

Machine Learning for Smarter Innovation

Week 1: Foundations & Clustering

Discovering Innovation Patterns with ML

BSc Course in AI-Enhanced Innovation

Prerequisites & What You Need

Setting You Up for Success

What You Need to Know

- Basic Python (variables, loops, functions)
- High school math (averages, distances)
- How to use Jupyter notebooks
- Basic data concepts (tables, rows, columns)

What We'll Provide

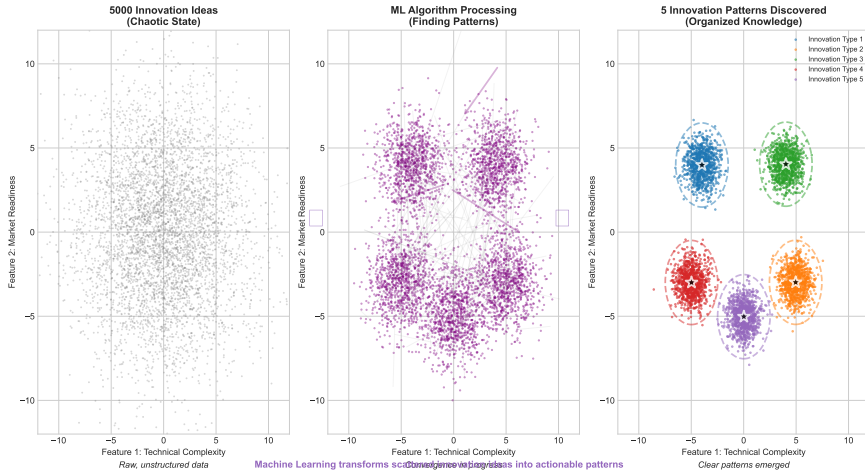
- All code templates
- Step-by-step instructions
- Visual explanations
- Practice datasets

No machine learning experience required!

Machine Learning + Innovation + Design Thinking

The Power of Convergent Methodologies

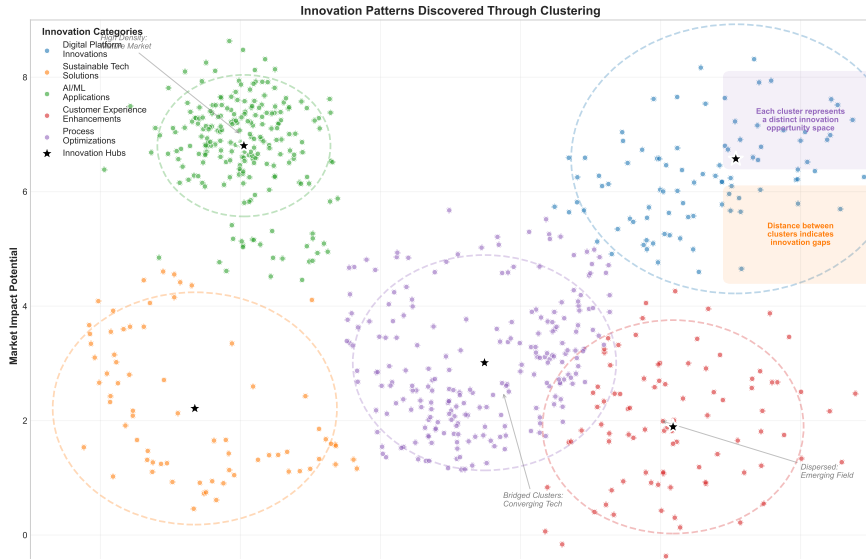
The Convergence Flow: From Chaos to Clarity



Where Data Science Meets Human Creativity

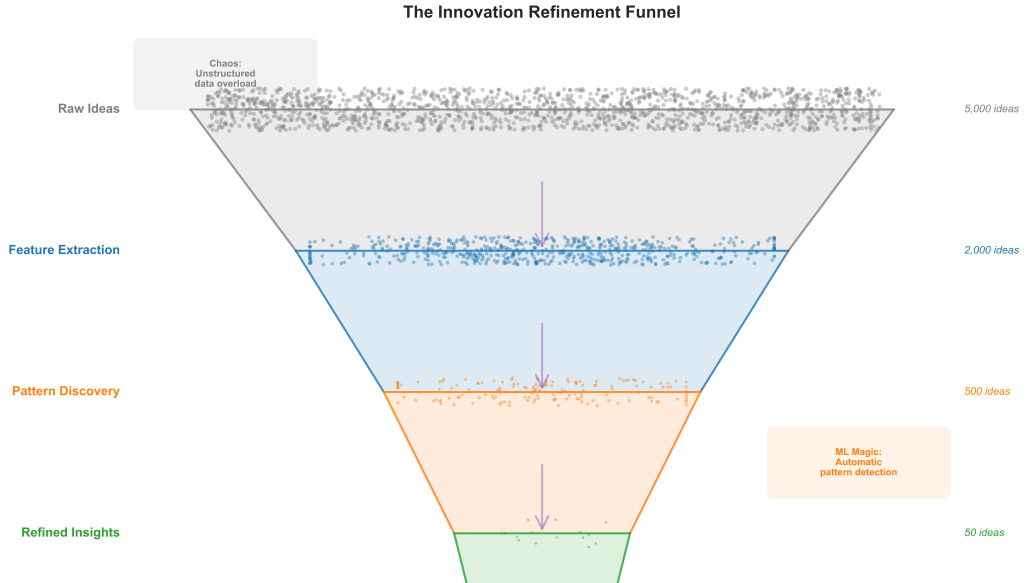
From Data Points to Innovation Insights

Bridging the Technical-Human Gap



The Innovation Refinement Funnel

From Chaos to Clarity Through Feature Analysis



PART 1

Foundation & Context

What we'll explore:

- Why traditional design hits limits
- How ML amplifies human insight
- The dual pipeline approach
- Your learning journey ahead

Setting the stage for transformation

Part 1: Learning Objectives

What You'll Learn in This Section

By the end of Part 1, you will be able to:

- **Understand** the limitations of traditional innovation approaches
- **Recognize** how ML enhances human creativity
- **Explain** the dual pipeline methodology
- **Navigate** the 10-week learning journey
- **Identify** Week 1's role in the overall course

Success Criteria

- Can articulate 3+ traditional design limitations
- Can describe ML's value proposition
- Can map ML pipeline to design pipeline
- Understand clustering's role in innovation

PART 1

Foundation & Context

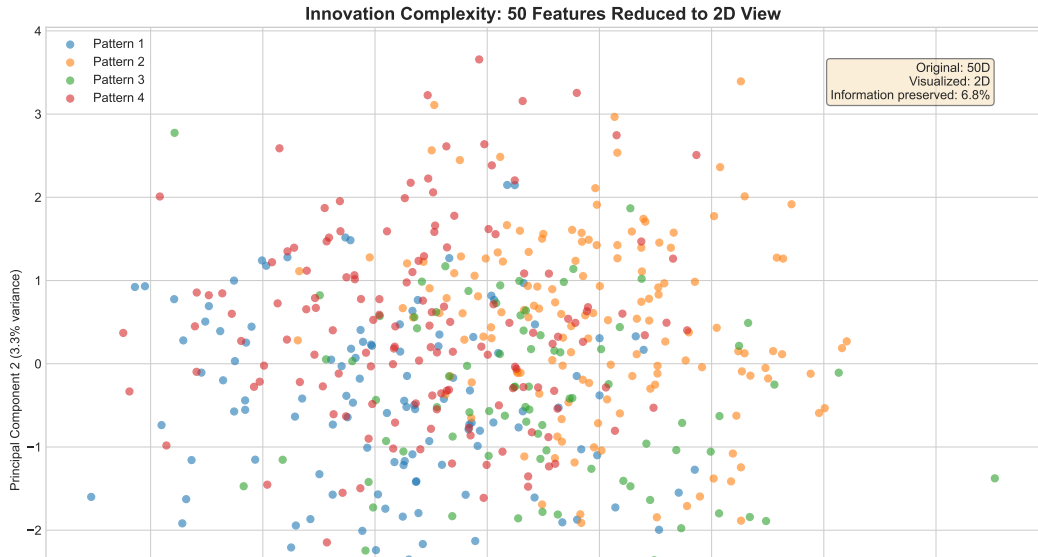
Understanding the Innovation Challenge

Finding Patterns in the Chaos



The Hidden Complexity

Each Innovation Depends on Hundreds of Features



The Innovation Challenge

Why Traditional Design Needs AI Enhancement

Traditional Design Limits

- **Scale:** Can analyze 50 ideas, not 50,000
- **Speed:** Months for insights
- **Bias:** Designer's perspective dominates
- **Patterns:** Miss hidden connections
- **Iteration:** Slow feedback loops

AI-Enhanced Innovation

- **Scale:** Analyze millions of data points
- **Speed:** Real-time insights
- **Objectivity:** Data-driven discovery
- **Patterns:** Find non-obvious relationships
- **Iteration:** Continuous learning

The Promise: 100x more insights, 10x faster innovation

Traditional Approach

- Manual interviews
- Limited sample size
- Qualitative insights
- Slow iteration

