

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

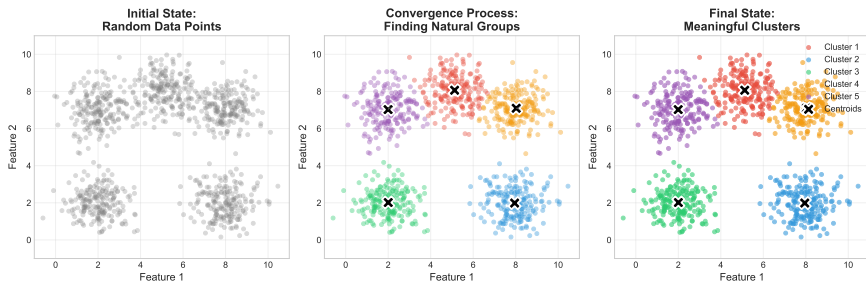
- All code templates
- Step-by-step instructions
- Visual explanations
- Practice datasets

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

Three powerful forces converge to amplify innovation impact

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

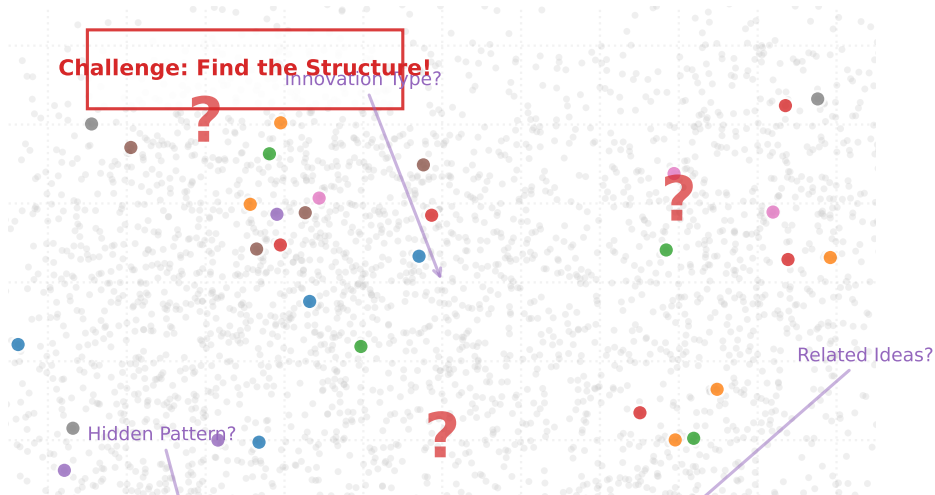
- Can articulate 3+ traditional design limitations
- Can describe ML's value proposition
- Can map ML pipeline to design pipeline
- Understand clustering's role in innovation

PART 1

Foundation & Context

Understanding the Innovation Challenge

5000+ Innovation Ideas: Where Do We Start?



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

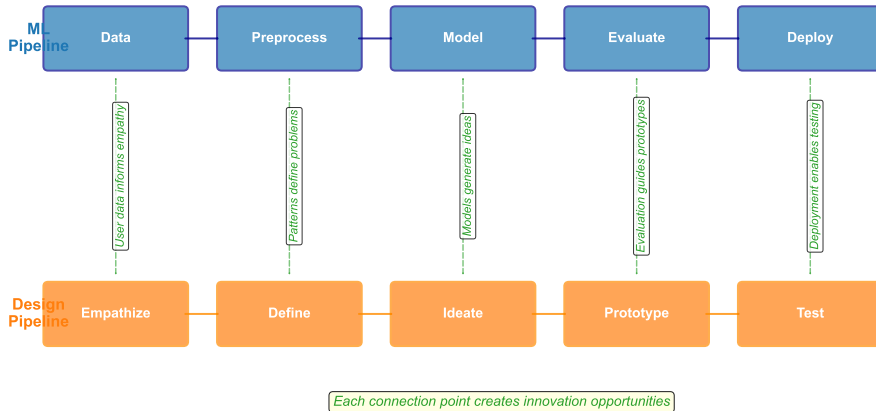
- **Scale:** Analyze millions of data points
- **Speed:** Real-time insights
- **Objectivity:** Data-driven discovery
- **Patterns:** Find non-obvious relationships
- **Iteration:** Continuous learning

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

The Dual Pipeline

Where ML Meets Design Thinking

The Convergence: ML Meets Design Thinking



The Dual Pipeline (Continued)

Understanding Both Worlds

ML Pipeline

Data → Preprocess → Model → Evaluate → Deploy

- Collect innovation data
- Clean and transform
- Train algorithms
- Validate accuracy
- Scale to production

Design Pipeline

Empathize → Define → Ideate → Prototype → Test

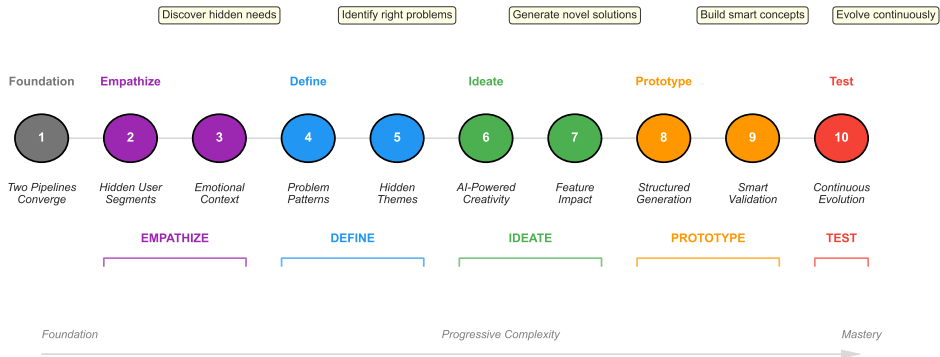
- Understand innovation needs
- Frame problems
- Generate solutions
- Build concepts
- Validate innovation impact

Integration = Innovation at Scale

Your Innovation Journey

10 Weeks to Understanding AI-Powered Design

10-Week Innovation Journey



Your Innovation Journey (Continued)

What You'll Learn in Each Stage

Innovation Stages

Discover (Weeks 1-2)

Find hidden innovation opportunities

Define (Weeks 3-4)

Identify the right problems to solve

Ideate (Weeks 5-6)

Generate novel solutions with AI

Building Innovation Skills

Prototype (Weeks 7-8)

Build smart, adaptive concepts

Test (Weeks 9-10)

Evolve through continuous learning

This Week:

Clustering for Innovation Pattern Discovery

What We'll Learn:

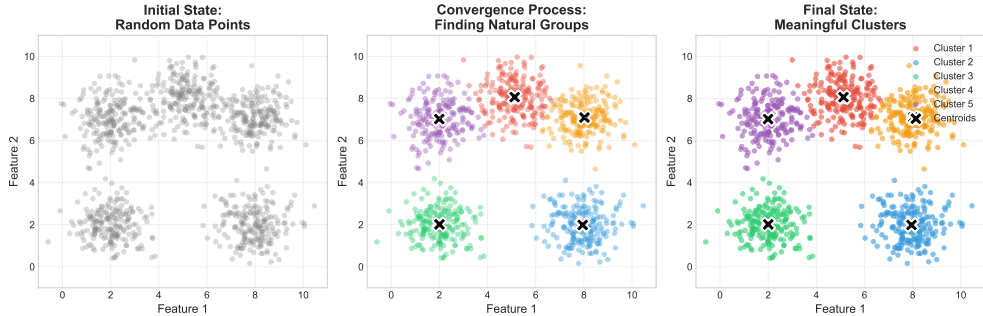
- How clustering reveals innovation categories
- K-means algorithm fundamentals
- Finding the optimal number of clusters
- Quality metrics for validation
- Advanced clustering techniques

Design Applications:

- Create innovation archetypes
- Map innovation evolution paths
- Identify opportunities systematically
- Prioritize design efforts
- Scale analysis to thousands of ideas

Goal: Transform scattered ideas into innovation patterns

The Convergence Flow: From Chaos to Clarity



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

Check Your Understanding - Part 1

Quick Knowledge Check

Progress: 1/3

True or False?

