ **Rainbow color scales** (non-perceptual, creates false boundaries)
❌ **Truncated y-axes** (exaggerates differences)
❌ **Bubble charts for precise comparison** (area is hard to judge)

Each of these increases cognitive load and decreases accuracy.

From Chart Types to Compositional Systems

Traditional approach:

- Think in fixed chart types (bar, line, pie, scatter)
- Pick a template
- Limited flexibility

Modern approach:

- Think in composable elements
- Build visualizations from components
- Infinite combinations possible

This is the shift from "choosing a chart" to "composing a visualization"

Enter: **Grammar of Graphics**

Introduction to Grammar of Graphics

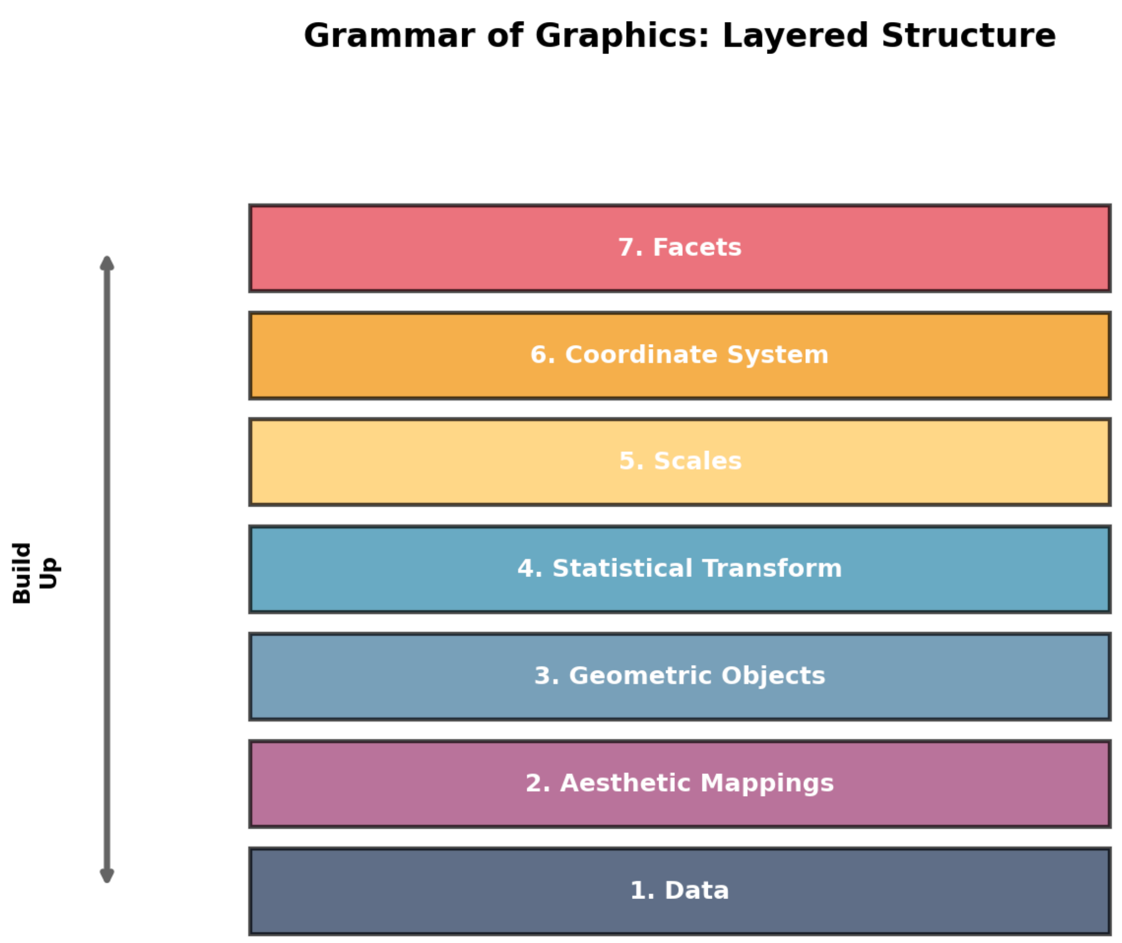
Just as language has grammar for constructing sentences, visualization has grammar for constructing graphics

Developed by: Leland Wilkinson (1999), refined by Hadley Wickham (ggplot2)

Key insight: Visualizations are not types, but mappings from data to visual properties

Benefits:

- 🎯 Systematic approach to visualization design
- 🎯 Clear separation of concerns
- 🎯 More expressive than chart templates
- 🎯 Foundation for modern tools (ggplot2, Altair, Plotly)