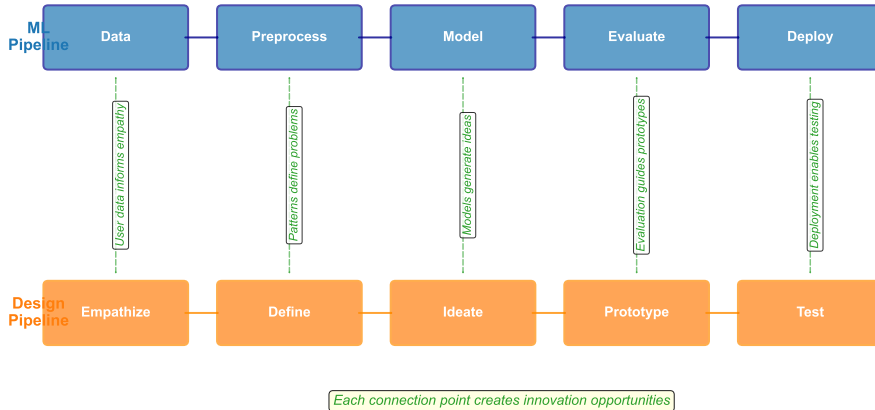
ML-Enhanced Approach

- Data-driven discovery
- Massive scale analysis
- Quantitative patterns
- Real-time adaptation

The Dual Pipeline

Where ML Meets Design Thinking

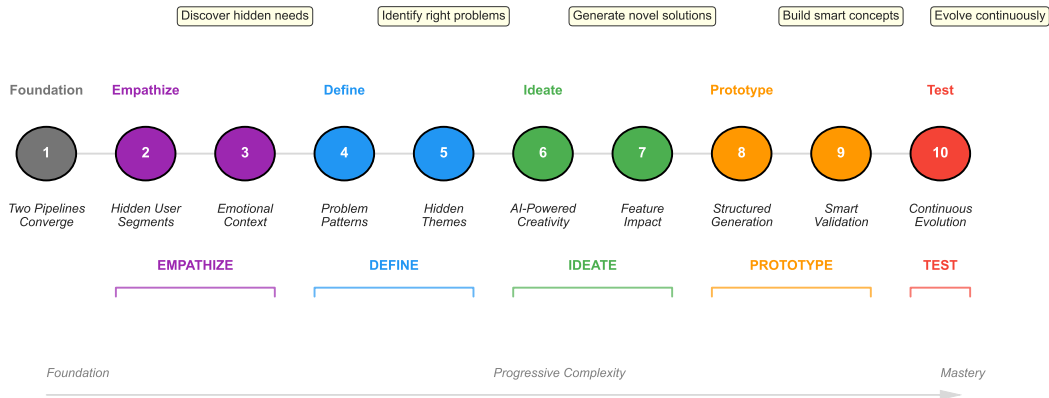
The Convergence: ML Meets Design Thinking



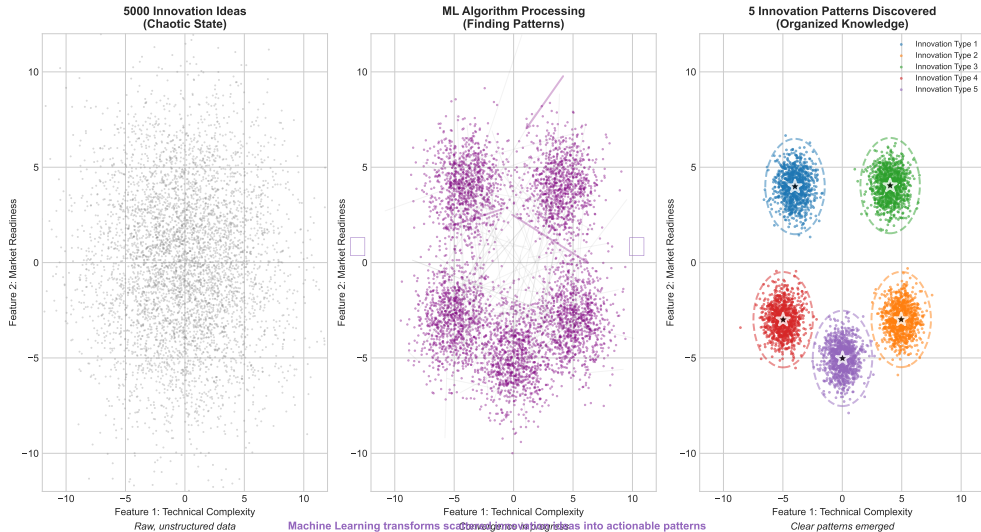
Your Innovation Journey

10 Weeks to Understanding AI-Powered Design

10-Week Innovation Journey



The Convergence Flow: From Chaos to Clarity



The Convergence Flow: Order from Chaos
Watch 5000 innovation ideas self-organize into meaningful patterns

PART 2

Technical Core

Machine Learning Algorithms & Implementation

The Innovation Classification Problem

5000 Ideas - How Do They Connect?

The Pain

Current Reality:

- One-size-fits-all solutions
- Generic innovation categories
- Missed opportunities
- Unhappy edge cases

The Cost:

- Most innovations get misclassified
- Features with low adoption rates
- Inefficient resource allocation

The Question

What if we could...

- Find natural innovation clusters?
- Discover innovation patterns?
- Innovate at scale?
- Identify opportunity gaps?

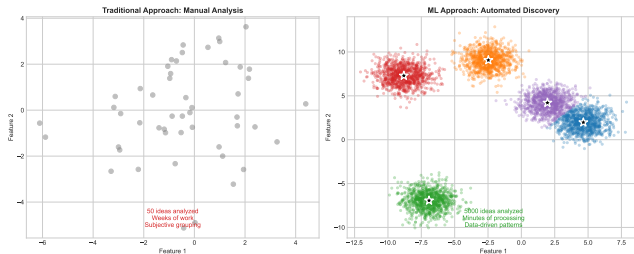
We can!

Solution: Clustering

Current Reality: The Problem

Why One-Size-Fits-All Doesn't Work

The Current Reality: Scale Challenge in Innovation



The Fragmentation Crisis

- 70% of innovations fail due to misalignment
- 85% miss their target audience
- 60% duplicate existing solutions

Why This Happens:

- Treating all ideas the same
- Missing subtle patterns
- No systematic categorization
- Human cognitive limits

ML clustering reveals the hidden structure in innovation chaos

Discovery Exercise: Which Archetype?

Match Each Innovation to Its Type

Innovation Examples:

- ① **Uber** - Connecting drivers with riders via app
- ② **Tesla Model 3** - Affordable electric vehicle
- ③ **Amazon Prime** - Fast delivery subscription
- ④ **iPhone Camera** - Annual improvements
- ⑤ **ChatGPT** - AI conversation interface

Think: What makes each one similar or different?

Match to Type:

- A. Disruptive Innovation
- B. Incremental Innovation
- C. Platform Innovation
- D. Service Innovation
- E. Business Model Innovation

Answers:

(Discuss with neighbor first)

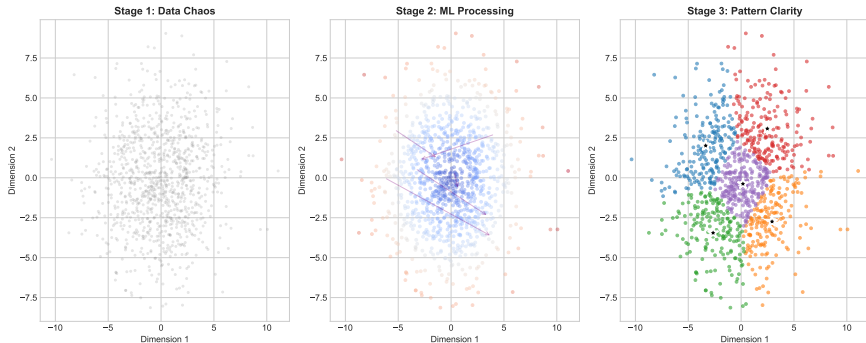
1→C (Platform), 2→A (Disruptive),
3→E (Business Model), 4→B (Incremental),
5→D (Service)

ML can do this matching at scale - for thousands of innovations

What is Clustering?

Like Organizing a Messy Room - Finding Things That Belong Together

From Chaos to Clarity: The ML Journey



Clustering Finds:

- Natural groupings
- Similar approaches
- Hidden patterns
- Innovation relationships

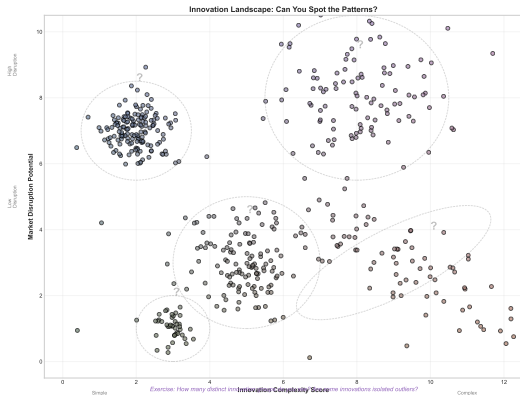
Key Insight:

Things that look similar often belong in the same group
(Just like organizing books by topic on a shelf)

Discovery: How Many Groups Do You See?

Visual Pattern Recognition Exercise

Look at this innovation data:



Your Observations:

- 1 Groups you see: _____
- 2 Main pattern: _____
- 3 Outliers: _____

Key Insight:

Humans are good at 2D patterns.
But innovation has 100+ dimensions!
That's where ML helps.

Questions:

- How many distinct groups?

Discovery: What Makes Things Similar?

Understanding Features That Matter

For Innovations, What Features Matter?

Innovation	Cost	Impact	Time
Smart Thermostat	Low	Medium	Quick
Electric Car	High	High	Long
Mobile App	Low	Low	Quick
Solar Panels	High	High	Long
AI Chatbot	Medium	Medium	Medium

Which innovations group together?