- ❶ Clustering requires labeled data (F)
- ❷ ML can process more data than humans (T)
- ❸ Design thinking has 5 stages (T)
- ❹ Clustering finds hidden patterns (T)

Can You Explain?

- What is the dual pipeline approach?
- Why combine ML with design thinking?
- What problem does clustering solve?

Ready for Part 2? Let's dive into the technical details!

Next: Clustering algorithms, evaluation metrics, and implementation

We've seen the challenge:

Thousands of innovation ideas with hidden connections

Traditional approach:

Manual segmentation based on demographics

The ML solution:

Let the data reveal its own natural groups

Enter: Clustering Algorithms

PART 2

Technical Core

What we'll learn:

- K-means clustering algorithm
- Finding optimal K with elbow method
- Distance metrics and quality measures
- Advanced techniques (DBSCAN, Hierarchical)
- Feature importance analysis

Learning the basics step by step

Part 2: Learning Objectives

Technical Skills You'll Develop

By the end of Part 2, you will understand:

- **How** K-means clustering works
- **What** the elbow method shows us
- **Why** we measure distances
- **How to check** if clusters are good
- **Differences** between algorithms
- **When to use** each method

Practical Skills

- Use K-means step by step
- Understand quality scores
- Pick the right algorithm
- Adjust settings properly
- Work with different patterns
- Prepare data for analysis

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

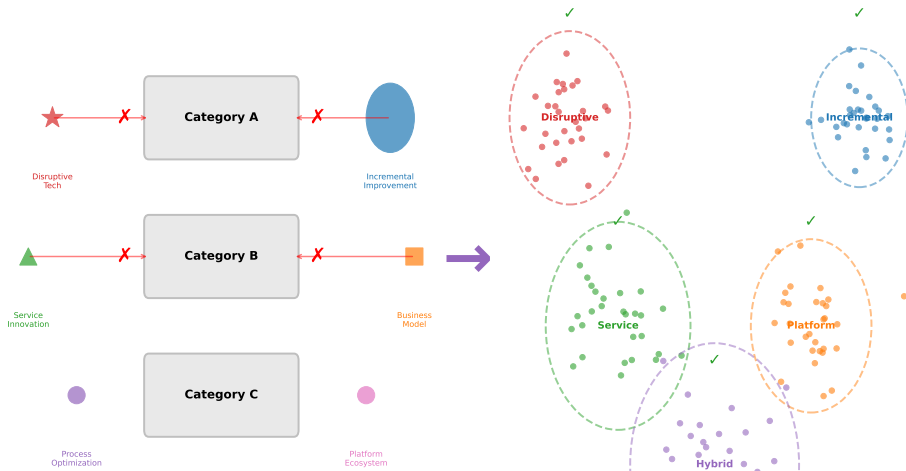
Current Reality: The Problem

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

The Problem with One-Size-Fits-All Innovation Categories

Current Reality: Generic Categories

ML Solution: Natural Clusters



Core Innovation Types

Disruptive Innovation

Completely new approaches that reshape markets

Incremental Innovation

Step-by-step improvements to existing solutions

Service Innovation

New ways to deliver value to customers

Emerging Patterns

Business Model Innovation

New ways to create and capture value

Process Innovation

Better ways to produce and deliver

Platform Innovation

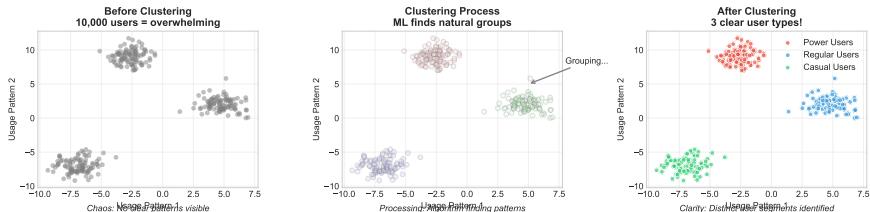
Creating ecosystems for innovation

Clustering will reveal which type each idea belongs to

What is Clustering?

Like Organizing a Messy Room - Finding Things That Belong Together

From Chaos to Clarity Through Clustering



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)

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

Initial Setup - Like Choosing City Centers

Steps 1-2: Setup

Step 1: Choose K

- Decide number of clusters
- Based on domain knowledge
- Or use elbow method

Step 2: Initialize Centroids

- Place K random points
- These are initial cluster centers
- Random but spread out

Key Decision: How many groups make sense?



Visualization: Initial random centroids placed

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

Iteration Process - Finding Natural Groups

Steps 3-5: Iterate

Step 3: Assign Points

- Calculate distance to each centroid
- Assign to nearest centroid
- Forms initial clusters

Step 4: Update Centroids

- Calculate mean of each cluster
- Move centroid to that mean
- Centers shift to better positions

Step 5: Check Convergence

- Repeat steps 3-4
- Stop when centroids don't move
- Usually 5-10 iterations



Iteration 1 → 3 → 5 → **Converged**

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)

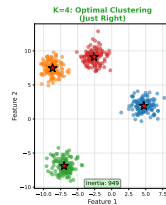
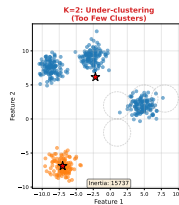
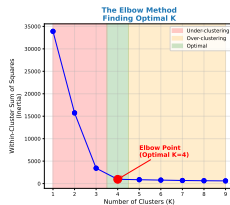
Finding the Elbow:

- Plot inertia vs K
- Look for the “elbow”
- Balance between:
 - Too few: Mixed groups
 - Too many: Overfitting

Optimal K = 5

Best trade-off between simplicity and accuracy

The Elbow Method: Finding the Right Number of Clusters

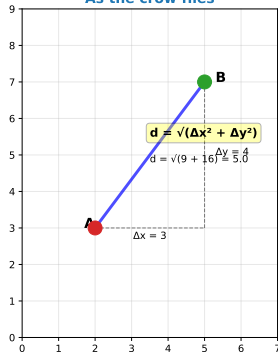


Distance Metrics

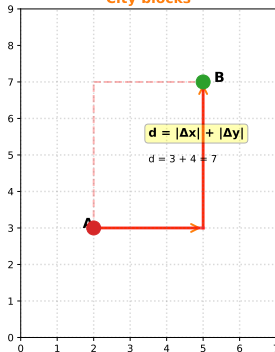
Different Ways to Measure "How Close" Things Are

Distance Metrics: How We Measure "Closeness"

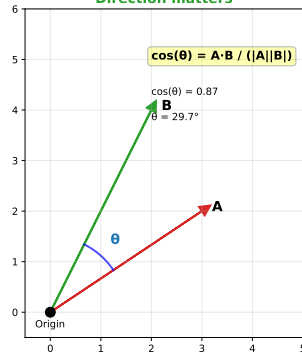
Euclidean Distance
"As the crow flies"



Manhattan Distance
"City blocks"



Cosine Similarity
"Direction matters"

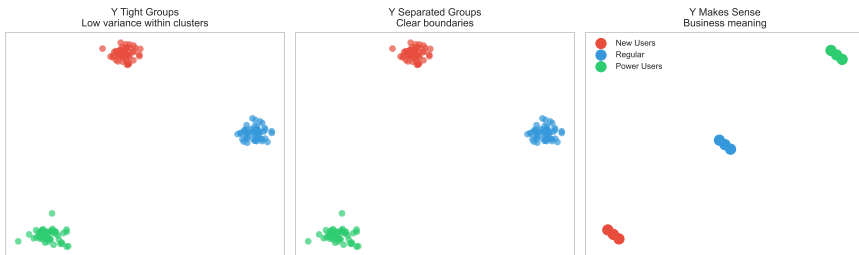


Each metric reveals different patterns in your data

Cluster Quality Metrics

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

Three Checks for Good Clusters



Silhouette Score:

- Ranges from -1 to +1
- Higher = better separation
- Our score: **0.73**

0.73 = Strong clusters!