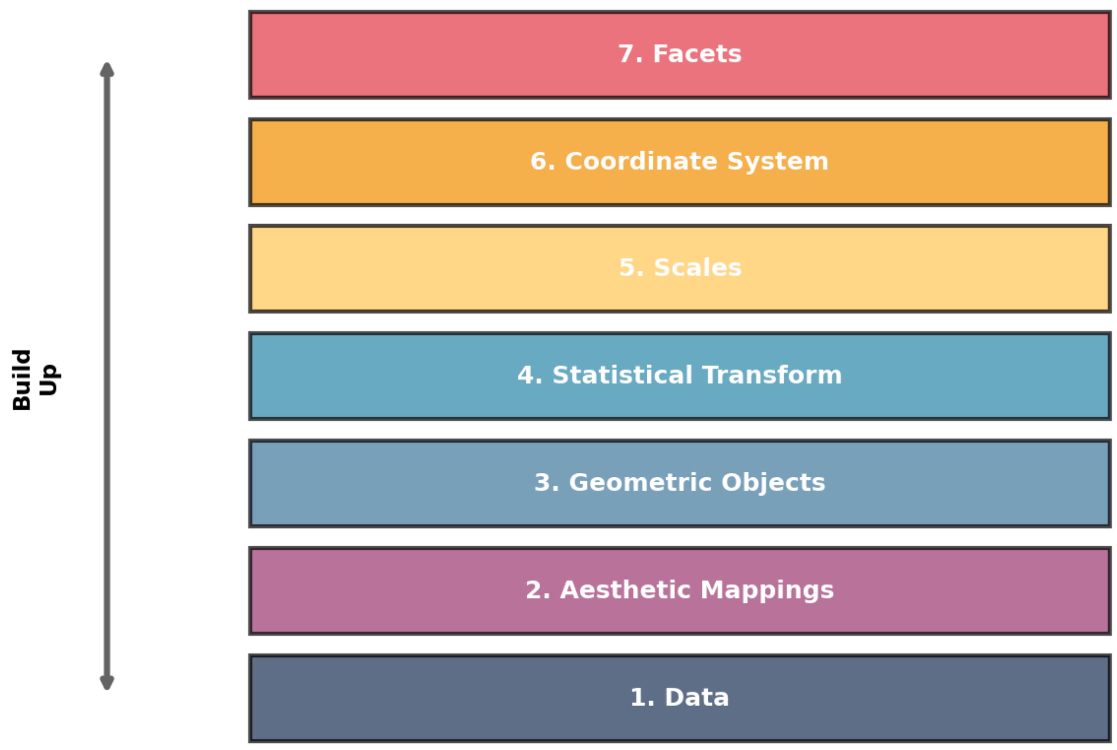
The Layered Grammar: Core Components

A visualization is built from layers, each with:

1. **Data** - The dataset to visualize
2. **Aesthetic Mappings (aes)** - Map data variables to visual properties
3. **Geometric Objects (geom)** - The visual marks (points, lines, bars)
4. **Statistical Transformations (stat)** - Data aggregations/computations
5. **Scales** - Map data ranges to visual ranges
6. **Coordinate Systems** - The space in which data is plotted
7. **Facets** - Subplots for different data subsets

Each component is independent and composable!

Grammar of Graphics: Layered Structure



Component 1: Data

The foundation of any visualization

Requirements:

- Structured format (typically tabular/dataframe)
- Each row = observation
- Each column = variable
- Can be raw or transformed

Example data structure:

```
| Month | Product  | Sales | Region |
|-------|----------|-------|--------|
| Jan   | Widget A | 1500  | North  |
| Jan   | Widget B | 2300  | North  |
| Feb   | Widget A | 1800  | North  |
...
```

Key insight: Same data + different mappings = different visualizations

Component 2: Aesthetic Mappings

Map data variables to visual properties

Common aesthetics:

- `x`, `y` - Position
- `color` / `fill` - Color of points/areas
- `size` - Size of points/text
- `shape` - Shape of points
- `alpha` - Transparency
- `linetype` - Type of line (solid, dashed)

Example:

```
aes(x = Month, y = Sales, color = Product, size = Region)
```

Critical: Aesthetics define *what* data is shown and *how* it maps to visual properties

Component 3: Geometric Objects (Marks)

The visual representation of data

Common geoms:

- `point` - Scatter plot points
- `line` - Connected lines
- `bar` / `col` - Bars/columns
- `boxplot` - Box-and-whisker plots
- `histogram` - Frequency distributions
- `area` - Filled areas
- `tile` / `raster` - Heatmap cells
- `text` - Labels

Same data + mapping, different geom = different chart:

- `geom_point()` → scatter plot
- `geom_line()` → line chart
- `geom_bar()` → bar chart

Component 4: Statistical Transformations

Compute derived values from data

Common transformations:

- `identity` - Use data as-is (default for scatter plots)
- `count` - Count observations (histograms)
- `bin` - Bin continuous data
- `smooth` - Fit smoothing line
- `boxplot` - Compute quartiles
- `density` - Compute density estimation

Example:

- Raw data: 1000 individual sales transactions
- After `stat_count` : Grouped counts per month
- After `stat_smooth` : Trend line with confidence interval

Often implicit: Bar chart automatically counts, histogram automatically bins

Component 5: Scales

Control how data values map to visual values

Examples:

- **Position scales**: Linear, logarithmic, date/time
- **Color scales**: Sequential, diverging, categorical palettes
- **Size scales**: Linear, square root (for area)

Key functions:

- Define domain (data range)
- Define range (visual range)
- Handle transformations
- Create legends/axes

Example:

```
Sales: $0 - $1M  →  Y-axis: 0px - 400px
Product: A, B, C  →  Colors: blue, red, green
```

Component 6: Coordinate Systems

The space in which data is plotted

Common coordinate systems:

- **Cartesian** (x, y) - Most common, rectangular
- **Polar** - Circular (pie charts, radar charts)
- **Geographic** - Map projections
- **Transformed** - Log scale, square root

Impact:

- Same data, different coordinate system = dramatically different interpretation
- Cartesian bar chart vs. Polar (coxcomb) chart

Design tip: Don't use polar coordinates unless circular relationships are meaningful!