- By cost? (Low vs High)
- By impact? (Low vs High)
- By timeline? (Quick vs Long)
- All combined?

Discovery Exercise

Group these by similarity:

- 1 Smart Thermostat + ?
- 2 Electric Car + ?
- 3 Mobile App + ?

The Challenge:

Real innovations have 100+ features!

- Market size - Technology readiness - Regulatory requirements - User demographics - Competition level - And many more...

Discovery: Manual Clustering Exercise

Try Clustering Yourself - Then See How ML Does It

Your Task:

Group these 12 innovations into 3 clusters:

- 1 Blockchain payment system
- 2 Voice-activated assistant
- 3 Renewable energy storage
- 4 Social media platform
- 5 Autonomous vehicle
- 6 Health tracking wearable
- 7 Cloud computing service
- 8 3D printing technology
- 9 Virtual reality training
- 10 Drone delivery system
- 11 Gene editing tool
- 12 Quantum computing

Your Groups:

Group 1: _____

Group 2: _____

Group 3: _____

Think About:

- What features did you consider?
- How did you decide on groups?
- Was it difficult to classify some items?
- Did any items fit multiple groups?

Let's see how ML approaches this...

Discovery: How ML Clusters These Innovations

Based on 50+ Hidden Features

Digital Platforms

4. Social media platform
7. Cloud computing service
2. Voice-activated assistant
1. Blockchain payment system

Physical Innovation

5. Autonomous vehicle
10. Drone delivery system
3. Renewable energy storage
8. 3D printing technology

Frontier Tech

11. Gene editing tool
12. Quantum computing
9. Virtual reality training
6. Health tracking wearable

ML considers features you might not think of:

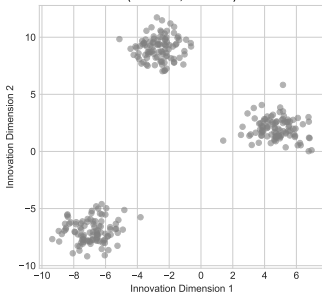
- Development complexity
- Market readiness level
- Infrastructure requirements
- Regulatory complexity
- User behavior patterns
- Technology stack similarity
- Investment requirements
- Innovation lifecycle stage

K-Means: The Basic Clustering Method (Part 1)

Initial Setup - Like Choosing City Centers

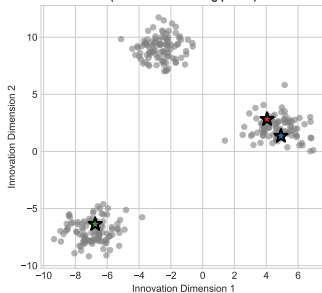
K-Means Algorithm: Step-by-Step Innovation Clustering

Step 1: Raw Innovation Data
(300 ideas, no labels)



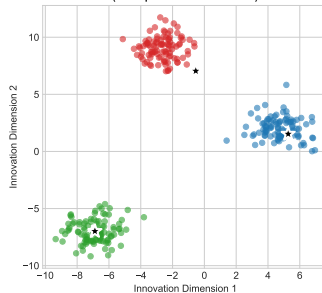
□ How many groups?

Step 2: Initialize Centers
($k=3$ random starting points)



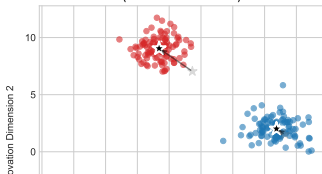
□ Start with $k=3$ centers

Step 3: Assign to Nearest Center
(Each point finds its cluster)

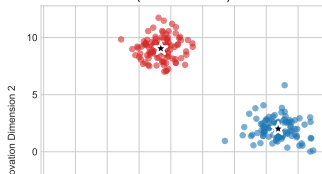


□ Distance-based assignment

Step 4: Update Centers
(Move to cluster mean)

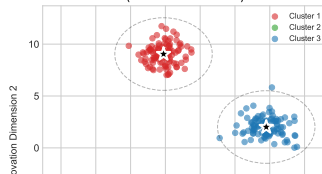


Step 5: Repeat Until Stable
(After 5 iterations)



□ Distance-based assignment

Step 6: Convergence!
(Stable clusters found)



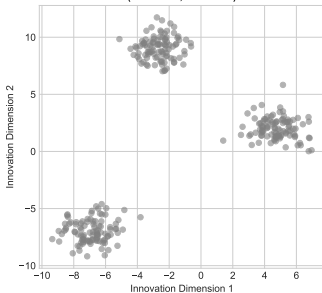
● Cluster 1
● Cluster 2
● Cluster 3

K-Means: The Basic Clustering Method (Part 2)

Iteration Process - Finding Natural Groups

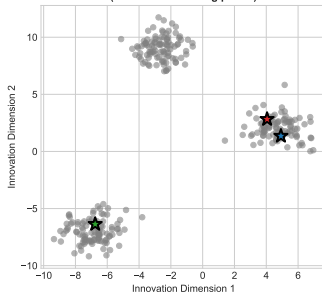
K-Means Algorithm: Step-by-Step Innovation Clustering

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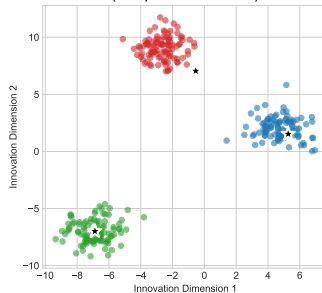
□ How many groups?

Step 2: Initialize Centers
($k=3$ random starting points)



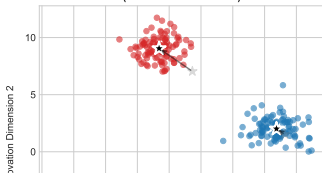
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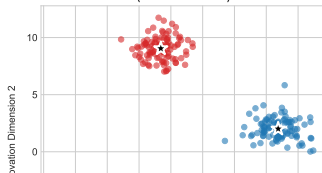


□ Distance-based assignment

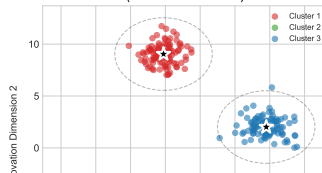
Step 4: Update Centers
(Move to cluster mean)



Step 5: Repeat Until Stable
(After 5 iterations)



Step 6: Convergence!
(Stable clusters found)



The Goldilocks Problem

Too Few vs. Too Many Groups

Too Few ($K=2$)

Oversimplification

- Mixed segments
- Lost nuance
- Generic solutions

Just Right (K)

Optimal Balance

- Clear segments
- Actionable insights
- Manageable complexity

Too Many (K)

Analysis Paralysis

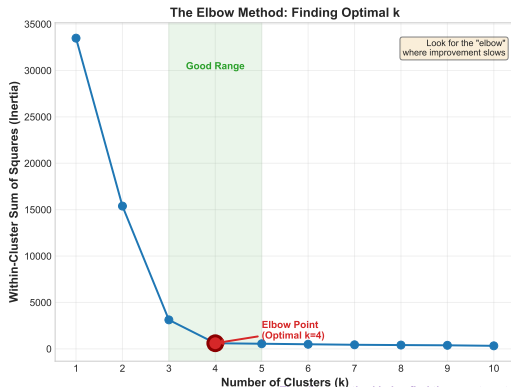
- Overfitting
- Tiny segments
- Impossible to act on

How do we find the sweet spot?

The Elbow Method

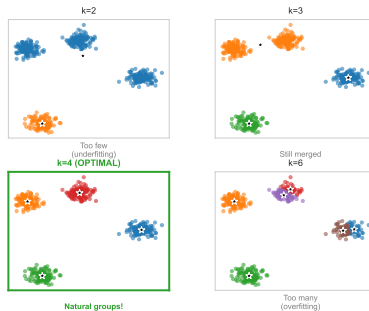
How Many Groups Should We Have? (Like Goldilocks - Not Too Few, Not Too Many)

Choosing the Right Number of Innovation Clusters



The elbow method helps find the sweet spot between too few and too many clusters

Visual Comparison: Different k Values



Finding the Elbow:

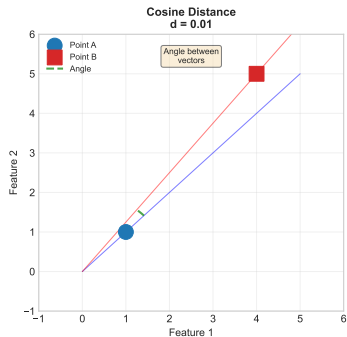
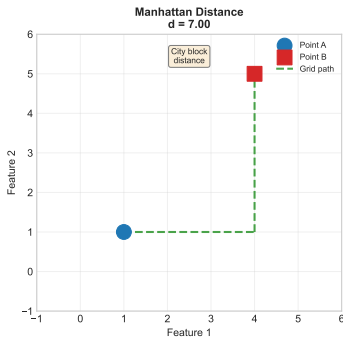
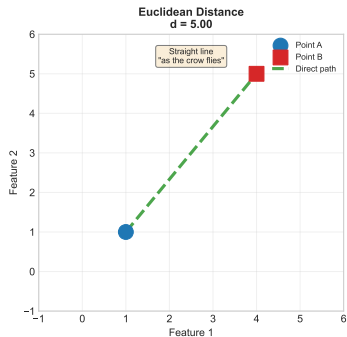
- Plot inertia vs K
- Look for the "elbow"

Optimal K = 5
Best trade-off point

Distance Metrics

Different Ways to Measure "How Close" Things Are

Distance Metrics: Different Ways to Measure Innovation Similarity

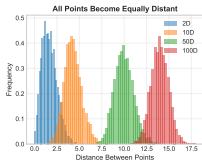
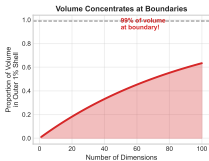


Each metric reveals different patterns in your data

Sidestep: The Curse of Dimensionality

Why High-Dimensional Spaces Are Strange and Empty

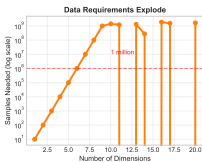
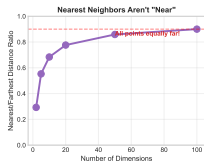
The Curse of Dimensionality: Why High-Dimensional Spaces Are Strange



In High Dimensions:
Everything is on the Surface



More than atoms
in universe!