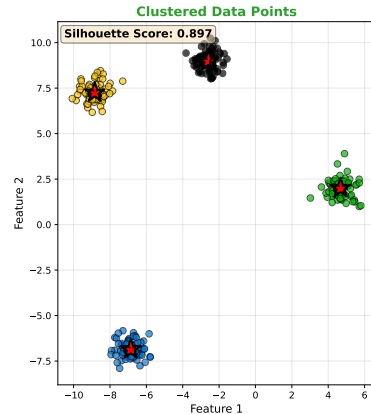
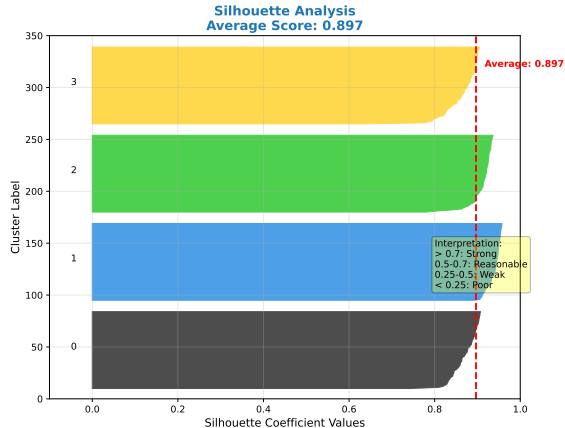
What it measures:

- Within-cluster cohesion
- Between-cluster separation
- Overall cluster validity

Evaluation Metric 1: Silhouette Score

Measuring Cluster Cohesion and Separation

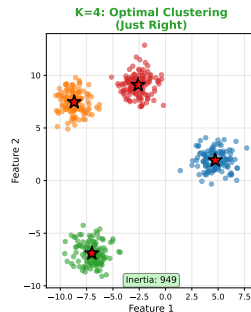
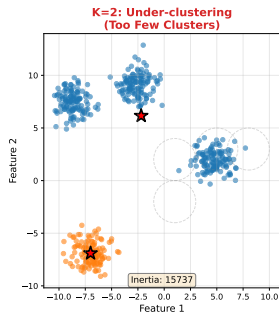
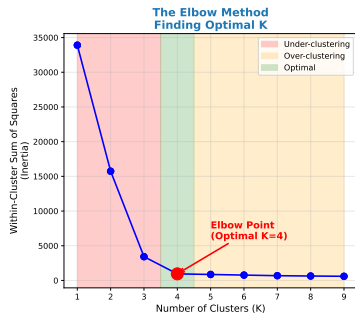
Silhouette Score: Measuring Cluster Cohesion and Separation



Evaluation Metric 2: Elbow Method

Finding the Right Number of Clusters

The Elbow Method: Finding the Right Number of Clusters

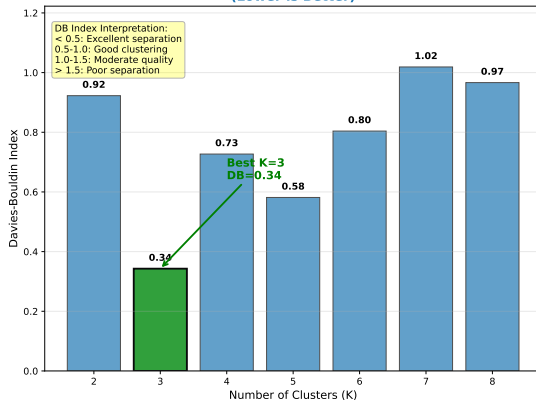


Evaluation Metric 3: Davies-Bouldin Index

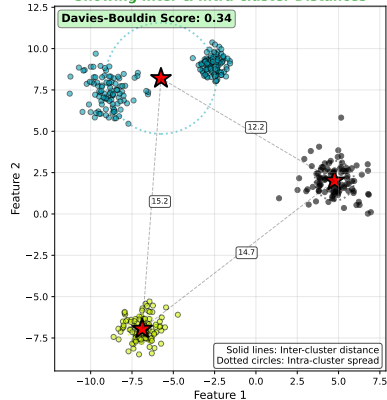
Balancing Within and Between Cluster Distances

Davies-Bouldin Index: Balancing Cluster Separation and Cohesion

Davies-Bouldin Index
(Lower is Better)



Cluster Visualization (K=3)
Showing Inter & Intra-cluster Distances



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

DBSCAN: Finding Groups Naturally

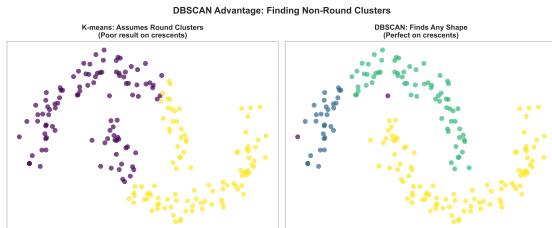
Like Finding Groups of People at a Party - Where Are the Crowds?

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

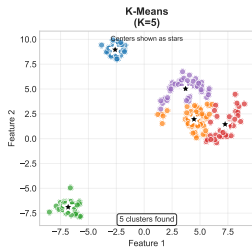
Perfect when:

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

Algorithm Visual Comparison

Same Data, Different Approaches

Clustering Algorithms Visual Comparison Same Data, Different Approaches

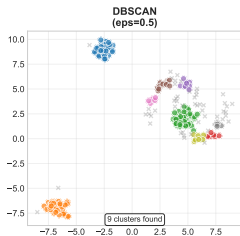


K-Means (K=5)

- ☐ Fast and scalable
- ☐ Spherical clusters
- ☐ Fixed K required
- ☐ Sensitive to outliers

Best for: Quick segmentation
with known cluster count

Complexity: $O(nkt)$

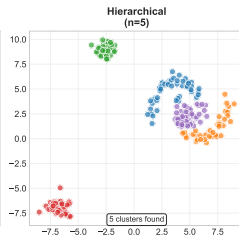


DBSCAN (eps=0.5)

- ☐ Finds arbitrary shapes
- ☐ Identifies outliers
- ☐ No K needed
- ☐ Sensitive to parameters

Best for: Anomaly detection
and irregular patterns

Complexity: $O(n \log n)$

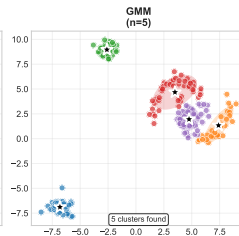


Hierarchical (n=5)

- ☐ Dendrogram output
- ☐ No K needed initially
- ☐ Interpretable
- ☐ Computationally expensive

Best for: Taxonomies and
exploring relationships

Complexity: $O(n^3)$



GMM (n=5)

- ☐ Soft assignments
- ☐ Elliptical clusters
- ☐ Probabilistic
- ☐ Assumes Gaussian distribution

Best for: Overlapping groups
and uncertainty modeling

Complexity: $O(nkt)$

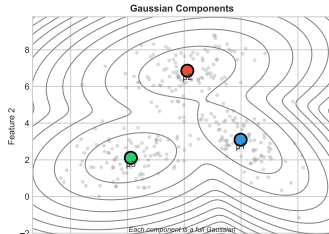
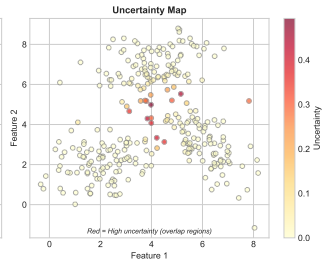
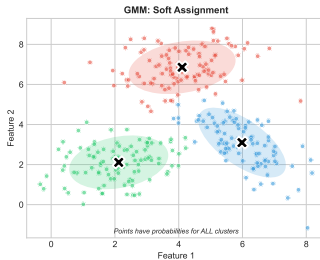
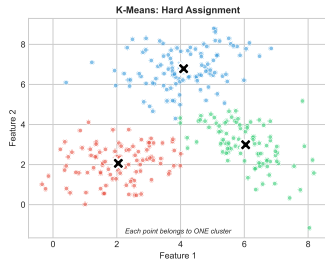
Dataset: Mix of 3 Gaussian blobs and 2 moon-shaped clusters (250 points total)