Component 7: Faceting (Small Multiples)

Create subplots for data subsets

Power of small multiples:

- ✅ Easy comparison across groups
- ✅ Reduces overplotting
- ✅ Maintains consistent scales
- ✅ Reduces cognitive load vs. overlaying

Types:

- **Grid**: Rows × Columns (e.g., by Region × Product)
- **Wrap**: Single variable, wraps to fit space

Example: Sales trends for each product category in separate panels

Small Multiples

PART 4: PYTHON VISUALIZATION IMPLEMENTATION

Slides 45-82

Grammar and Cognitive Load

How Grammar of Graphics reduces cognitive load:

✅ **Separation of concerns** - Each component has one job
✅ **Consistent structure** - Same logic across all visualizations
✅ **Explicit mappings** - No hidden assumptions
✅ **Composability** - Build complex from simple
✅ **Systematic thinking** - Framework guides design decisions

Result: Less accidental complexity, more intentional design

The grammar makes design decisions explicit, reducing extraneous load.

Transition to Python: Implementing the Grammar

Now we'll see how to implement these concepts in Python

Python visualization ecosystem:

- 📊 **Matplotlib** - Low-level, full control, foundation for others
- 📊 **Seaborn** - Statistical graphics, built on Matplotlib
- 📊 **Plotly** - Interactive visualizations
- 📊 **Altair** - Declarative, pure Grammar of Graphics implementation

Today's focus: Matplotlib + Seaborn

Why?

- Industry standard
- Flexible and powerful
- Foundation for understanding other libraries

Python Visualization Ecosystem Overview

Matplotlib Architecture:

```
┌─────────────────────────────┐
│       Pyplot (plt)          │  ← High-level interface
├─────────────────────────────┤
│       Artist API            │  ← Mid-level (figures, axes)
├─────────────────────────────┤
│       Backend (rendering)   │  ← Low-level rendering
└─────────────────────────────┘
```

Seaborn sits on top:

- Provides high-level statistical plots
- Better default aesthetics
- Grammar-inspired interface
- Built on Matplotlib

Learning path: Start with pyplot, understand axes/figures, then use Seaborn for statistical plots.

Matplotlib: Anatomy of a Figure

Every Matplotlib visualization has two main components:

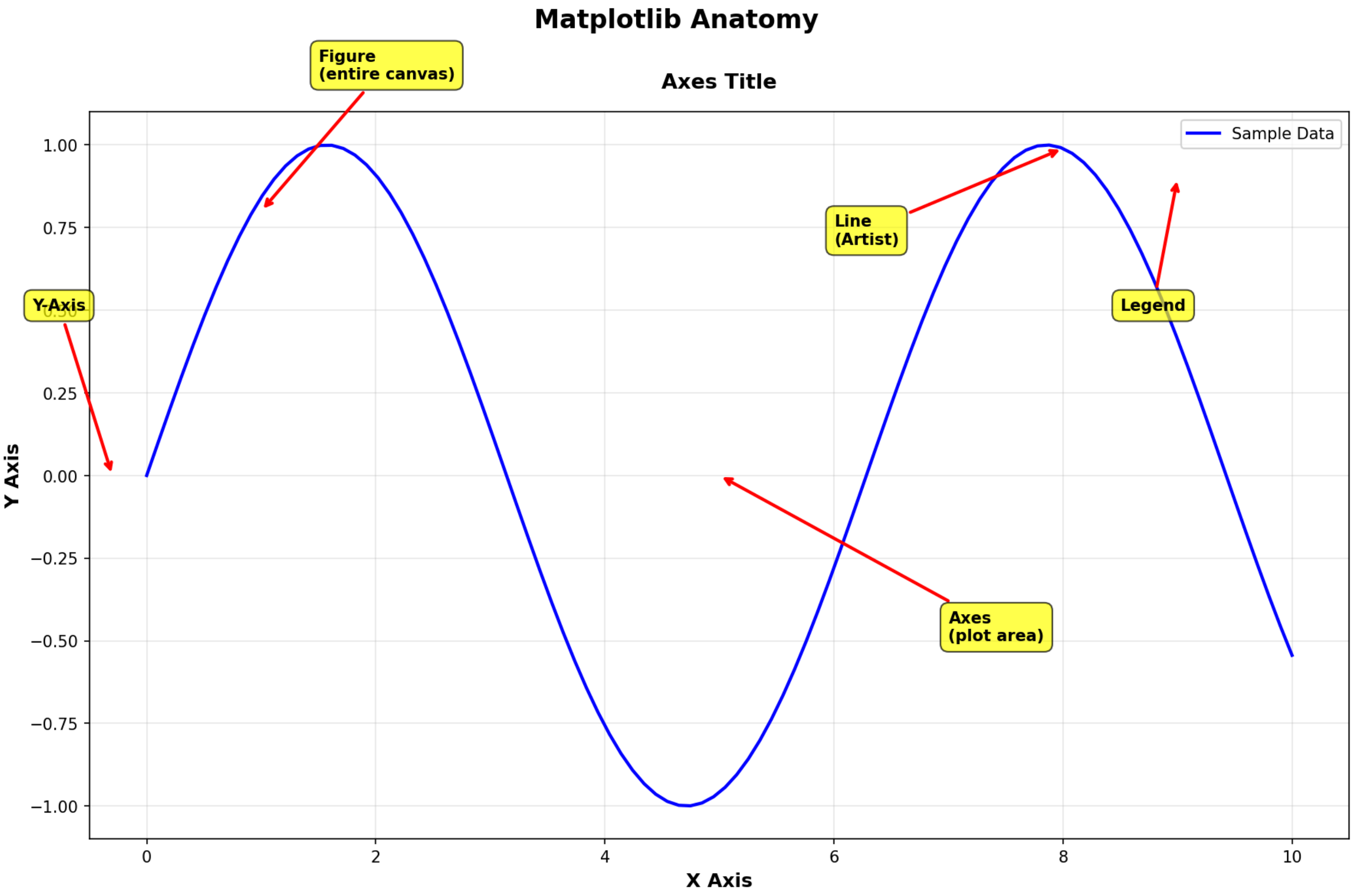
```python
import matplotlib.pyplot as plt
```

```
# Create figure and axes
fig, ax = plt.subplots()  # Returns Figure and Axes objects

# fig = Canvas (the whole image)
# ax = Plot area (where data is drawn)
```