Innovation data has 100+ dimensions - that's why we need specialized ML algorithms!

The Paradox

In 100 dimensions:

- 99.99% of space is empty
- All points are outliers
- Nearest neighbors aren't near

Why This Matters

Innovation has 100+ features!

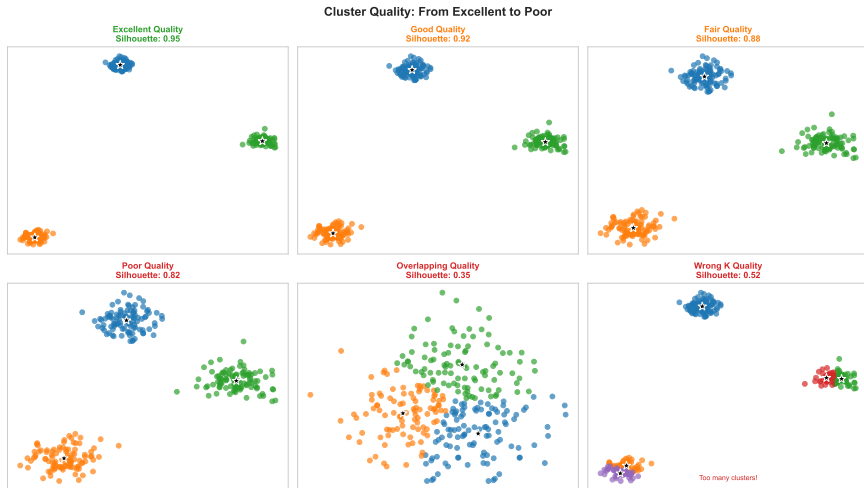
- Distance metrics break down
- Need special techniques
- Dimensionality reduction crucial
- That's why we use PCA/t-SNE

As dimensions increase:

- Points become equally distant

Cluster Quality Metrics

Are Our Groups Any Good? (Like Checking Your Work)



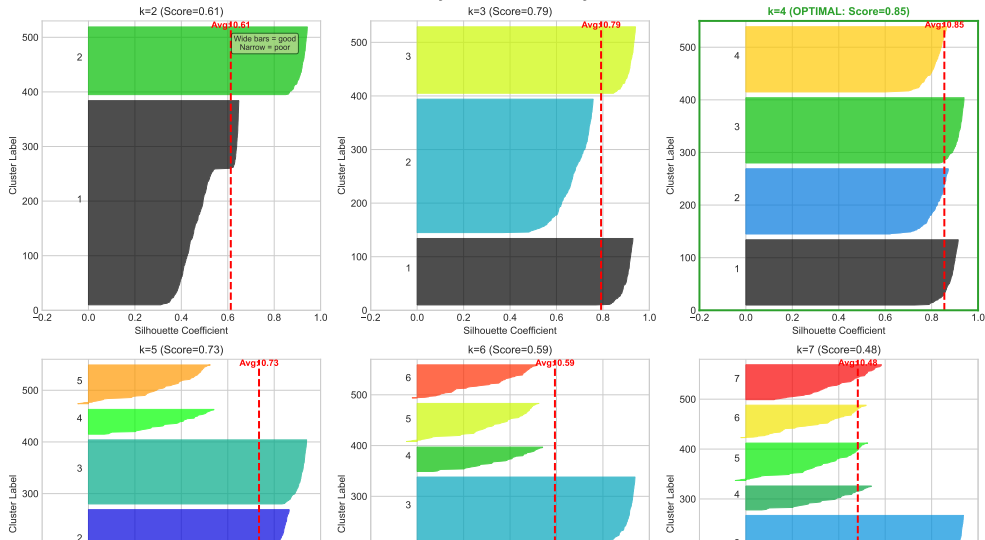
Silhouette Score:

What it measures:

Evaluation Metric 1: Silhouette Score

Measuring Cluster Cohesion and Separation

Silhouette Analysis: Cluster Quality Validation



Discovery: Finding the Right K

What Happens With Different Numbers of Clusters?

Experiment with K:

K	What Happens
K=2	Everything too mixed
K=4	Natural groups emerge
K=8	Some groups split unnecessarily
K=20	Too fragmented to use

Your Turn:

If you have 100 customer types, what K would you choose?

- K=100? (one per type)
- K=5? (major groups)
- K=20? (detailed segments)

The Trade-offs:

Too Few (Under-fit)

- Mixed segments
- Lost insights
- Generic solutions

Just Right

- Clear segments
- Actionable groups
- Meaningful patterns

Too Many (Over-fit)

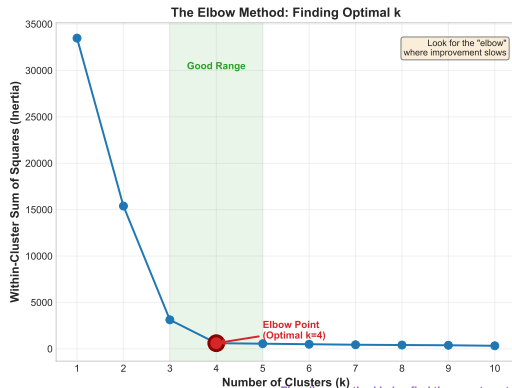
- Fragmented insights
- Hard to implement
- Statistical noise

The Elbow Method helps find the sweet spot automatically

Evaluation Metric 2: Elbow Method

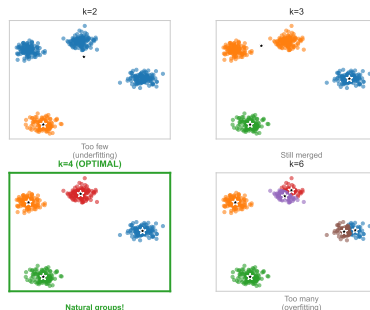
Finding the Right Number of Clusters

Choosing the Right Number of Innovation Clusters



The elbow method helps find the sweet spot between too few and too many clusters

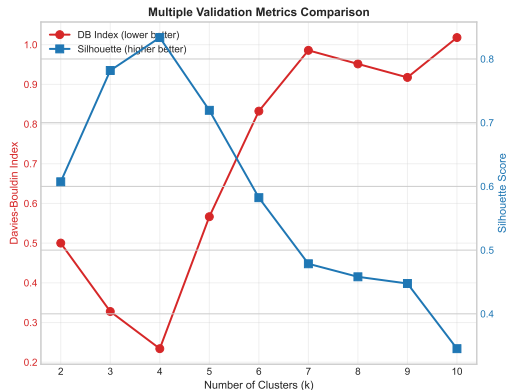
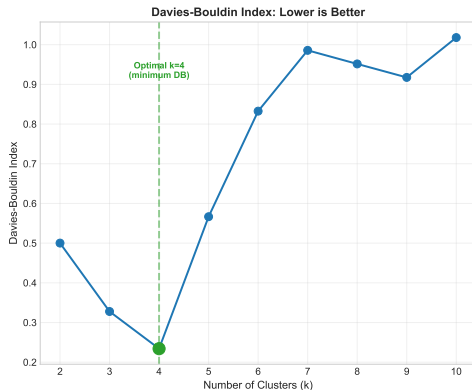
Visual Comparison: Different k Values



Evaluation Metric 3: Davies-Bouldin Index

Balancing Within and Between Cluster Distances

Cluster Validation: Davies-Bouldin Index



K-Means Assumes Spherical Clusters

But what about:

- Innovations connected through technology stacks
- Domain-specific innovation clusters
- Evolution patterns (incremental, disruptive)
- Outliers and noise points

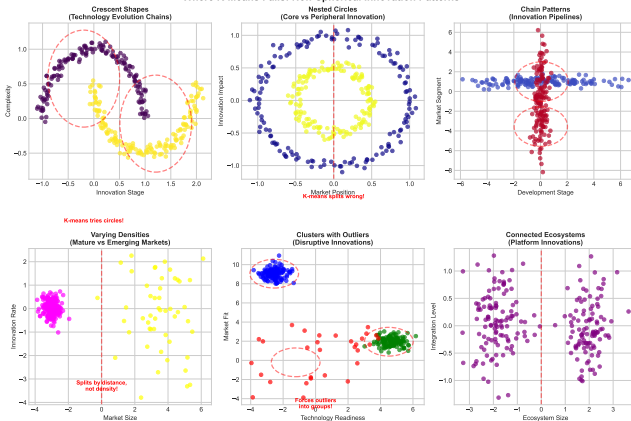
K-Means Forces Round Pegs into Round Holes

Solution: Density-Based Clustering

Discovery: When K-Means Fails

Can You Spot Why K-Means Won't Work Here?

Where K-Means Fails: Non-Spherical Innovation Patterns



Real innovation patterns rarely form perfect circles - that's why we need advanced clustering methods! Breaks connections!