Gaussian Mixture Models (GMM)

Soft Clustering for Overlapping Innovation Categories

Gaussian Mixture Models (GMM): Soft Clustering for Innovation

Beyond Hard Boundaries: Probabilistic Innovation Classification



GMM vs K-means

- GMM Advantages:**
- Soft assignments (probabilities)
 - Captures cluster shape (elliptical)
 - Handles overlapping clusters
 - Provides uncertainty estimates
 - Models data generation process

- K-means Advantages:**
- Faster computation
 - Simpler interpretation
 - Less parameters
 - More stable results
 - Works well for spherical clusters

- When to use GMM:**
- Overlapping innovation categories
 - Need probability scores
 - Non-spherical clusters
 - Uncertainty quantification needed

Innovation Category Probabilities

Innovation	Tech	Service	Social
AI Assistant	0.85	0.10	0.05
Sharing Platform	0.30	0.45	0.25
Green Energy	0.60	0.15	0.25
Digital Health	0.40	0.50	0.10

GMM provides probability of belonging to each category

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

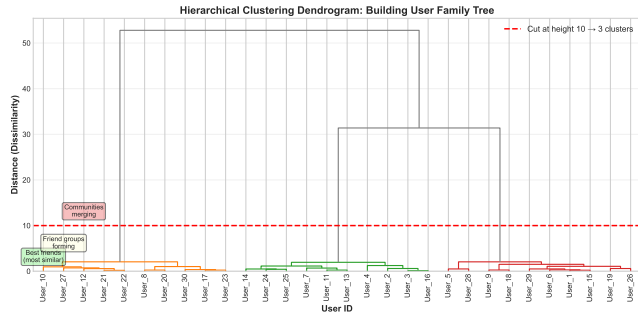
Building a Tree of Relationships

Dendrogram Benefits:

- Shows cluster hierarchy
- Multiple granularities
- Natural relationships
- No preset K needed

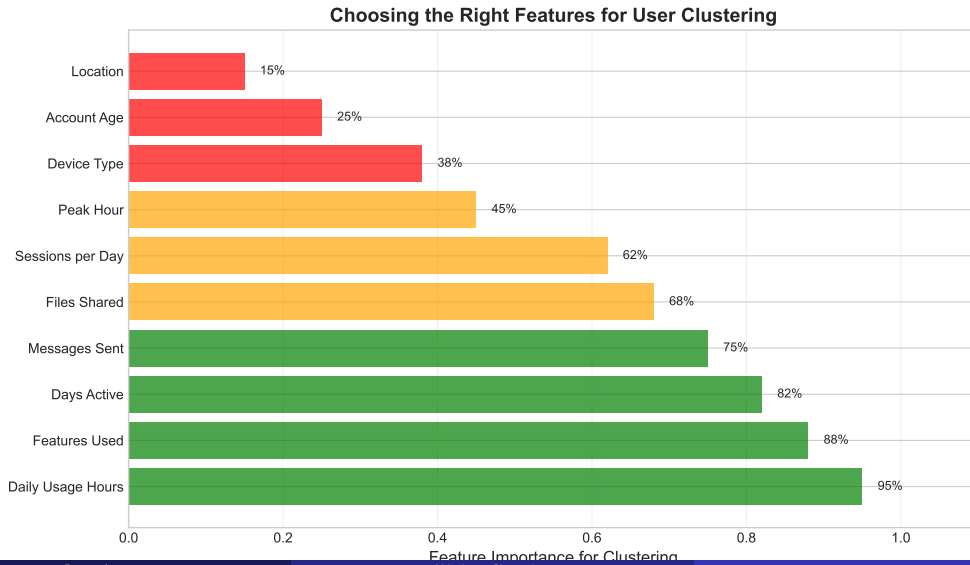
Cut the tree at any level:

- High cut = Few clusters
- Low cut = Many clusters
- Choose based on needs



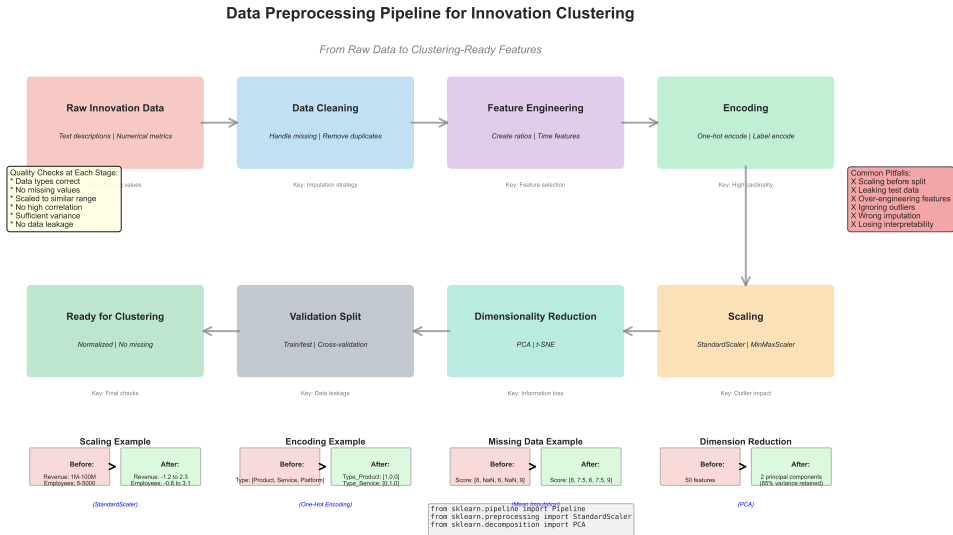
What Drives the Clusters?

Feature Importance Analysis



Data Preprocessing Pipeline

From Raw Data to Clustering-Ready Features



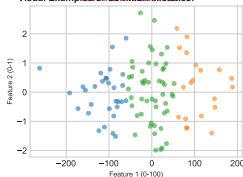
Common Mistakes & Troubleshooting

Learn from These Pitfalls

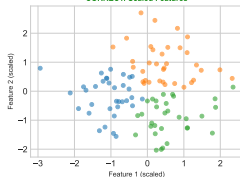
Common Clustering Mistakes & Troubleshooting Guide

Learn from These Mistakes to Master Clustering

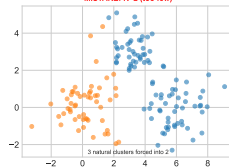
Visual Examples of Common Mistakes:



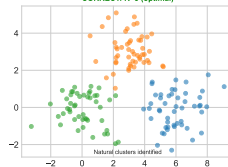
CORRECT: Scaled Features



MISTAKE: K=2 (too few)



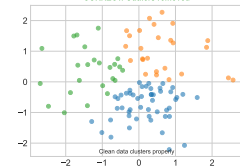
CORRECT: K=3 (optimal)



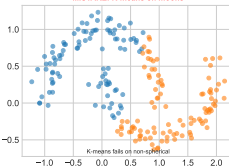
MISTAKE: Outliers distort



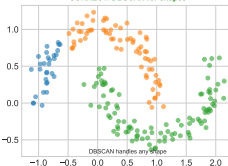
CORRECT: Outliers removed



MISTAKE: K-means on moons



CORRECT: DBSCAN for shapes



Troubleshooting Guide:

GOLDEN RULES:

1. Always scale your features
2. Visualize before clustering
3. Try multiple algorithms
4. Validate with domain knowledge
5. Check cluster stability

Problem

Low silhouette score

Different runs = different results

Takes too long to converge

WARNING SIGNS:

- * Silhouette < 0.3
- * Clusters change each run
- * Single point clusters
- * All points in one cluster

Symptoms

Try different K or algorithm

Set random_state, increase n_init

Reduce features, subsample data

Solution

Use elbow method

Use domain knowledge

Compare K-means

SUCCESS INDICATORS:

- * Silhouette > 0.5
- * Stable across runs
- * Balanced cluster sizes
- * Makes business sense

Parameter Tuning Guidelines

Recommended Ranges and Best Practices

Clustering Parameter Tuning Guidelines

Recommended Ranges, Methods, and Best Practices

K-Means

Parameter	Range	Default	Tuning Method
n_clusters (K)	2-10	3-5	Elbow/Silhouette
init	['k-means++', 'random']	Always k-means++	
n_init	10-100	10	More for stability
max_iter	100-1000	300	Increase if no convergence
tol	1e-6 to 1e-2	1e-4	Smaller for precision

Tuning Strategies

Grid Search

Pros: Exhaustive, Reproducible, Simple

Cons: Slow, Curse of dimensionality

Use when: Small parameter space

Random Search

Pros: Faster, Better for many params, Parallelizable

Cons: May miss optimum, Not reproducible

Use when: Large parameter space

Bayesian Opt

Pros: Efficient, Learns from history, Fewer iterations

Cons: Complex, Overhead for simple problems

Use when: Expensive evaluations

DBSCAN

Parameter	Range	Default	Tuning Method
eps	0.01-2.0	0.5	k-distance plot
min_samples	3-20	2*dims	Domain knowledge
metric	['euclidean', 'manhattan']	Data dependent	
algorithm	['auto', 'ball_tree']	Auto is fine	
leaf_size	10-50	30	Memory vs speed

Validation Metrics

Metric	Range	Interpretation	Use For
Silhouette	[-1, 1]	Higher is better	General quality
Davies-Bouldin	[0, ∞)	Lower is better	Cluster separation
Calinski-Harabasz	[0, ∞)	Higher is better	Dense clusters
Inertia	[0, ∞)	Lower is better	K-means only
BIC/AIC	{-∞, ∞}	Lower is better	GMM selection

GMM

Parameter	Range	Default	Tuning Method
n_components	2-10	3-5	BIC/AIC
covariance_type	['full', 'diag', 'spherical']	Start full, simplify	
max_iter	50-500	100	Monitor convergence
n_init	1-10	1	More for stability
init_params	['kmeans', 'random']	kmeans faster	

Tuning Best Practices

1. Start with defaults, then tune
2. Use cross-validation when possible
3. Consider computational budget
4. Log all experiments
5. Visualize parameter effects
6. Use domain knowledge
7. Check stability across runs
8. Don't overfit to metrics

IMPORTANT:
No metric is perfect!
Always validate with:
• Visual inspection
• Domain expertise
• Business goals

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

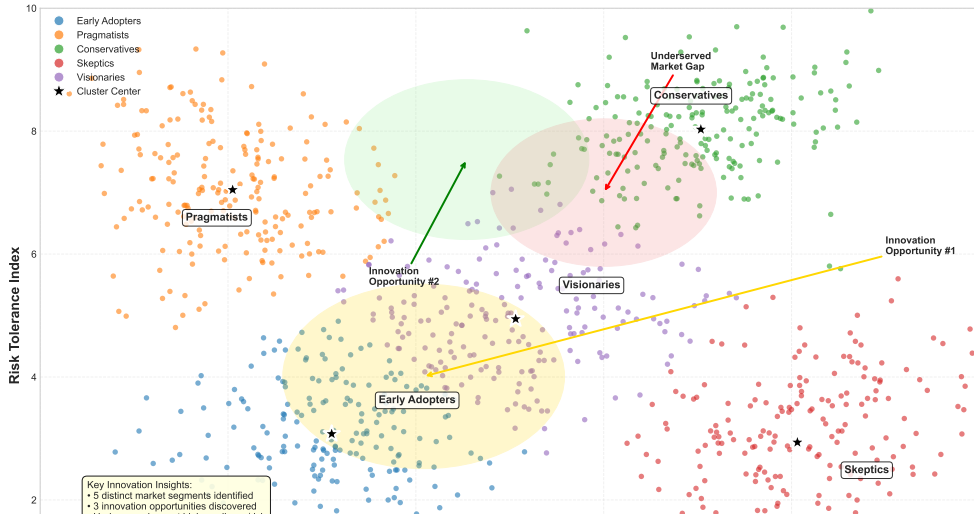
Design Integration

Bridging Technology & Human Experience

From Data Points to Innovation Insights

Bridging the Technical-Human Gap

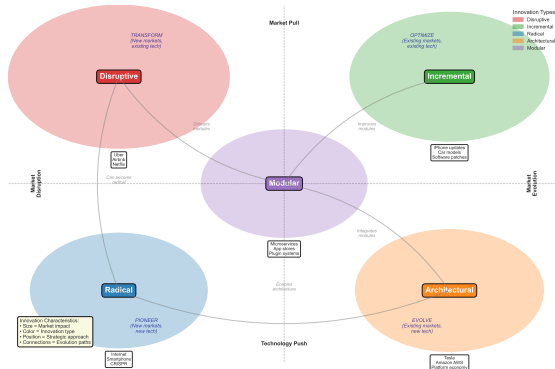
Innovation Pattern Discovery Through Clustering Revealing Hidden Market Opportunities



AI-Generated Innovation Archetypes

Data-Driven Character Development and Pattern Mapping

Innovation Archetypes Discovery
Five Distinct Patterns from Clustering Analysis

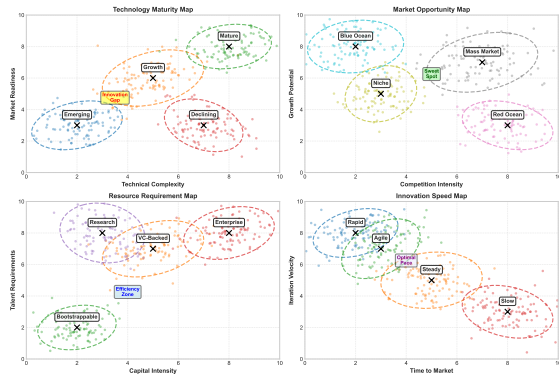


Innovation Types:

- Disruptive Innovation
- Incremental Improvement
- Platform-Based

Part 0/4

Innovation Pattern Maps
Four Perspectives on Innovation Categories



Key Insight: Each map reveals different opportunity zones where innovation categories intersect

Pattern Insights:

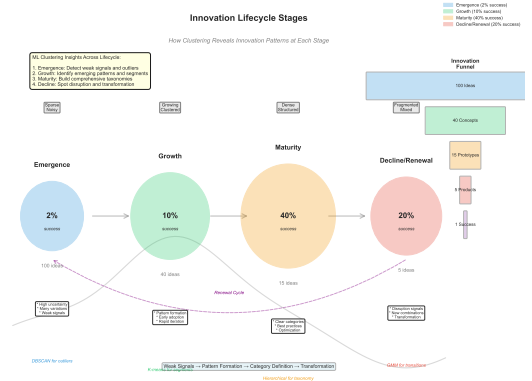
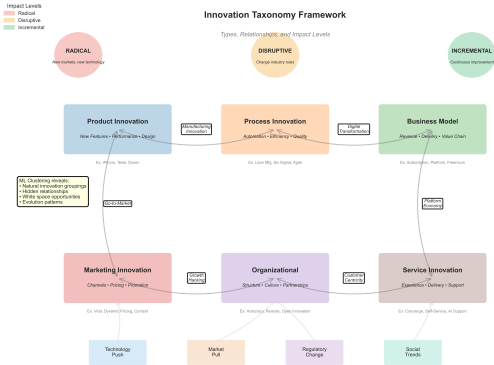
- Each cluster's unique traits
- Innovation velocity differences