Key concepts:

- **Figure**: The entire canvas (can contain multiple plots)
- **Axes**: Individual plot(s) within the figure
- **Axis**: The x and y number lines
- **Artists**: Everything you see (lines, text, ticks, etc.)



Creating Your First Plot

Basic bar chart in Matplotlib:

```
import matplotlib.pyplot as plt
import numpy as np

# Data
categories = ['Product A', 'Product B', 'Product C', 'Product D']
sales = [2500, 3200, 2800, 3500]

# Create plot
fig, ax = plt.subplots(figsize=(8, 5))
ax.bar(categories, sales, color='steelblue')

# Customize
ax.set_xlabel('Product Category', fontsize=12)
ax.set_ylabel('Sales ($)', fontsize=12)
ax.set_title('Q1 2026 Sales by Product', fontsize=14, fontweight='bold')
```

```
# Add value labels on bars
for i, v in enumerate(sales):
    ax.text(i, v + 50, str(v), ha='center', fontweight='bold')

plt.tight_layout()
plt.show()
```

Output: Clean bar chart with direct labeling (reducing cognitive load!)

Customizing Plots: Colors, Labels, Styles

Applying perception principles:

```
import matplotlib.pyplot as plt

# Create data
months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun']
sales_2025 = [45000, 48000, 52000, 49000, 55000, 58000]
sales_2026 = [47000, 51000, 56000, 54000, 60000, 65000]

# Create plot with good practices
fig, ax = plt.subplots(figsize=(10, 6))

# Use position (best encoding for quantitative comparison)
ax.plot(months, sales_2025, marker='o', linewidth=2,
        label='2025', color='#2E86AB')  # Distinct colors
ax.plot(months, sales_2026, marker='s', linewidth=2,
        label='2026', color='#A23B72')

# Clear labels (reduce extraneous load)
ax.set_xlabel('Month', fontsize=11)
ax.set_ylabel('Sales ($)', fontsize=11)
ax.set_title('Sales Comparison: 2025 vs 2026',
             fontsize=13, fontweight='bold', pad=15)

# Legend with clear positioning
ax.legend(frameon=True, loc='upper left', fontsize=10)

# Remove top and right spines (reduce clutter)
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

# Add grid for easier reading (but subtle)
ax.grid(True, alpha=0.3, linestyle='--')

plt.tight_layout()
plt.show()
```

Matplotlib: Common Plot Types

Quick reference for basic plots:

```
import matplotlib.pyplot as plt
import numpy as np

# Sample data
x = np.arange(10)
y1 = np.random.rand(10) * 100
y2 = np.random.rand(10) * 100

fig, axes = plt.subplots(2, 3, figsize=(12, 8))

# Scatter plot
axes[0,0].scatter(y1, y2, alpha=0.6, s=100)
axes[0,0].set_title('Scatter Plot')

# Line plot
```

```
axes[0,1].plot(x, y1, marker='o')
axes[0,1].set_title('Line Plot')

# Bar chart
axes[0,2].bar(x, y1, color='coral')
axes[0,2].set_title('Bar Chart')

# Histogram
axes[1,0].hist(y1, bins=10, edgecolor='black', alpha=0.7)
axes[1,0].set_title('Histogram')

# Box plot
axes[1,1].boxplot([y1, y2], labels=['Group A', 'Group B'])
axes[1,1].set_title('Box Plot')

# Heatmap (using imshow)
data = np.random.rand(10, 10)
im = axes[1,2].imshow(data, cmap='YlOrRd')
axes[1,2].set_title('Heatmap')
plt.colorbar(im, ax=axes[1,2])

plt.tight_layout()
plt.show()
```

Key insight: Same pyplot interface, different geom!