K-Means Problems

K-Means assumes:

- Spherical (round) clusters
- Similar sizes
- Similar densities
- No outliers

Real Innovation Patterns

But innovations have:

- Evolution chains
- Technology ecosystems
- Varying market sizes
- Disruptive outliers

Exercise:

Draw clusters on the left image.
Where does K-means fail?

Look at these patterns:

- Crescent shapes

DBSCAN: Finding Groups Naturally

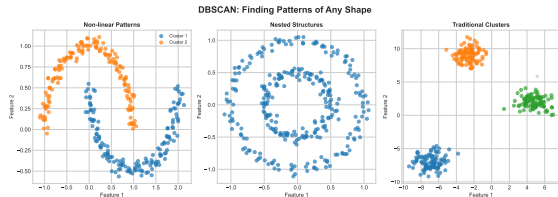
Like Finding Groups of People at a Party - Where Are the Crowds?

DBSCAN Advantages:

- No need to specify K (*finds groups automatically*)
- Finds arbitrary shapes (*not just circles*)
- Identifies outliers (*points that don't belong*)
- Handles noise well (*robust to random points*)

Perfect for:

- Non-spherical patterns
- Varying densities
- Outlier detection
- Exploratory analysis



DBSCAN: Understanding Parameters

Two Simple Settings Control Everything

Epsilon (Distance)

What it does:

Sets the maximum distance to consider points as neighbors

Think of it as:

How far can points be apart and still be friends?

Too small: Many tiny clusters

Too large: Everything merges

MinPts (Density)

What it does:

Minimum neighbors needed to form a dense region

Think of it as:

How many friends make a group?

Too small: Noise becomes clusters

Too large: Small clusters vanish

Rule of thumb: $\text{MinPts} = 2 \times \text{dimensions}$

Clustering Algorithm Comparison

Technical Characteristics at a Glance

Algorithm	Speed	Shape	Outliers	Params	Best For
K-Means	Fast $O(nkt)$	Spherical clusters	Sensitive	K only	Quick segments
DBSCAN	Medium $O(n \log n)$	Any shape	Robust (detects)	eps, MinPts	Complex shapes
Hierarchical	Slow $O(n^2)$	Any shape	Moderate	Distance threshold	Multi-level analysis
GMM	Medium $O(nkt)$	Elliptical clusters	Moderate	K, covariance	Overlapping groups

Each algorithm has its strengths - choose wisely!

When to Use Each Algorithm

Practical Decision Guide

K-Means

Perfect when:

- Speed is critical
- Clusters are roughly equal size
- You know K in advance
- Data has spherical patterns

Hierarchical

Perfect when:

- Need multiple granularities
- Want to visualize relationships
- Small to medium datasets
- Exploring data structure

DBSCAN

Perfect when:

- Clusters have irregular shapes
- Outliers need identification
- Density varies across data
- You don't know K

GMM

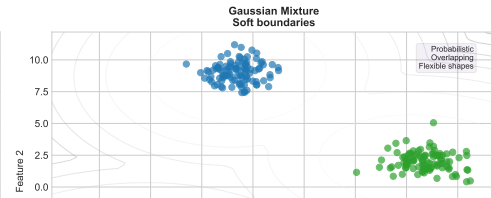
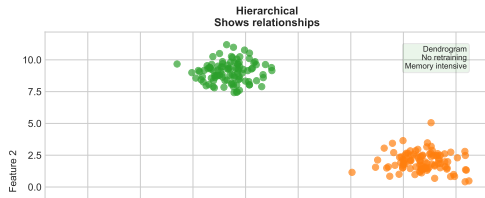
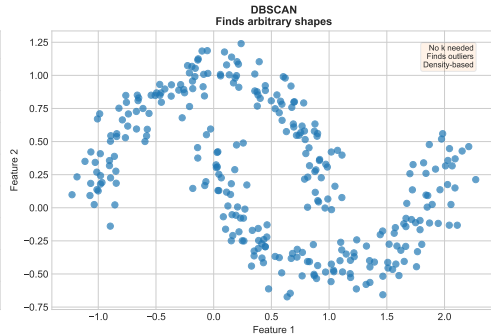
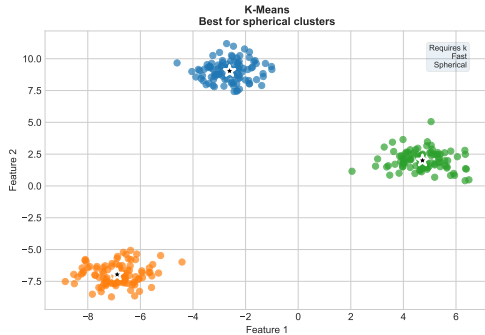
Perfect when:

- Groups overlap
- Need probability scores
- Elliptical cluster shapes
- Soft assignments needed

Algorithm Visual Comparison

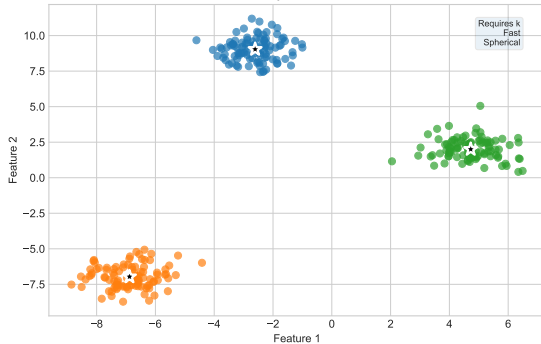
Same Data, Different Approaches

Clustering Algorithm Comparison

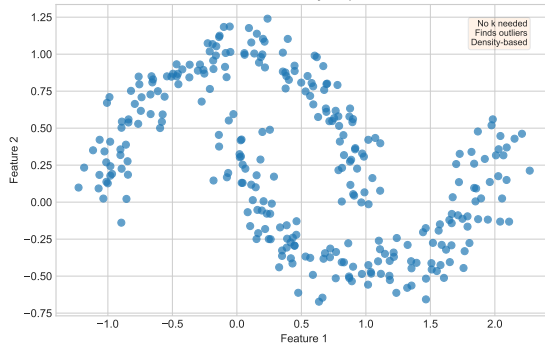


Clustering Algorithm Comparison

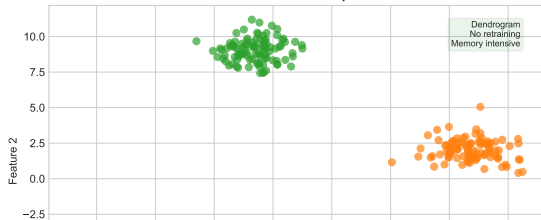
K-Means
Best for spherical clusters



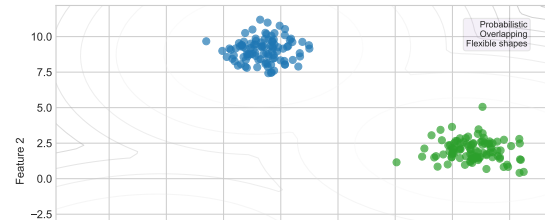
DBSCAN
Finds arbitrary shapes



Hierarchical
Shows relationships



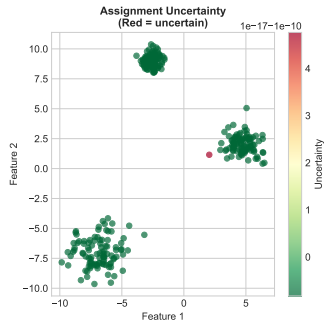
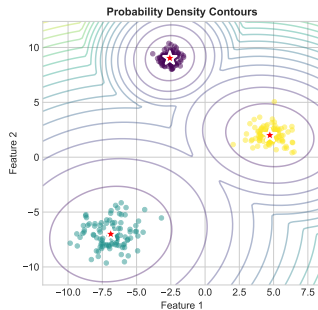
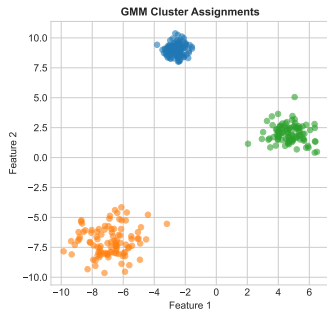
Gaussian Mixture
Soft boundaries



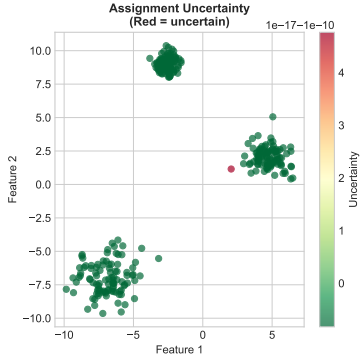
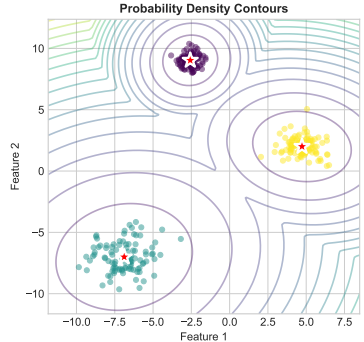
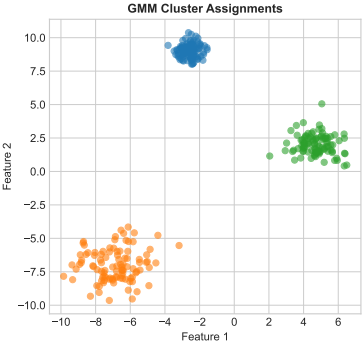
Gaussian Mixture Models (GMM)

