Machine Learning for Smarter Innovation

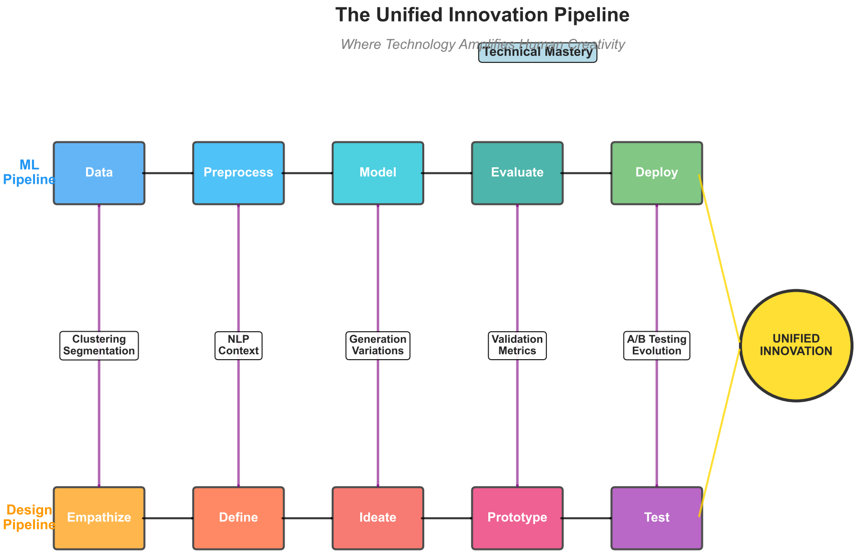
Week 1: Foundations & Clustering

Discovering Innovation Patterns with ML

BSc Course in AI-Enhanced Innovation

Machine Learning + Innovation + Design Thinking

The Power of Convergent Methodologies



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

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

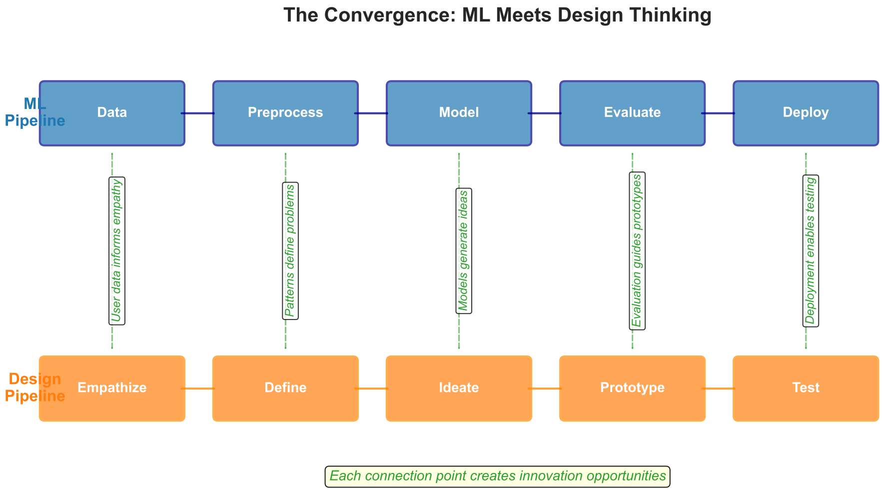
AI-Enhanced Innovation

- **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 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

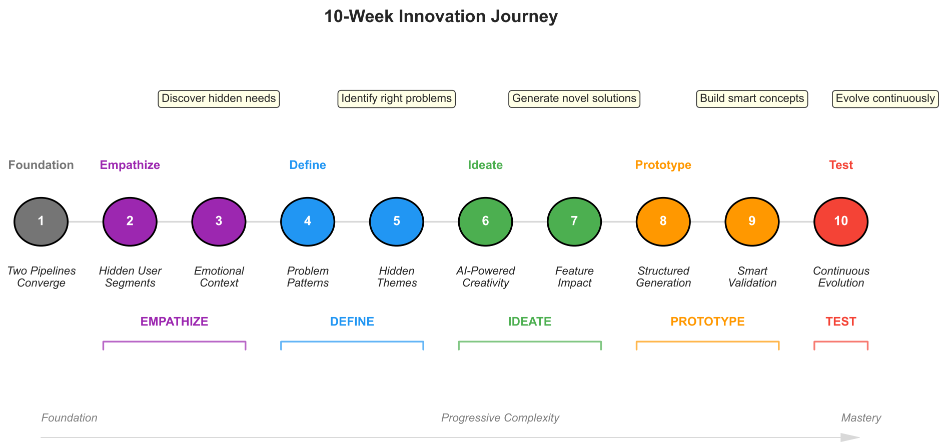
Empathize → Define → Ideate → Prototype → Test