Introduction to Seaborn

Seaborn = Statistical Data Visualization

Built on Matplotlib, but provides:

- Better default aesthetics
- Grammar-inspired interface
- Statistical transformations built-in
- Works directly with pandas DataFrames
- Themes and color palettes

Installation:

```
pip install seaborn
```

Import convention:

```
import seaborn as sns
import matplotlib.pyplot as plt
```

Philosophy: Make complex statistical plots simple, apply perception principles by default.

Seaborn: Working with DataFrames

Seaborn loves pandas DataFrames:

```
import seaborn as sns
import pandas as pd

# Create sample data
data = pd.DataFrame({
    'month': ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun'] * 2,
    'sales': [2500, 2700, 3000, 2900, 3200, 3400,
              2600, 2800, 3100, 3000, 3300, 3500],
    'region': ['North']*6 + ['South']*6
})

# Create plot using column names (Grammar-like!)
sns.lineplot(data=data, x='month', y='sales', hue='region',
             marker='o', linewidth=2)
plt.title('Sales by Region Over Time')
plt.show()
```

Notice: Direct mapping from data columns to aesthetics!

Seaborn Plot Types

Common Seaborn plots mapped to tasks:

Distribution:

- `histplot()` - Histograms with KDE
- `kdeplot()` - Kernel density estimation
- `boxplot()` - Box-and-whisker
- `violinplot()` - Violin plot (box + density)

Relationships:

- `scatterplot()` - Scatter with regression
- `lineplot()` - Line with confidence intervals
- `regplot()` - Scatter + regression line

Categories:

- `barplot()` - Bars with confidence intervals
- `countplot()` - Count plot
- `pointplot()` - Point estimates with error bars

Seaborn Example: Distribution Plot

Visualizing distributions with built-in statistics:

```
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt

# Generate sample data
np.random.seed(42)
data1 = np.random.normal(100, 15, 500)
data2 = np.random.normal(120, 20, 500)

# Create figure
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Histogram with KDE
sns.histplot(data1, kde=True, color='steelblue', ax=axes[0])
axes[0].set_title('Sales Distribution - Product A')
axes[0].set_xlabel('Daily Sales ($)')

# Violin plot comparing two groups
import pandas as pd
df = pd.DataFrame({
    'Sales': np.concatenate([data1, data2]),
    'Product': ['A']*500 + ['B']*500
})

sns.violinplot(data=df, x='Product', y='Sales', ax=axes[1])
axes[1].set_title('Sales Distribution Comparison')

plt.tight_layout()
plt.show()
```

Automatic statistical transformations!

Seaborn: Faceting (Small Multiples)

Create small multiples with FacetGrid:

```python
import seaborn as sns
import pandas as pd

# Load sample data
tips = sns.load_dataset('tips')

# Create FacetGrid (Component 7: Faceting!)
g = sns.FacetGrid(tips, col='time', row='smoker', height=4)
g.map(sns.scatterplot, 'total_bill', 'tip', alpha=0.7)
g.add_legend()
g.set_titles(col_template="{col_name}", row_template="{row_name}")
g.set_axis_labels("Total Bill ($)", "Tip ($)")

plt.show()
```

Result: 4 panels (Lunch/Dinner × Smoker/Non-smoker)

Grammar in action:

- Data: tips dataset
- Aesthetics: x=total_bill, y=tip
- Geom: scatter
- Facets: time × smoker

Color Palettes in Python: Perception-Aware Choices

Choosing the right color palette matters!

```python
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Sample data
data = np.random.randn(100, 4)

fig, axes = plt.subplots(1, 3, figsize=(15, 4))

# ❌ BAD: Rainbow (perceptually non-uniform, creates false boundaries)
axes[0].imshow(data, cmap='jet', aspect='auto')
axes[0].set_title('❌ Rainbow (Jet) - Avoid!')

# ✅ GOOD: Sequential (perceptually uniform)
axes[1].imshow(data, cmap='viridis', aspect='auto')
axes[1].set_title('✅ Viridis - Sequential Data')

# ✅ GOOD: Diverging (for data with meaningful midpoint)
axes[2].imshow(data, cmap='RdBu_r', aspect='auto')
axes[2].set_title('✅ Red-Blue - Diverging Data')

plt.tight_layout()
plt.show()
```

Seaborn color palettes:

- Categorical: `'Set2'`, `'tab10'`, `'Paired'`
- Sequential: `'Blues'`, `'Greens'`, `'rocket'`
- Diverging: `'RdBu'`, `'coolwarm'`, `'vlag'`