Soft Clustering for Overlapping Innovation Categories

Gaussian Mixture Model: Probabilistic Clustering



Gaussian Mixture Model: Probabilistic Clustering



Fixed K Gives One View

But real relationships are hierarchical:

- Organization: Company → Department → Team → Individual
- Geography: Country → Region → City → Neighborhood
- Products: Category → Subcategory → Brand → SKU
- Innovations: All → Categories → Sub-types → Specific solutions

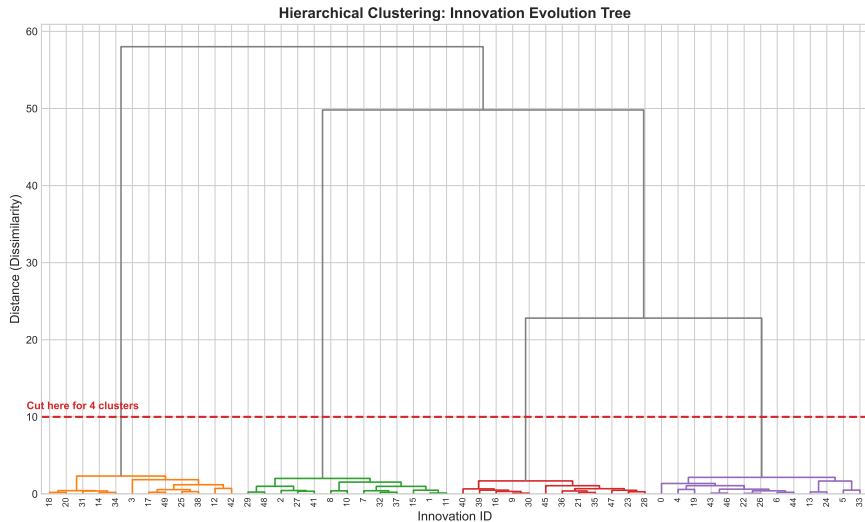
K-means: Pick 5 groups and that's it

What if we need flexibility?

Solution: See the full hierarchy, cut where needed

Hierarchical Clustering

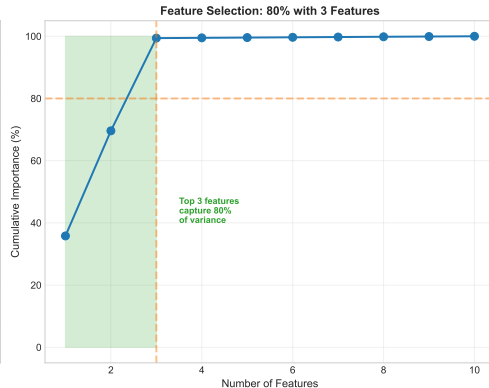
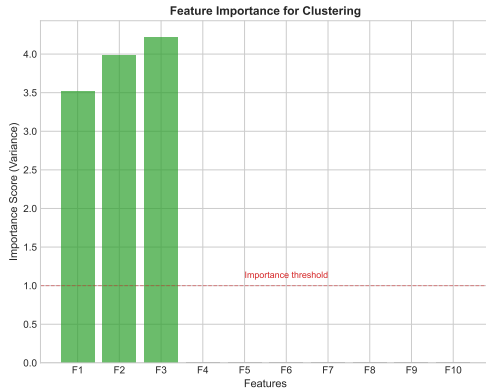
Building a Tree of Relationships



What Drives the Clusters?

Feature Importance Analysis

Feature Importance Analysis

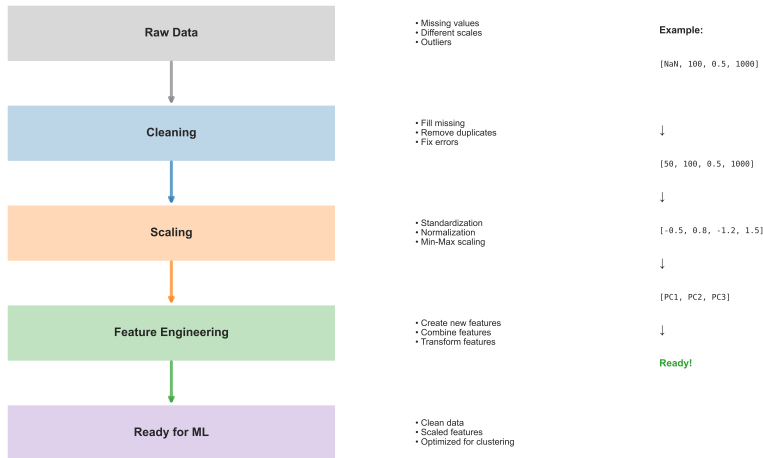


Key Insight: Usage frequency matters most!

Data Preprocessing Pipeline

From Raw Data to Clustering-Ready Features

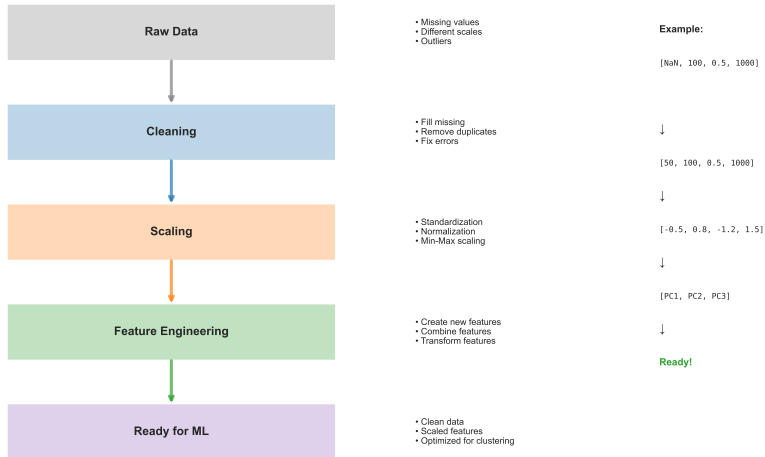
Data Preprocessing Pipeline for Clustering



Data Preprocessing Pipeline - Example

Real Innovation Data Transformation

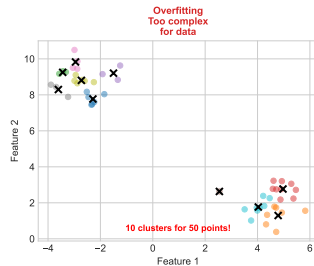
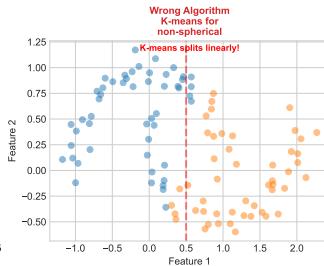
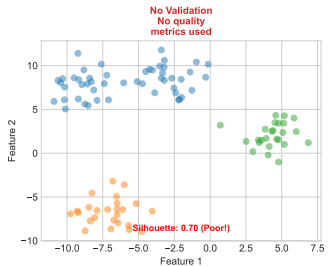
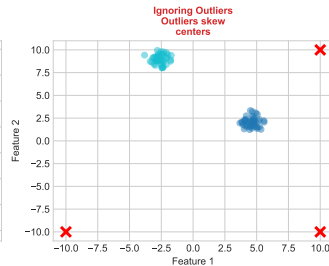
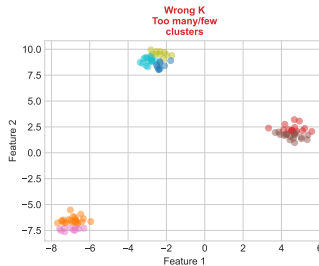
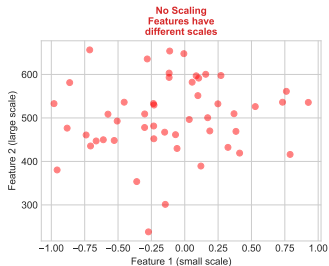
Data Preprocessing Pipeline for Clustering



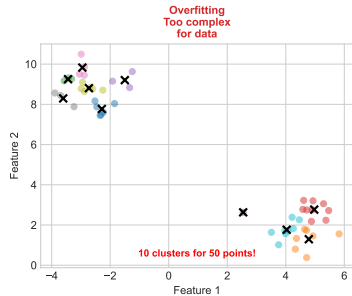
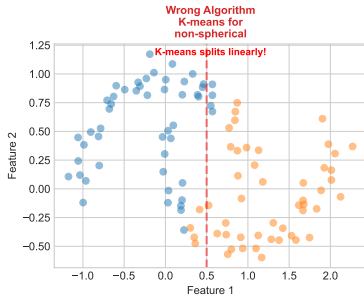
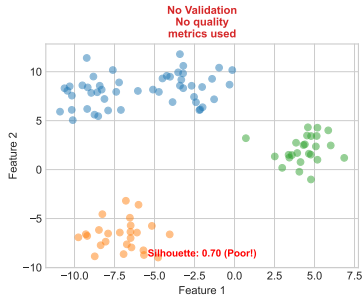
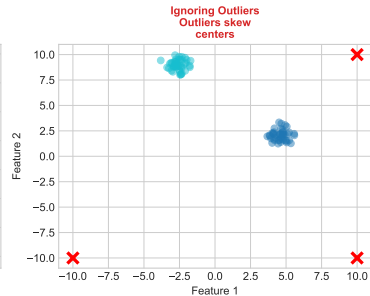
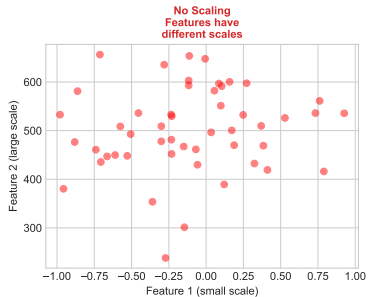
Common Mistakes & Troubleshooting