Week 1: Clustering

Slide 52 of 80

Innovation Framework

Taxonomy and Lifecycle Stages



Framework Levels:

- Types & relationships
- Impact measurements
- Strategic positioning

Part 0/4

Lifecycle Stages:

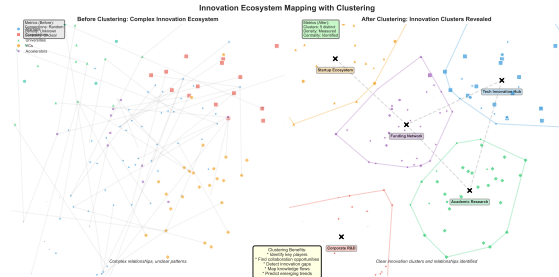
- Ideation & discovery
- Development & testing
- Launch & scaling

Week 1: Clustering

Slide 53 of 80

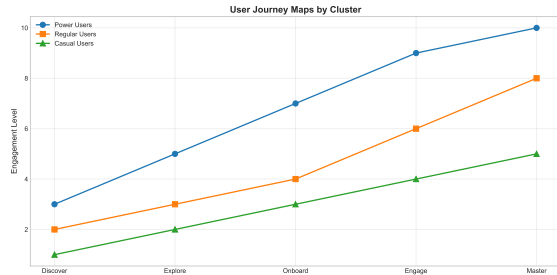
Innovation Ecosystem & Journey Mapping

From Networks to Evolution Paths



Ecosystem Elements:

- Network connections
- Stakeholder clusters
- Value flows

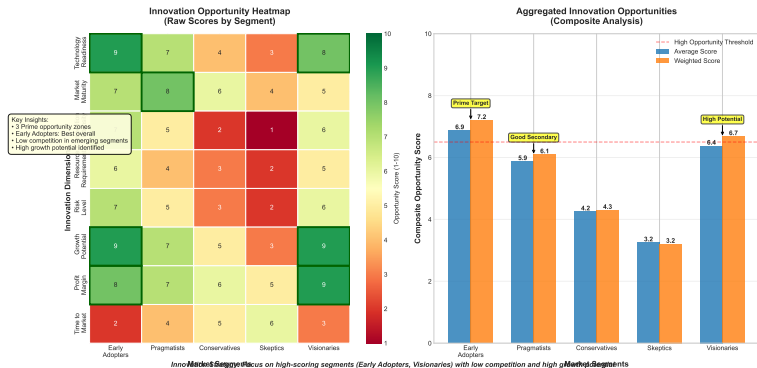


Evolution Paths:

- Different speeds
- Varying trajectories
- Unique milestones

Innovation Opportunities by Cluster

Where Each Category Has Potential



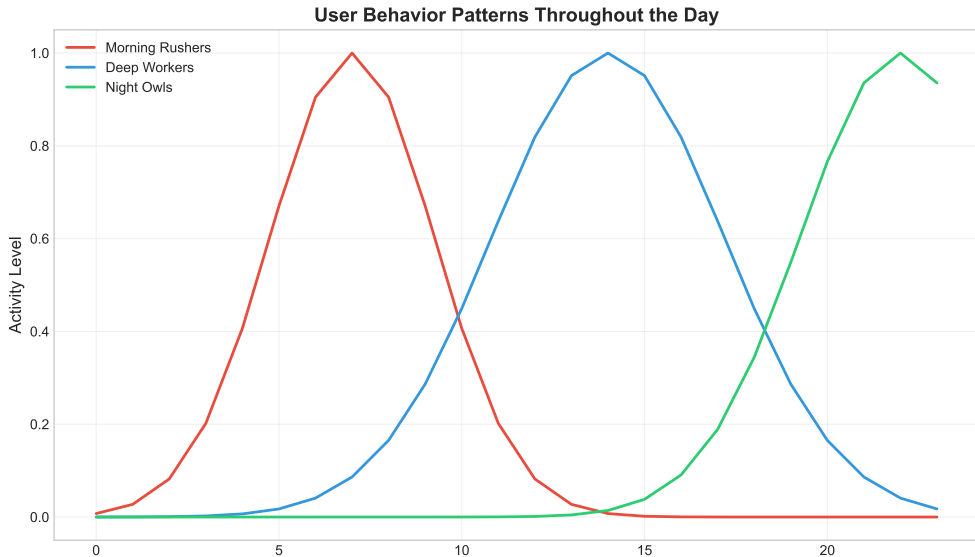
Key Findings:

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

Design implication:
One solution won't fit all!

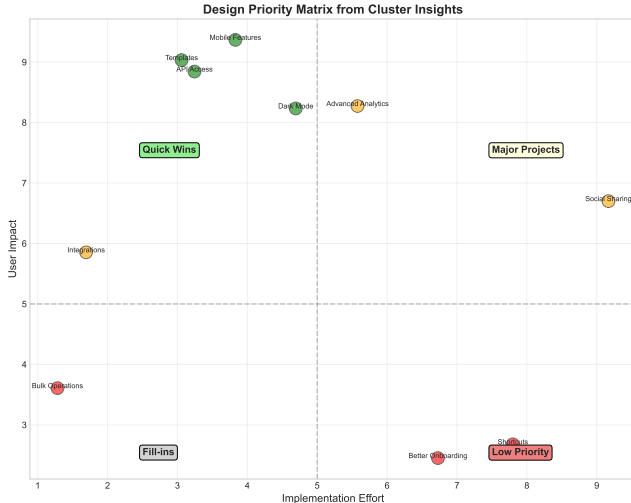
Innovation Patterns Revealed

What Clusters Tell Us About Evolution



Design Priority Matrix

Where to Focus Your Efforts



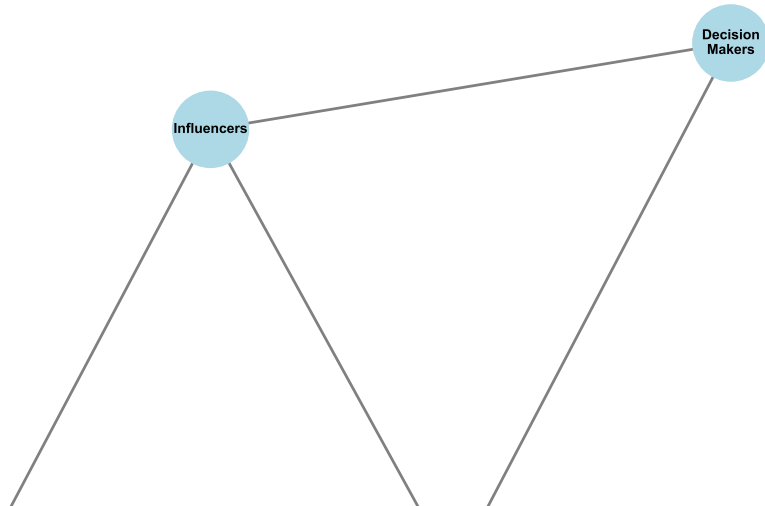
Priority Quadrants:

- **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

Stakeholder Network from Cluster Analysis



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

PART 4

Summary & Practice

What we'll do:

- See real-world success patterns
- Consolidate key learnings
- Practice with exercises
- Preview next week
- Explore resources

From learning to doing

PART 4

Summary & Practice

Real-World Applications & Next Steps

How Clustering is Used

Common Applications and Results

Clustering in Real-World Applications



Academic Applications:

- Student performance analysis (*grouping by learning styles*)
- Research paper categorization (*organizing by topics*)
- Course recommendation systems (*matching students to courses*)
- Exam question classification (*grouping by difficulty*)

Benefits You'll See:

- Better understanding of patterns
- Faster data analysis
- More accurate groupings
- Clearer insights from data

Key Takeaways

What We've Learned

Technical Skills

- K-means clustering algorithm
- Choosing optimal K with elbow method
- Silhouette scores for validation
- DBSCAN for complex shapes
- Hierarchical clustering