Applying Preattentive Features in Code

Using color for visual pop-out:

```python
import matplotlib.pyplot as plt
import numpy as np

# Data
categories = ['Q1', 'Q2', 'Q3', 'Q4']
sales_2025 = [450, 480, 520, 490]
sales_2026 = [470, 510, 560, 540]

fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# WITHOUT preattentive highlighting
axes[0].bar(categories, sales_2025, color='steelblue', alpha=0.7)
axes[0].set_title('Without Visual Emphasis')
axes[0].set_ylabel('Sales (K$)')

# WITH preattentive highlighting (Q3 is best quarter)
colors = ['#CCCCCC', '#CCCCCC', '#E63946', '#CCCCCC']  # Pop-out!
axes[1].bar(categories, sales_2026, color=colors, alpha=0.9)
axes[1].set_title('With Visual Emphasis - Q3 Highlighted')
axes[1].set_ylabel('Sales (K$)')

plt.tight_layout()
plt.show()
```

Result: Q3 immediately pops out (preattentive color feature)

Reducing Clutter: Before and After

Applying "reduce extraneous load" principle:

```python
import matplotlib.pyplot as plt
import numpy as np

months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun']
sales = [2500, 2700, 3000, 2900, 3200, 3400]

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# ❌ CLUTTERED (high extraneous load)
axes[0].plot(months, sales, marker='o', linewidth=3, color='red',
             markersize=12)
axes[0].set_title('BEFORE: High Extraneous Load', fontsize=14,
                  fontweight='bold', color='darkred')
axes[0].set_facecolor('#FFEEEE')  # Distracting background
axes[0].grid(True, linewidth=2, color='blue')  # Heavy grid
axes[0].spines['top'].set_linewidth(3)
axes[0].spines['right'].set_linewidth(3)
axes[0].spines['bottom'].set_linewidth(3)
axes[0].spines['left'].set_linewidth(3)

# ✅ CLEAN (low extraneous load)
axes[1].plot(months, sales, marker='o', linewidth=2, color='#2E86AB',
             markersize=7)
axes[1].set_title('AFTER: Low Extraneous Load', fontsize=13)
axes[1].set_xlabel('Month', fontsize=10)
axes[1].set_ylabel('Sales ($)', fontsize=10)
axes[1].spines['top'].set_visible(False)  # Remove clutter
axes[1].spines['right'].set_visible(False)
axes[1].grid(True, alpha=0.2, linestyle='--')  # Subtle grid

plt.tight_layout()
plt.show()
```

Direct Labeling vs. Legend

Reduce cognitive load by eliminating legend lookup:

```python
import matplotlib.pyplot as plt

months = ['Jan', 'Feb', 'Mar', 'Apr']
product_a = [2500, 2700, 3000, 2900]
product_b = [2200, 2400, 2600, 2500]
product_c = [1800, 2000, 2200, 2100]

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# WITH LEGEND (requires lookup - adds cognitive load)
axes[0].plot(months, product_a, marker='o', label='Product A')
axes[0].plot(months, product_b, marker='s', label='Product B')
axes[0].plot(months, product_c, marker='^', label='Product C')
axes[0].legend()
axes[0].set_title('With Legend (More Cognitive Load)')
axes[0].set_ylabel('Sales ($)')

# WITH DIRECT LABELS (immediate understanding)
axes[1].plot(months, product_a, marker='o', color='#2E86AB')
axes[1].plot(months, product_b, marker='s', color='#A23B72')
axes[1].plot(months, product_c, marker='^', color='#F18F01')
# Add direct labels
axes[1].text(3.05, product_a[-1], 'Product A', va='center', fontsize=10,
             color='#2E86AB', fontweight='bold')
axes[1].text(3.05, product_b[-1], 'Product B', va='center', fontsize=10,
             color='#A23B72', fontweight='bold')
axes[1].text(3.05, product_c[-1], 'Product C', va='center', fontsize=10,
             color='#F18F01', fontweight='bold')
axes[1].set_title('With Direct Labels (Less Cognitive Load)')
axes[1].set_ylabel('Sales ($)')
axes[1].set_xlim(-0.2, 3.8)

plt.tight_layout()
plt.show()
```

Principle: Direct labeling reduces the need to constantly refer back to legend.

Exercise: Bar Chart vs. Pie Chart

Implementing Cleveland & McGill's findings:

```python
import matplotlib.pyplot as plt

# Data
categories = ['North', 'South', 'East', 'West', 'Central']
values = [25, 22, 18, 20, 15]

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# PIE CHART (uses angle - weak encoding)
axes[0].pie(values, labels=categories, autopct='%1.1f%%', startangle=90)
axes[0].set_title('Pie Chart: Angle Encoding\n(Harder to Compare)')

# BAR CHART (uses position - strong encoding)
axes[1].barh(categories, values, color='steelblue')
axes[1].set_xlabel('Sales (%)')
axes[1].set_title('Bar Chart: Position Encoding\n(Easier to Compare)')
axes[1].spines['top'].set_visible(False)
axes[1].spines['right'].set_visible(False)

# Add value labels
for i, v in enumerate(values):
    axes[1].text(v + 0.5, i, str(v) + '%', va='center')

plt.tight_layout()
plt.show()
```