Learn from These Pitfalls

Common Clustering Mistakes to Avoid



Common Clustering Mistakes to Avoid

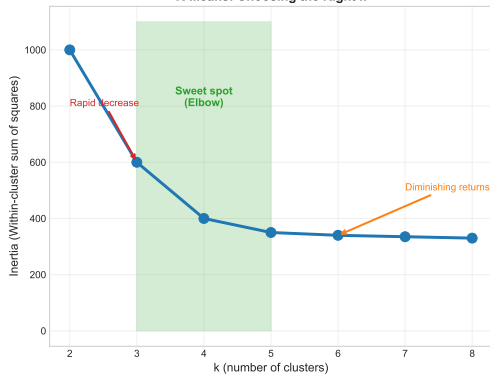


Parameter Tuning Guidelines (Part 1)

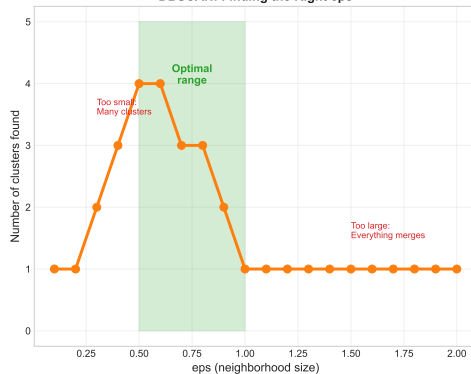
K-Means and DBSCAN Parameters

Parameter Tuning Guidelines - Part 1: Distance-Based Methods

K-Means: Choosing the Right k



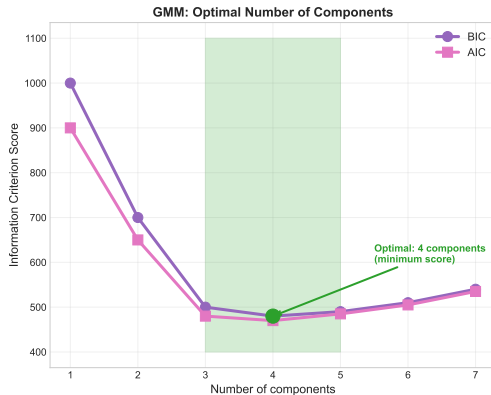
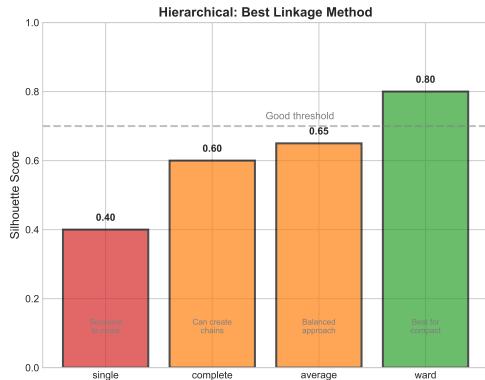
DBSCAN: Finding the Right eps



Parameter Tuning Guidelines (Part 2)

Hierarchical and GMM Parameters

Parameter Tuning Guidelines - Part 2: Advanced Methods



Quick Quiz

① K in K-means stands for:

- ☐ Kernel
- ☒ Number of clusters
- ☐ Constant

② DBSCAN finds:

- ☐ Only circles
- ☒ Any shape clusters
- ☐ Exactly K groups

Can You Calculate?

If Silhouette Score = 0.75:

- Is this good? **Yes!**
- Range is $[-1, 1]$
- Higher = better separation

Remember:

- Elbow method finds optimal K
- Scale your data first!

Great job! Now let's apply these concepts!

Next: Design integration, innovation patterns, and real-world applications

We've learned the technical tools:

Clustering, metrics, quality measures

But clusters are just numbers...

Until we connect them to innovation opportunities

Let's transform data into innovation insights

Each cluster represents innovation opportunities and patterns

PART 3

Innovation Pattern Analysis

What we'll create:

- Data-driven innovation archetypes
- Innovation pattern maps per category
- Cluster-specific journeys
- Opportunity heat maps
- Design priority matrices

Where ML reveals innovation patterns

Part 3: Learning Objectives

Innovation Applications You'll Explore

By the end of Part 3, you will be able to:

- **Create** innovation archetypes
- **Map** innovation patterns
- **Design** opportunity matrices
- **Analyze** innovation lifecycles
- **Build** ecosystem maps
- **Prioritize** innovation efforts

Design Outcomes

- Innovation taxonomy framework
- Cluster-based strategies
- Data-driven prioritization
- Opportunity identification
- Pattern recognition skills
- Ecosystem understanding

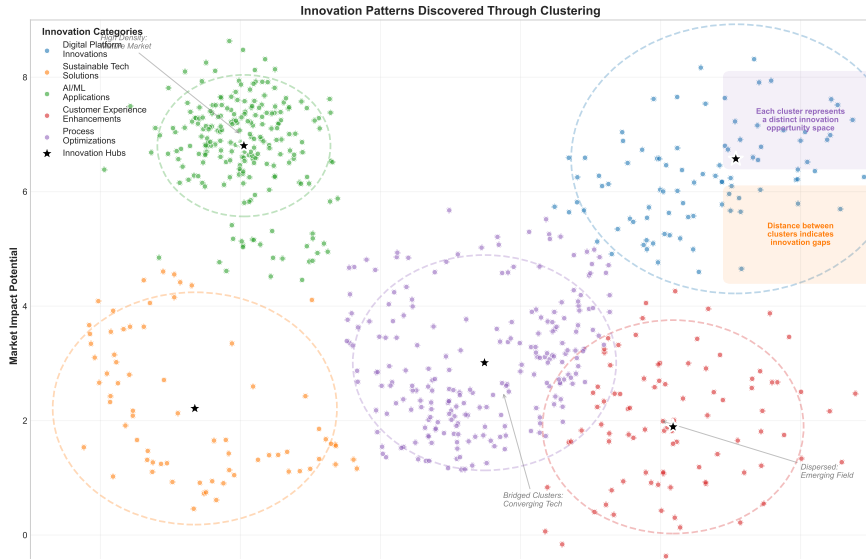
PART 3

Design Integration

Bridging Technology & Human Experience

From Data Points to Innovation Insights

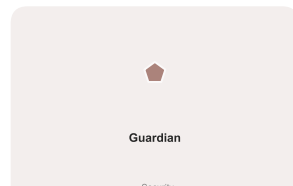
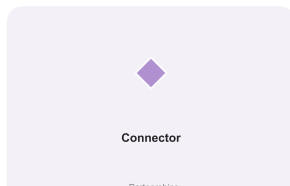
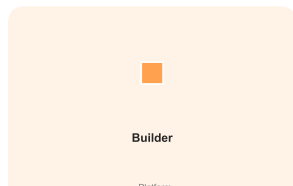
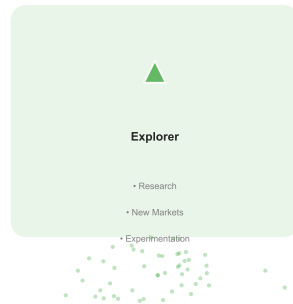
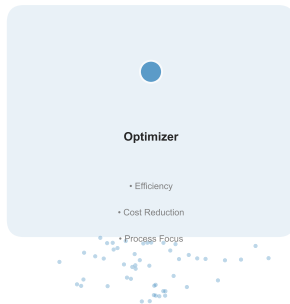
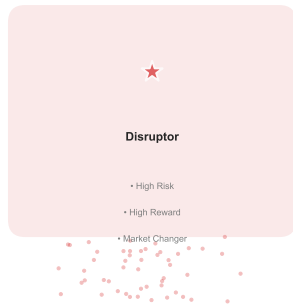
Bridging the Technical-Human Gap



AI-Generated Innovation Archetypes

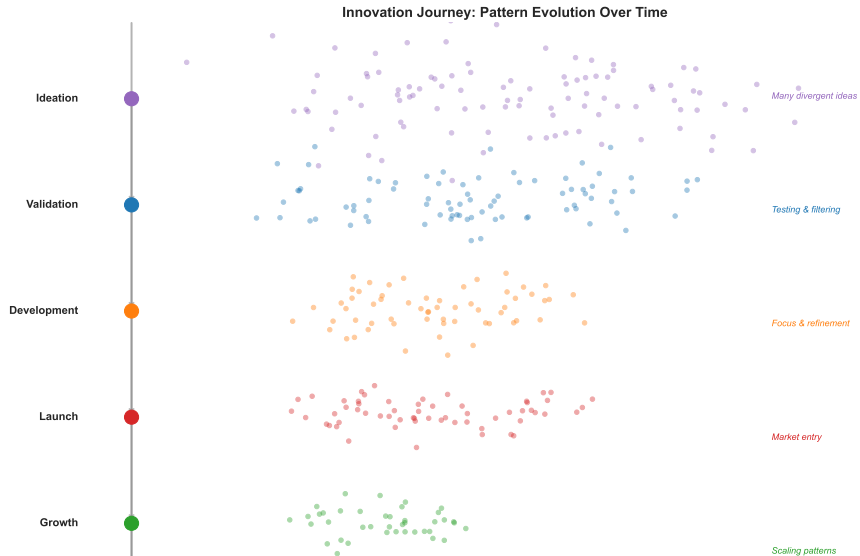
Data-Driven Character Development

Innovation Archetypes: 6 Distinct Patterns



Innovation Pattern Maps

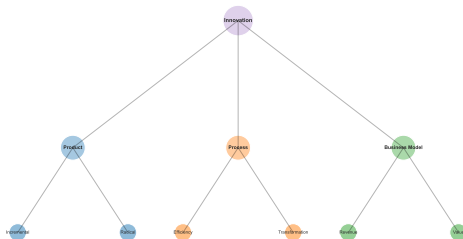
Cluster-Specific Insights



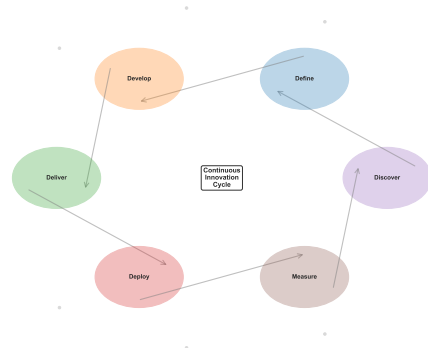
Innovation Framework

Taxonomy and Lifecycle Stages

Innovation Taxonomy: Hierarchical Classification



Innovation Lifecycle: Continuous Improvement Process



Framework Levels:

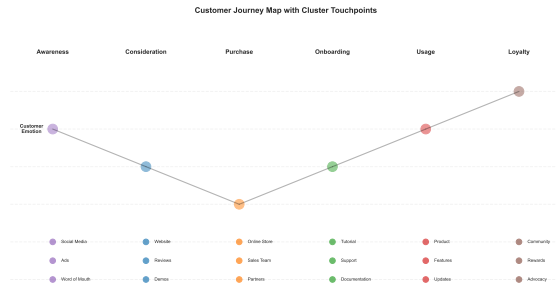
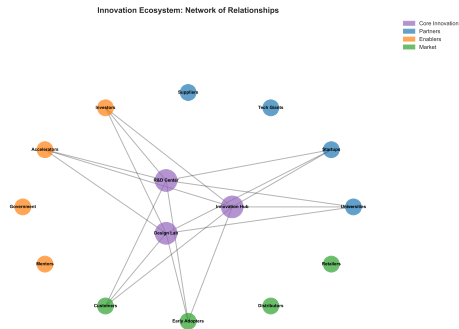
- Types & relationships
- Impact measurements
- Strategic positioning

Lifecycle Stages:

- Ideation & discovery
- Development & testing
- Launch & scaling

Innovation Ecosystem & Journey Mapping

From Networks to Evolution Paths



Ecosystem Elements:

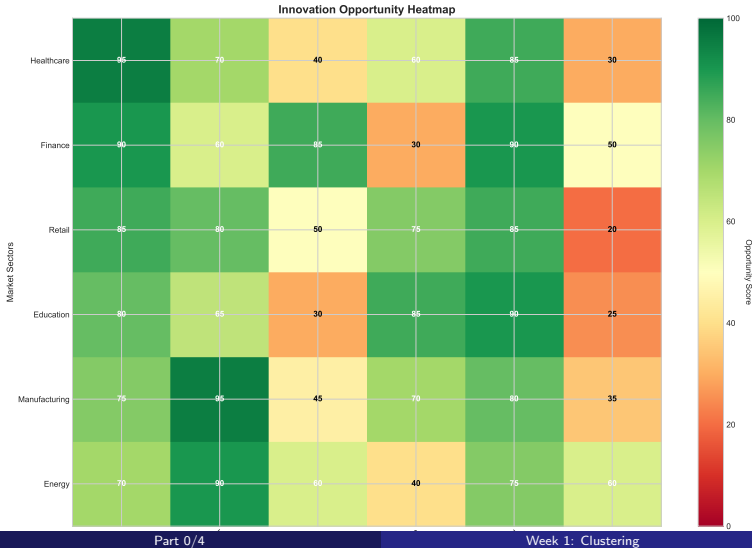
- Network connections
- Stakeholder clusters
- Value flows

Evolution Paths:

- Different speeds
- Varying trajectories
- Unique milestones

Innovation Opportunities by Cluster

Where Each Category Has Potential



Key Findings:

- Emerging tech: Early stage
- Disruptive: Scalability
- Incremental: Integration
- Platform-based: Network effects

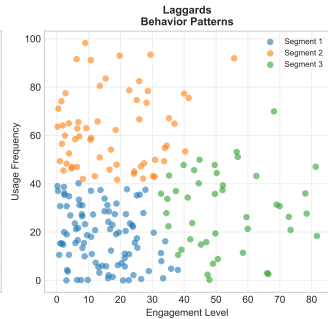
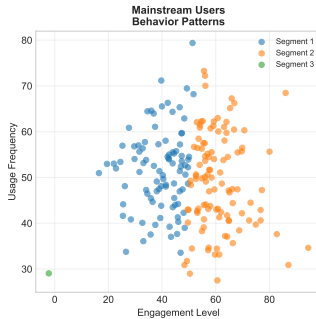
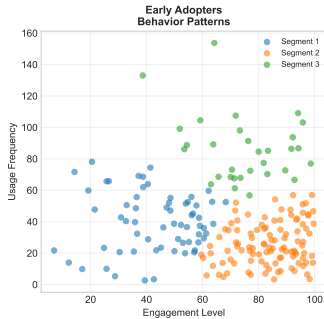
Design implication:

One solution won't fit all!

Innovation Patterns Revealed

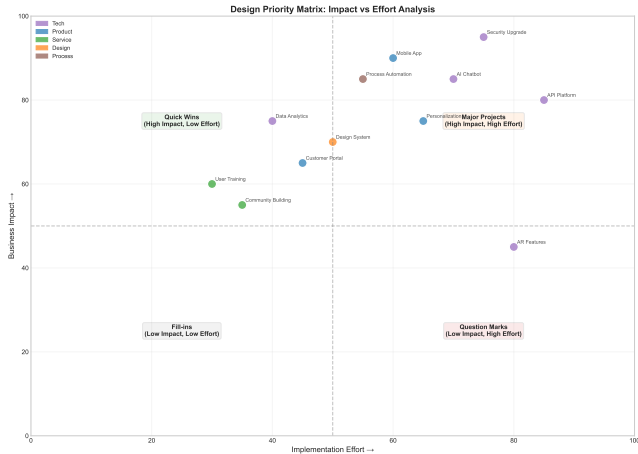
What Clusters Tell Us About Evolution

User Behavior Pattern Clustering



Design Priority Matrix

Where to Focus Your Efforts

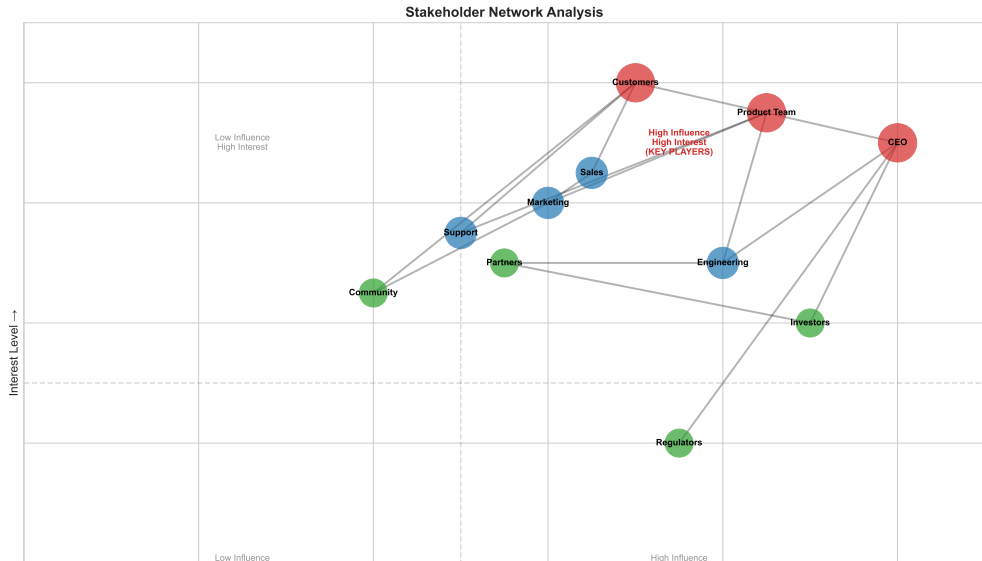


Priority Quadrants:

- **High Impact + High Effort**
Strategic initiatives
- **High Impact + Low Effort**
Quick wins
- **Low Impact + Low Effort**
Fill-ins
- **Low Impact + High Effort**
Avoid

Understanding Innovation Ecosystems

Network Analysis of Innovation Connections



Match the Application

Match algorithm to use case:

- ① Customer segmentation → **K-means**
- ② Finding outliers → **DBSCAN**
- ③ Creating taxonomy → **Hierarchical**
- ④ Overlapping groups → **GMM**

Design Thinking

How does clustering help in:

- **Empathize**: Find user groups
- **Define**: Identify patterns
- **Ideate**: Discover opportunities
- **Prototype**: Target solutions
- **Test**: Validate segments

Excellent! Ready to practice with real data?

Next: Summary, real-world case studies, and hands-on practice exercise

You've learned:

- The clustering algorithms
- How to validate quality
 - Design applications

Now let's see it in action

How these techniques work in practice
to find patterns in data