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

Integration = Innovation at Scale

Your Innovation Journey

10 Weeks to AI-Powered Design Mastery



Your Innovation Journey (Continued)

What You'll Master in Each Stage

Stage	**Weeks**	**Innovation Unlocked**
Discover	1-2	Find hidden innovation opportunities
Define	3-4	Identify the right problems to solve
Ideate	5-6	Generate novel solutions with AI
Prototype	7-8	Build smart, adaptive concepts
Test	9-10	Evolve through continuous learning

This Week: Clustering for Innovation Pattern Discovery

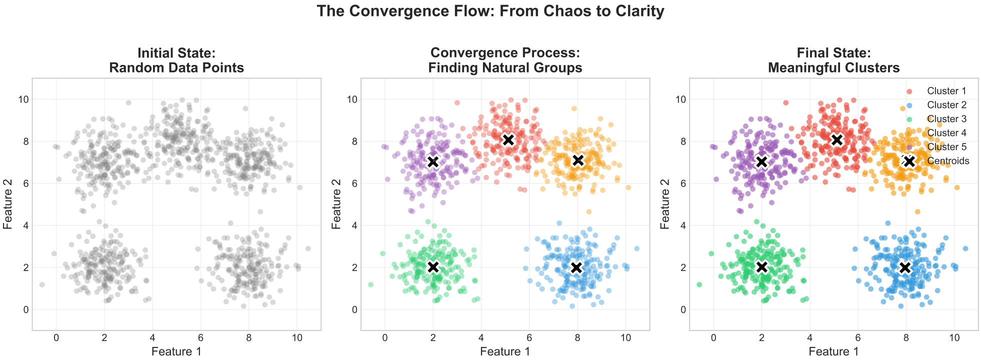
What We'll Learn:

- 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: Order from Chaos

Watch 5000 innovation ideas self-organize into meaningful patterns

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 master:

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

Building your ML toolkit

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!

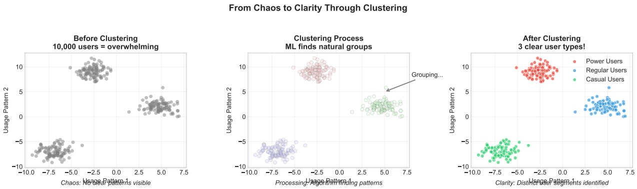
Solution: Clustering

What is Clustering?

Finding Natural Groups in Innovation Data

Clustering Finds:

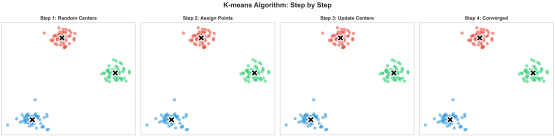
- Natural groupings
- Similar approaches
- Hidden patterns
- Innovation relationships



Key Insight:
Innovations with similar features address similar opportunities

The Process:

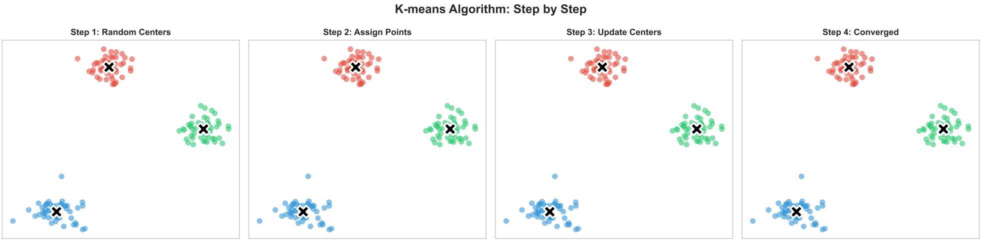
1. Choose K (number of clusters)
2. Place K random centroids
3. Assign points to nearest centroid
4. Move centroids to cluster mean
5. Repeat until stable