Question: Which makes it easier to see that North > South > West?
Answer: Bar chart (position is more accurate than angle)

Putting It All Together: Complete Example

Building a perceptually-optimized visualization from scratch:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Sample data
data = pd.DataFrame({
    'Quarter': ['Q1', 'Q2', 'Q3', 'Q4'] * 3,
    'Revenue': [450, 480, 520, 490, 470, 510, 560, 540, 490, 530, 580, 560],
    'Year': ['2024']*4 + ['2025']*4 + ['2026']*4
})

# Apply all principles
sns.set_style("whitegrid", {'grid.linestyle': '--', 'grid.alpha': 0.3})
fig, ax = plt.subplots(figsize=(10, 6))

# Use position encoding (best for quantitative)
sns.lineplot(data=data, x='Quarter', y='Revenue', hue='Year',
             marker='o', linewidth=2.5, palette=['#CCCCCC', '#999999', '#E63946'],
             ax=ax)

# Clear, direct labels
ax.set_xlabel('Quarter', fontsize=12)
ax.set_ylabel('Revenue ($K)', fontsize=12)
ax.set_title('Quarterly Revenue Growth 2024-2026\n2026 Shows Strong Performance',
             fontsize=14, fontweight='bold', pad=20)

# Reduce extraneous load
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.legend(title='Year', frameon=False, loc='upper left')

# Add annotation for insight
ax.annotate('Best Quarter', xy=('Q3', 580), xytext=('Q4', 595),
            arrowprops=dict(arrowstyle='->', color='#E63946', lw=2),
            fontsize=10, color='#E63946', fontweight='bold')