Design Applications

- Data-driven innovation archetypes
- Segment-specific journeys
- Opportunity identification
- Priority matrices
- Scaled innovation analysis

Clustering transforms data into actionable innovation insights

Implementation Checklist

Ensuring Successful Clustering Projects

Data Preparation

- ☐ Collect relevant features
- ☐ Handle missing values
- ☐ Standardize/normalize data
- ☐ Remove outliers if needed
- ☐ Feature engineering complete
- ☐ Data quality verified

Quality Assurance

- ☐ Silhouette score ≥ 0.5
- ☐ Cluster sizes balanced
- ☐ Visual inspection done
- ☐ Stability tested
- ☐ Business sense verified
- ☐ Edge cases handled

Algorithm Selection

- ☐ Choose distance metric
- ☐ Select clustering method
- ☐ Determine optimal K
- ☐ Validate with metrics

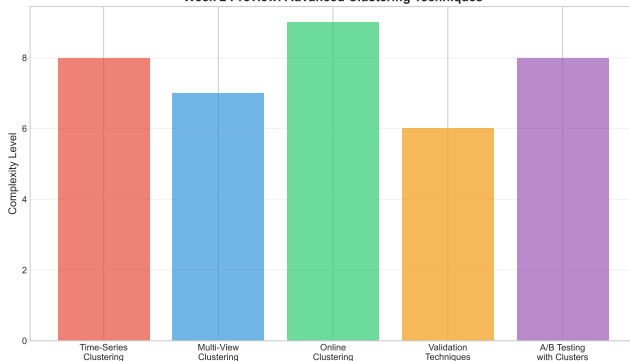
Common Pitfalls

- × Forgetting to scale features
- × Wrong distance metric
- × Forcing unnatural K
- × Ignoring outliers

Next Week: Advanced Clustering

Going Deeper into Innovation Patterns

Week 2 Preview: Advanced Clustering Techniques



Week 2 Topics:

- Density-based clustering
- Gaussian mixture models
- Clustering validation
- Feature engineering
- Real-time clustering

Design Focus:

- Dynamic innovation tracking
- Evolving innovation landscapes
- Predictive opportunity analysis
- Micro-innovation detection

Technical Resources

Papers:

- MacQueen, J. (1967). K-means
- Ester et al. (1996). DBSCAN
- Rousseeuw (1987). Silhouettes

Tools:

- scikit-learn clustering
- Orange data mining
- KNIME analytics

Design Resources

Books:

- “Design Thinking” - Tim Brown
- “Sprint” - Jake Knapp
- “Lean UX” - Jeff Gothelf

Applications:

- Miro (journey mapping)
- Figma (archetype creation)
- Optimal Workshop

Questions? Let's discuss!

Clustering Algorithms:

- **K-Means:** Partitions data into K predefined clusters
- **DBSCAN:** Density-based spatial clustering
- **Hierarchical:** Builds cluster tree (dendrogram)
- **GMM:** Gaussian Mixture Models, soft clustering

Key Parameters:

- **K:** Number of clusters
- **eps:** Neighborhood radius (DBSCAN)
- **min_samples:** Minimum points for density
- **n_init:** Number of random initializations

Evaluation Metrics:

- **Silhouette:** Cluster cohesion vs separation $[-1,1]$
- **Inertia:** Sum of squared distances to centroids
- **Davies-Bouldin:** Ratio of within to between distances
- **Calinski-Harabasz:** Ratio of dispersions

Innovation Terms:

- **Empathy Mapping:** Understanding user perspectives
- **Pain Points:** User problems/frustrations
- **User Archetypes:** Representative user groups
- **Innovation Ecosystem:** Connected stakeholders

Implementation Checklist

Your Step-by-Step Guide to Success

Data Preparation:

- ☐ Collect innovation feedback data
- ☐ Clean and remove duplicates
- ☐ Handle missing values
- ☐ Normalize/standardize features
- ☐ Create feature vectors

Algorithm Selection:

- ☐ Analyze data distribution
- ☐ Choose appropriate algorithm
- ☐ Set initial parameters
- ☐ Prepare validation strategy

Implementation:

- ☐ Run clustering algorithm
- ☐ Calculate evaluation metrics
- ☐ Visualize results (PCA/t-SNE)
- ☐ Validate with domain experts
- ☐ Iterate and refine

Innovation Application:

- ☐ Map clusters to user personas
- ☐ Identify innovation opportunities
- ☐ Create targeted solutions
- ☐ Design prototype features
- ☐ Test with user groups

Ready? Start with data preparation and work your way down!

Appendix: K-Means Mathematics (Optional)

The Mathematical Foundation - For Those Interested

What K-means tries to minimize:

$$J = \sum_{i=1}^n \sum_{j=1}^k w_{ij} ||x_i - \mu_j||^2$$

In simple terms: Make points close to their group centers

Where:

- n = number of data points
- k = number of clusters
- $w_{ij} = 1$ if x_i belongs to cluster j , 0 otherwise
- μ_j = centroid of cluster j

Update Rules:

- 1 Assignment: $c^{(i)} = \arg \min_j ||x^{(i)} - \mu_j||^2$
- 2 Update: $\mu_j = \frac{1}{|S_j|} \sum_{i \in S_j} x^{(i)}$

Appendix: Distance Metrics (Optional)

Different Ways to Measure "How Far Apart" Things Are

Euclidean Distance:

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

Manhattan Distance:

$$d(x, y) = \sum_{i=1}^n |x_i - y_i|$$

Minkowski Distance:

$$d(x, y) = \left(\sum_{i=1}^n |x_i - y_i|^p \right)^{1/p}$$

Cosine Similarity:

$$\cos(\theta) = \frac{x \cdot y}{||x|| \cdot ||y||}$$

Jaccard Distance:

$$J(A, B) = 1 - \frac{|A \cap B|}{|A \cup B|}$$

Mahalanobis Distance:

$$d(x, y) = \sqrt{(x - y)^T S^{-1} (x - y)}$$

Appendix: Silhouette Score Explained

How We Know If Groups Are Good

Silhouette Score for point i :

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

Where:

- $a(i)$ = average distance to points in same cluster
- $b(i)$ = average distance to points in nearest neighbor cluster

Interpretation:

- $s(i) \approx 1$: Well clustered
- $s(i) \approx 0$: On border between clusters
- $s(i) \approx -1$: Misclassified

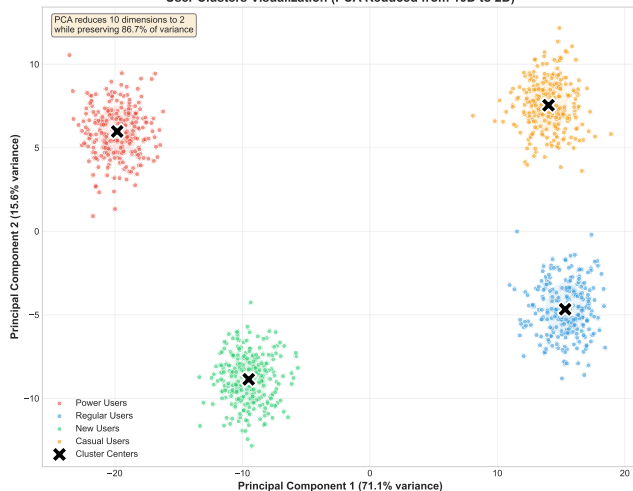
Overall Score:

$$S = \frac{1}{n} \sum_{i=1}^n s(i)$$

Appendix: Visualizing High-Dimensional Data

Making Complex Data Viewable in 2D

User Clusters Visualization (PCA Reduced from 10D to 2D)



PCA Process:

- 1 Standardize data
- 2 Compute covariance matrix
- 3 Find eigenvectors/values
- 4 Select top 2 components
- 5 Transform data

Variance Explained:

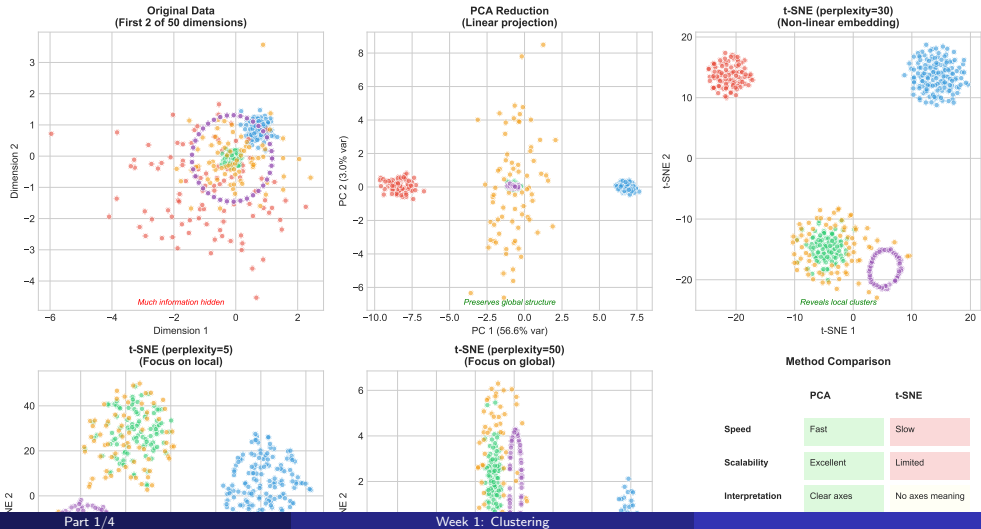
- PC1: 45.2%
- PC2: 28.7%
- Total: 73.9%

Dimensionality Reduction: PCA vs t-SNE

Revealing Hidden Patterns in High-Dimensional Innovation Space

Dimensionality Reduction: PCA vs t-SNE for Innovation Data

Revealing Hidden Patterns in High-Dimensional Innovation Space



Appendix: How DBSCAN Works

Finding Groups Based on How Close Points Are

Key Parameters:

- ϵ (eps): Maximum distance between points
- MinPts: Minimum points to form dense region

Point Classification:

- **Core point:** Has \geq MinPts within ϵ
- **Border point:** Within ϵ of core point
- **Noise point:** Neither core nor border

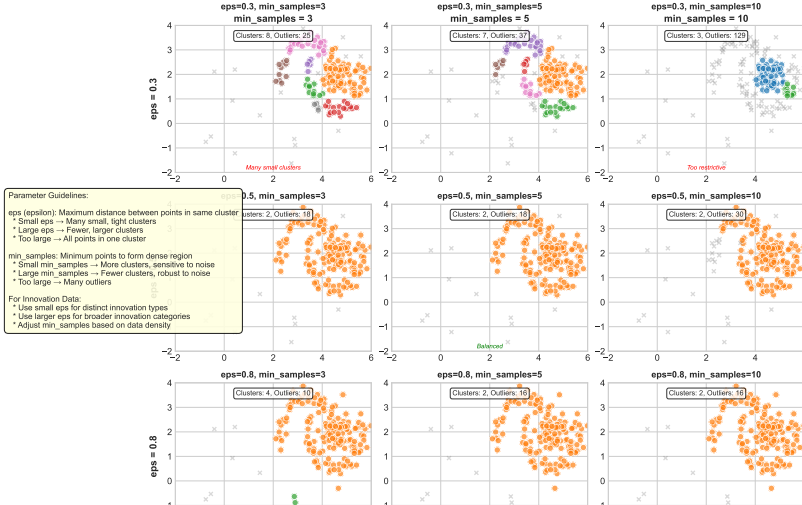
Algorithm Steps:

- 1 Find all core points
- 2 Form clusters from core points within ϵ
- 3 Assign border points to clusters
- 4 Mark remaining as noise

DBSCAN Parameter Tuning

Impact of eps and min_samples on Clustering Results

DBSCAN Parameter Tuning: Impact on Innovation Clustering



Appendix: Python Implementation

Ready-to-Use Code Snippets

K-Means Clustering

```
1 from sklearn.cluster import KMeans
2 import numpy as np
3
4 # Generate sample data
5 X = np.random.randn(1000, 2)
6
7 # Configure and fit K-means
8 kmeans = KMeans(
9     n_clusters=3,
10    random_state=42,
11    n_init=10
12 )
13 labels = kmeans.fit_predict(X)
14
15 # Get cluster centers
16 centers = kmeans.cluster_centers_
17
18 # Calculate inertia
19 inertia = kmeans.inertia_
```

DBSCAN Clustering

```
1 from sklearn.cluster import DBSCAN
2
3 # Configure DBSCAN
4 dbscan = DBSCAN(
5     eps=0.3,
6     min_samples=5,
7     metric='euclidean'
8 )
9
10 # Fit and predict
11 labels = dbscan.fit_predict(X)
12
13 # Analyze results
14 outliers = labels == -1
15 n_clusters = len(set(labels)) - 1
16
17 print(f"Clusters: {n_clusters}")
18 print(f"Outliers: {sum(outliers)}")
19 print(f"Coverage: {100*(1-sum(outliers)/len(labels)):.1f}%")
```

Appendix: Evaluation Metrics Code

Measuring Clustering Quality

Silhouette Analysis

```
1 from sklearn.metrics import silhouette_score
2 from sklearn.metrics import silhouette_samples
3
4 # Calculate overall score
5 score = silhouette_score(X, labels)
6 print(f"Silhouette Score: {score:.3f}")
7
8 # Per-sample scores
9 sample_scores = silhouette_samples(X, labels)
10
11 # Per-cluster average
12 for i in range(n_clusters):
13     cluster_scores = sample_scores[labels == i]
14     avg = cluster_scores.mean()
15     print(f"Cluster {i}: {avg:.3f}")
```

Finding Optimal K

```
1 # Elbow method
2 inertias = []
3 silhouettes = []
4 K_range = range(2, 10)
5
6 for k in K_range:
7     km = KMeans(n_clusters=k,
8                 random_state=42)
9     labels = km.fit_predict(X)
10
11     inertias.append(km.inertia_)
12     silhouettes.append(
13         silhouette_score(X, labels)
14     )
15
16 # Find elbow point
17 # Plot inertias vs K
18 # Choose K at elbow
```

Appendix: Implementation Guidelines

Practical Considerations

Data Preparation

- Standardize features
- Handle missing values
- Remove outliers (if needed)
- Feature selection/engineering
- Consider scaling methods

Validation Methods

- Silhouette score
- Davies-Bouldin index
- Calinski-Harabasz score
- Visual inspection
- Domain expert review

Algorithm Selection

- K-means: Spherical, similar size
- DBSCAN: Arbitrary shapes
- Hierarchical: Nested structure
- GMM: Overlapping clusters

Common Pitfalls

- Not scaling features
- Wrong distance metric
- Ignoring outliers
- Over-clustering
- Forcing clusters

Glossary of Technical Terms

Key Concepts Reference

Algorithms:

- **K-means:** Partitions data into K spherical clusters
- **DBSCAN:** Density-based clustering for arbitrary shapes
- **GMM:** Gaussian Mixture Models for soft clustering
- **Hierarchical:** Tree-based clustering approach

Metrics:

- **Silhouette:** Measures cluster separation (-1 to 1)
- **Inertia:** Sum of squared distances to centroids
- **Davies-Bouldin:** Ratio of within to between cluster distance

Concepts:

- **Centroid:** Center point of a cluster
- **Elbow Method:** Technique to find optimal K
- **Outlier:** Data point not belonging to any cluster
- **Convergence:** When algorithm stops improving

Preprocessing:

- **Standardization:** Zero mean, unit variance
- **Normalization:** Scale to [0,1] range
- **PCA:** Principal Component Analysis
- **t-SNE:** t-distributed Stochastic Neighbor Embedding