Strengths:

- Fast and scalable
- Easy to understand
- Works well for spherical clusters

K-Means in Action
Step-by-Step Convergence



Iteration 1 $\rightarrow$ Iteration 3 $\rightarrow$ Iteration 5 $\rightarrow$ **Converged**

The Goldilocks Problem

Too Few vs. Too Many Groups

Too Few (K

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?

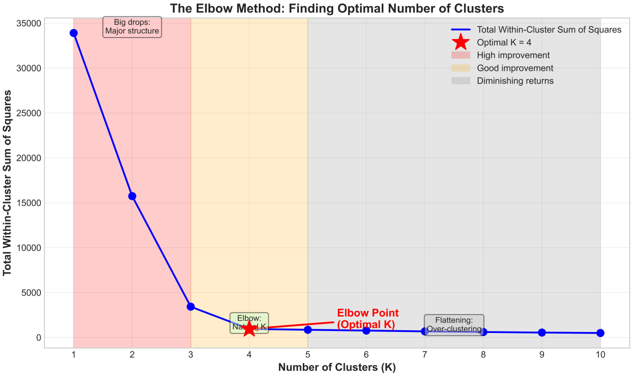
The Elbow Method

Finding the Optimal Number of Clusters

Finding the Elbow:

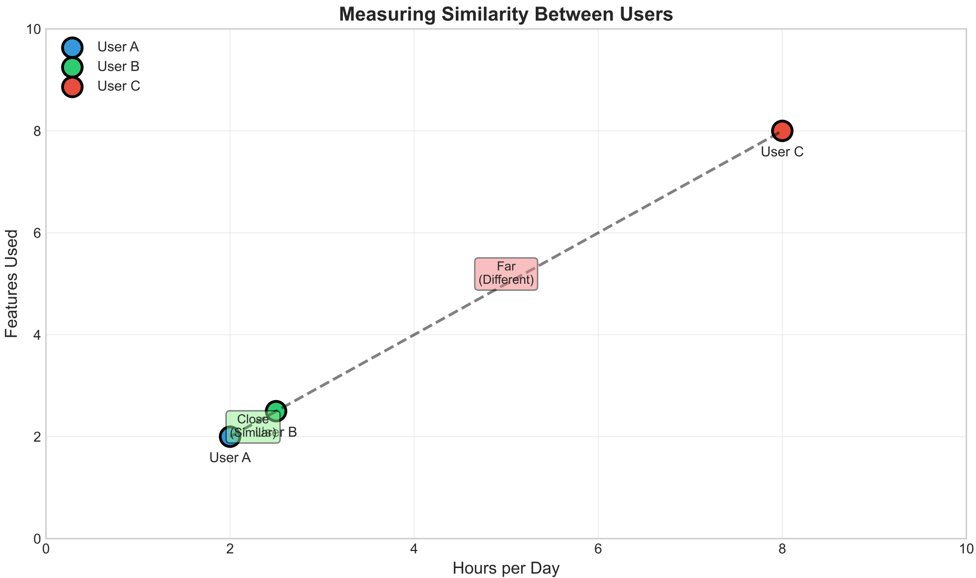
- Plot inertia vs K
- Look for the “elbow”
- Balance between:
    - Too few: Mixed groups
    - Too many: Overfitting

Optimal K = 5
Best trade-off between simplicity and accuracy



Distance Metrics

How We Measure Similarity



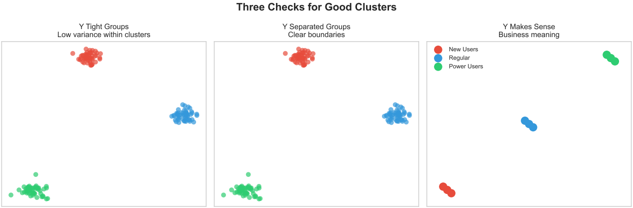
Silhouette Score:

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

What it measures:

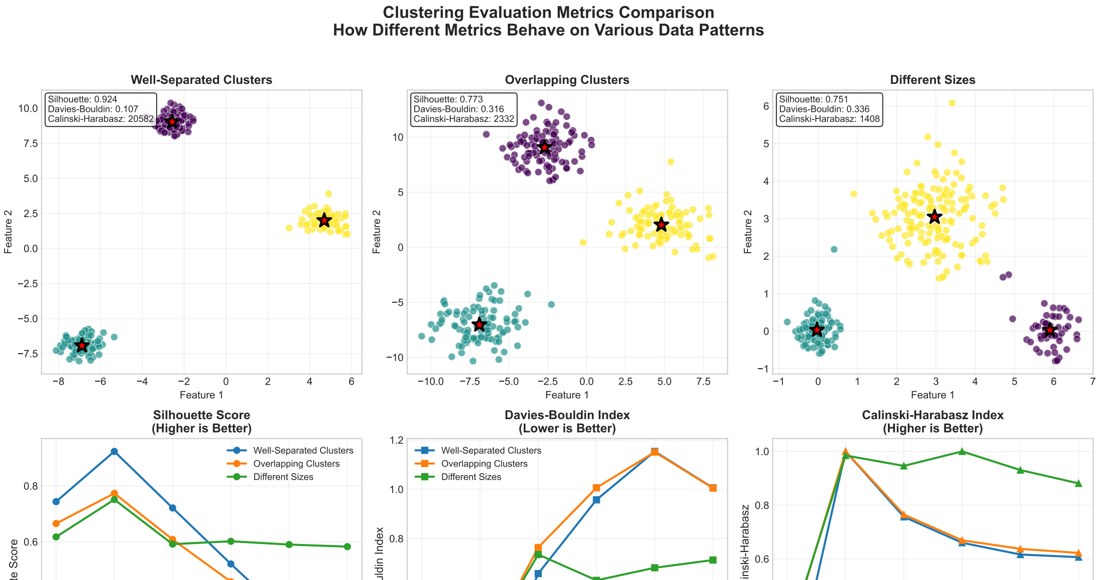
- Within-cluster cohesion
- Between-cluster separation
- Overall cluster validity

0.73 = Strong clusters!



Comparing Evaluation Metrics

Different Metrics for Different Data Patterns



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

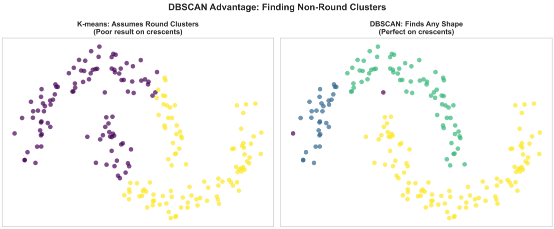
Solution: Density-Based Clustering

DBSCAN Advantages:

- No need to specify K
- Finds arbitrary shapes
- Identifies outliers
- Handles noise well

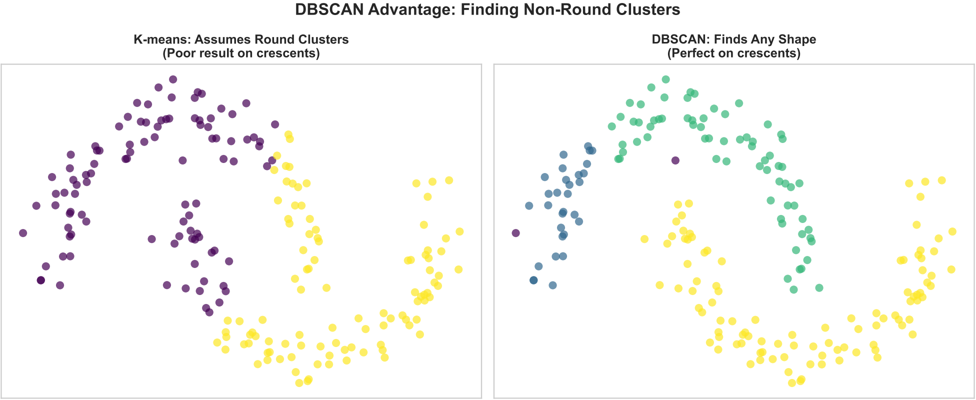
Perfect for:

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



DBSCAN: Complex Patterns

When K-Means Isn't Enough



K-Means: Forces spherical shapes — DBSCAN: Finds natural boundaries

Choosing the Right Algorithm

Comparison of Clustering Methods

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

Choose K-Means when:

- Speed is critical
- Clusters are roughly equal size
- You know K in advance

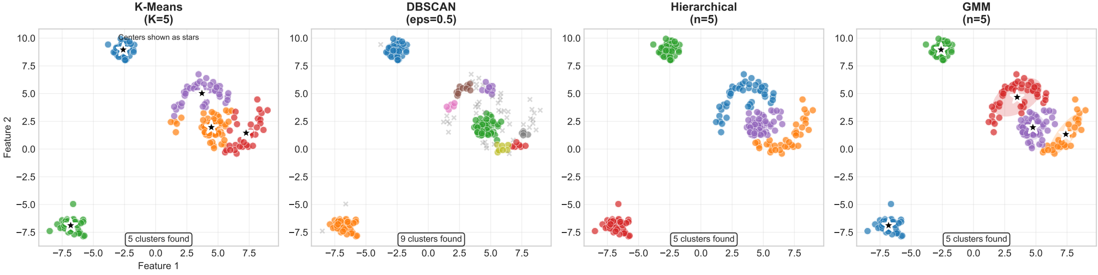
Choose DBSCAN when:

- Clusters have irregular shapes
- Outliers need identification
- Density varies across data

Algorithm Visual Comparison

Same Data, Different Approaches

Clustering Algorithms Visual Comparison
Same Data, Different Approaches



K-Means (K=5)	DBSCAN (eps=0.5)	Hierarchical (n=5)	GMM (n=5)
Fast and scalable Spherical clusters Fixed K required Sensitive to outliers	Finds arbitrary shapes Identifies outliers No K needed Sensitive to parameters	Dendrogram output No K needed initially Interpretable Computationally expensive	Soft assignments Elliptical clusters Probabilistic Assumes Gaussian distribution
Best for: Quick segmentation with known cluster count	*Best for: Anomaly detection and irregular patterns*	*Best for: Taxonomies and exploring relationships*	*Best for: Overlapping groups and uncertainty modeling*
Complexity: O(nkt)	Complexity: O(n log n)	Complexity: O(n²)	Complexity: O(nkt)

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

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?

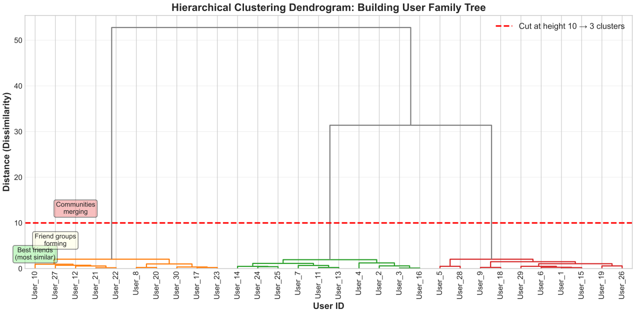
Solution: See the full hierarchy, cut where needed

Dendrogram Benefits:

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

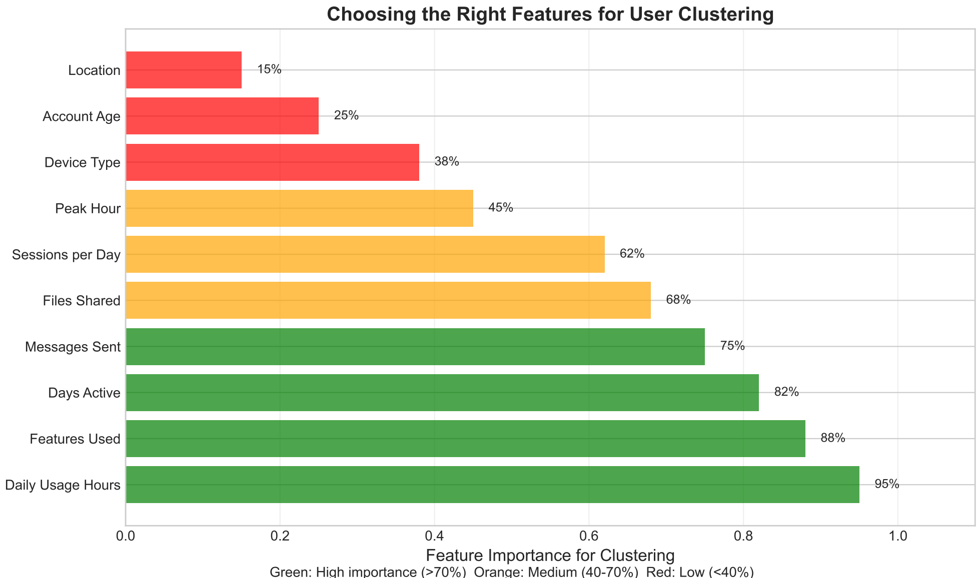
Cut the tree at any level:

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



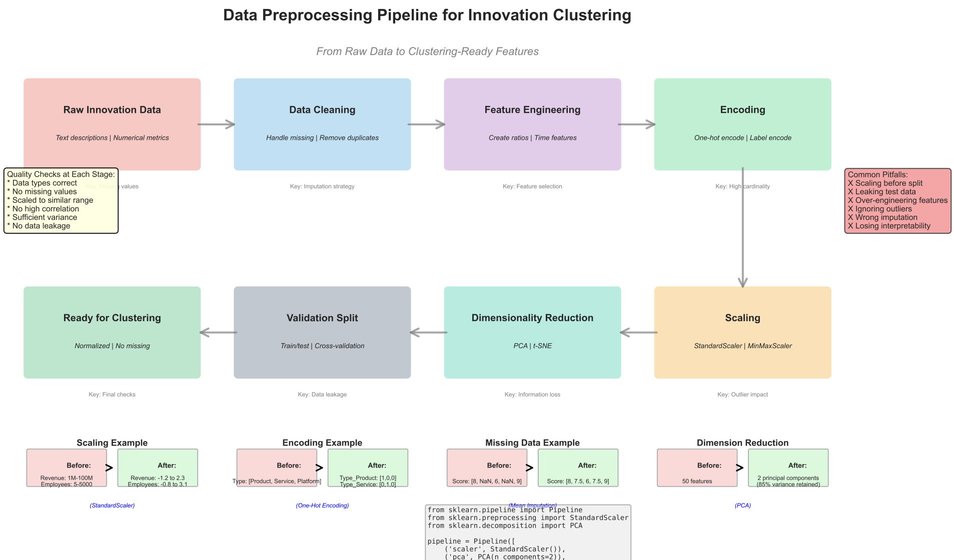
What Drives the Clusters?

Feature Importance Analysis



Data Preprocessing Pipeline

From Raw Data to Clustering-Ready Features



We've mastered 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

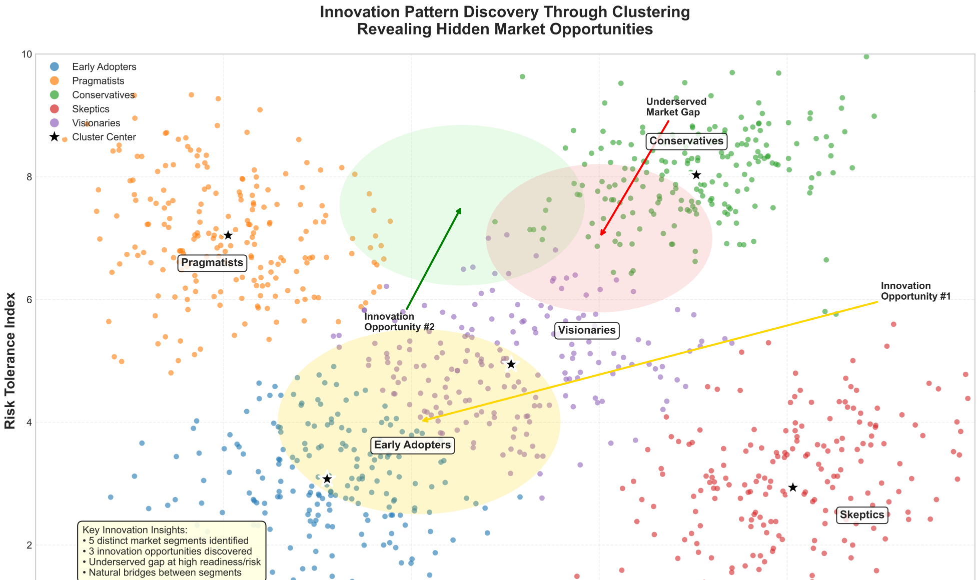
What we'll create:

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

Where ML reveals innovation patterns

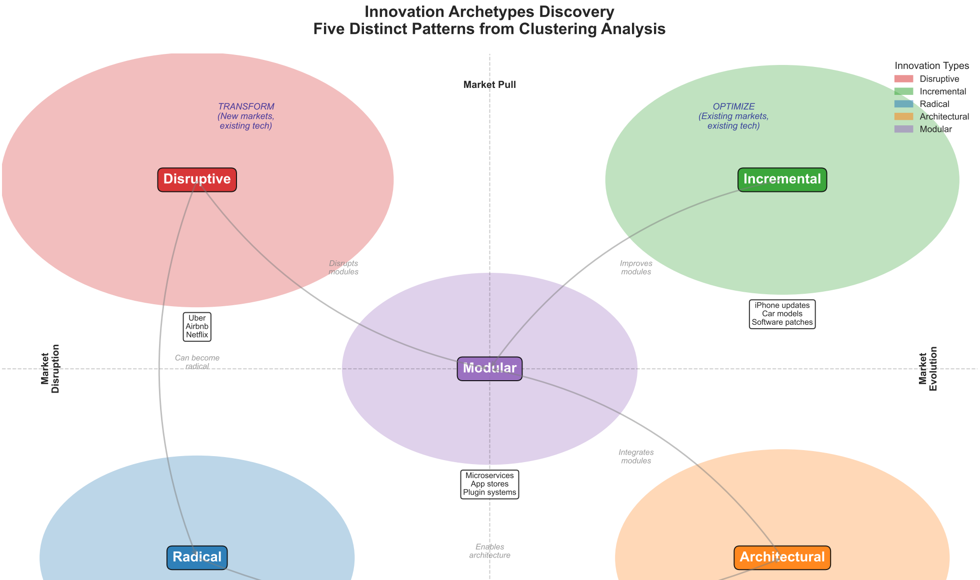
From Data Points to Innovation Insights

Bridging the Technical-Human Gap



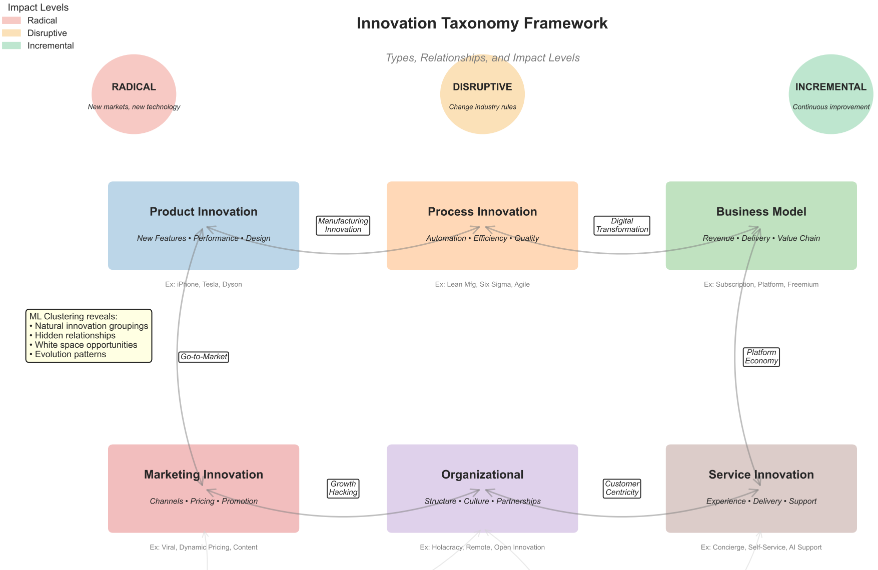
AI-Generated Innovation Archetypes