plt.tight_layout()
plt.show()
```

Principles applied: Position encoding, color for emphasis, reduced clutter, direct annotation

Common Mistakes to Avoid

Real-world examples of what NOT to do:

1. ❌ **Too many colors** - Rainbow schemes for categories
2. ❌ **3D without purpose** - Distorts perception
3. ❌ **Dual Y-axes** - Misleading comparisons
4. ❌ **Truncated axes** - Exaggerates differences
5. ❌ **Pie charts with 10+ slices** - Impossible to compare
6. ❌ **Busy backgrounds** - Distracts from data
7. ❌ **Tiny fonts** - Can't read = won't use
8. ❌ **No labels** - Forces guessing

Remember: Every element should serve the data and the user's task!

Visualization Design Checklist

Before finalizing any visualization, ask:

1. Data & Task

- ☐ What data type am I showing?
- ☐ What task does the user need to perform?
- ☐ Is this the right chart for the task?

2. Perception

- ☐ Am I using the most effective encoding?
- ☐ Are preattentive features highlighting what matters?
- ☐ Can users see the pattern in < 5 seconds?

3. Cognitive Load

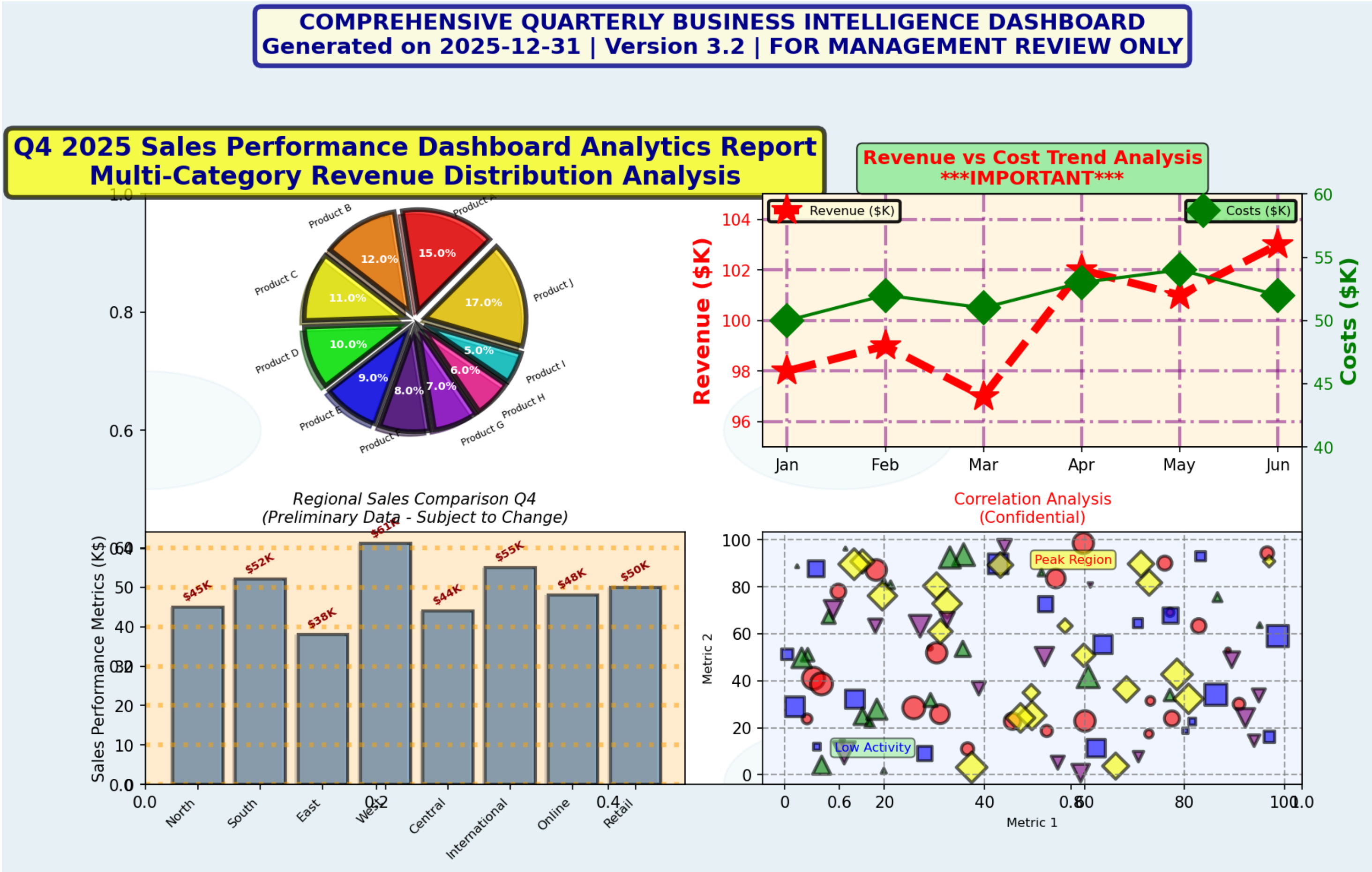
- ☐ Have I removed all chart junk?
- ☐ Is the visual hierarchy clear?
- ☐ Are labels direct and clear?

4. Accessibility

- ☐ Is it colorblind-friendly?
- ☐ Are fonts large enough?
- ☐ Does it work in grayscale?

Exercise 1: Critique This Visualization

Task: Identify all perception and cognitive load issues in this dashboard



Issues to find:

1. **Encoding problems** - What visual encodings are inappropriate?
2. **Cognitive load violations** - What adds unnecessary complexity?
3. **Gestalt principle violations** - What grouping issues exist?
4. **Color usage problems** - Where is color misused?
5. **Missing context** - What information is unclear or missing?

Hint: Look for:

- Pie charts with too many slices
- Rainbow/non-perceptual color scales
- Truncated axes
- Dual y-axes with different scales
- Chart junk (decorative elements)
- Poor labeling and tiny text
- Inconsistent styling
- Cluttered layouts

Work in pairs: 5 minutes to list all issues you can find

Expected findings: This visualization violates at least 10 principles we learned today!

Exercise 2: Redesign Challenge

Given: Bad dashboard with high cognitive load

Your task:

1. List all sources of extraneous load
2. Propose a redesigned layout
3. Justify your encoding choices
4. Apply Gestalt principles

Deliverable: Sketch or code the improved version

Time: 15 minutes

Exercise 3: Build a Grammar-Based Plot

Task: Create a visualization using Grammar of Graphics thinking

Dataset: Sales by product, region, and quarter

Requirements:

1. Define your data mappings (aesthetics)
2. Choose appropriate geom
3. Consider statistical transformation
4. Use faceting if appropriate
5. Apply perception principles

Implement in Python (Matplotlib or Seaborn)

Exercise 4: Color Palette Selection

Scenario: You need to visualize temperature data from -10°C to +40°C

Questions:

1. What type of color palette should you use?
2. Why is rainbow/jet inappropriate?
3. What's a good alternative?
4. How do you handle the zero point?

Implement:

```python
import matplotlib.pyplot as plt
import numpy as np

# Your code here to create heatmap with appropriate palette
```

Exercise 5: Preattentive Highlighting

Task: Create a sales report where Q4 must pop out

Data: Quarterly sales for 5 products

Requirements:

- Use preattentive features (color, size, position)
- Make Q4 immediately visible
- Minimize cognitive load
- Include direct labels

Code it: Use Matplotlib or Seaborn

Real-World Application: Dashboard Design

Scenario: Executive wants dashboard for:

- Monthly revenue trends
- Top 5 products
- Regional performance
- YoY comparison

Your design must:

1. Apply visual hierarchy (Gestalt)
2. Use appropriate encodings
3. Minimize cognitive load
4. Enable 5-second insights

Discussion: What would you include? What would you exclude?

Connection to Data Science Workflows

Where visualization fits in your projects:

```
Data Collection → Cleaning → EDA → Modeling → Evaluation → Communication
                    ↓         ↓       ↓          ↓
                Visualization is critical at every stage!
```

Roles of visualization:

- **EDA**: Understand patterns, find outliers
- **Model Selection**: Compare performance
- **Debugging**: Identify issues
- **Communication**: Share insights
- **Decision Support**: Enable action

Remember: Good visualization = Better models = Better decisions