Data-Driven Character Development



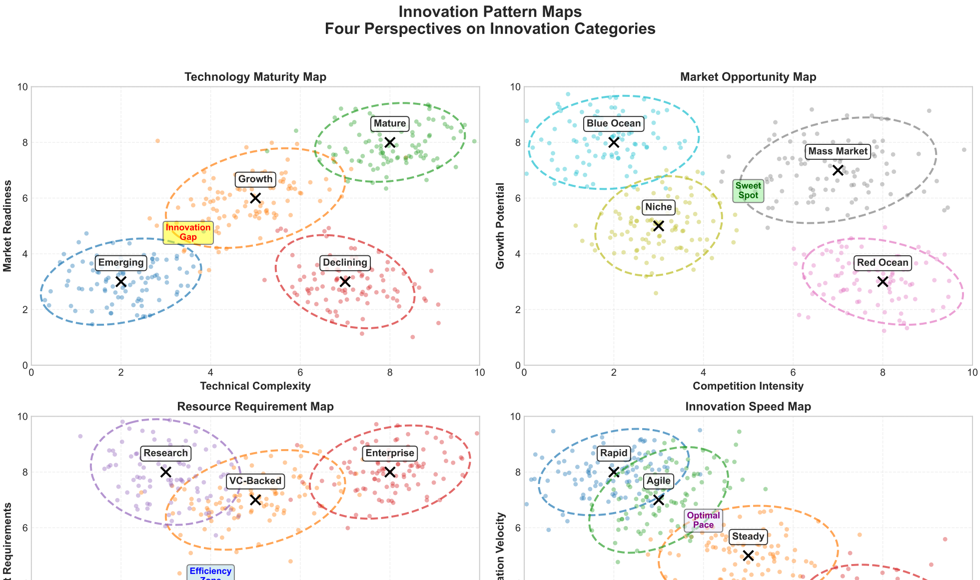
Innovation Taxonomy Framework

Types, Relationships, and Impact Levels



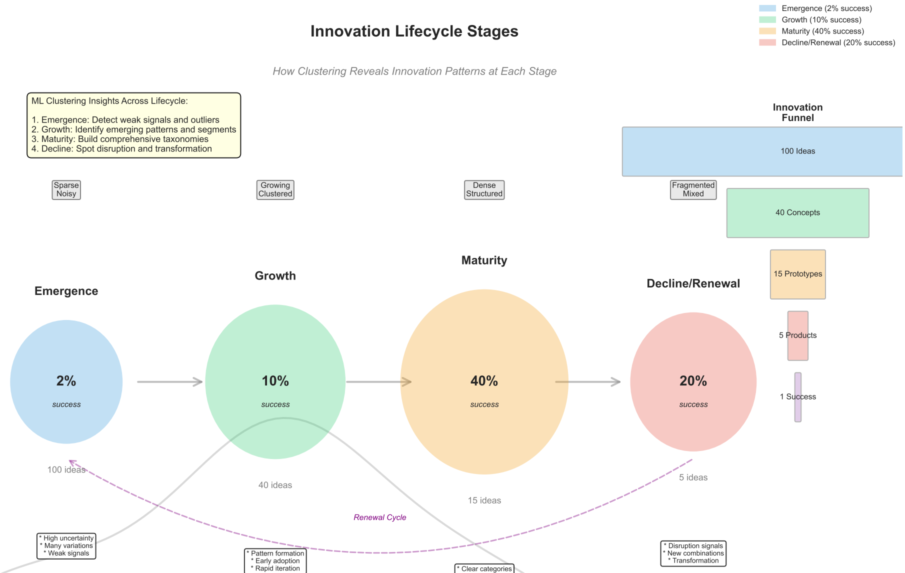
Innovation Pattern Mapping by Cluster

Understanding Each Category's Impact



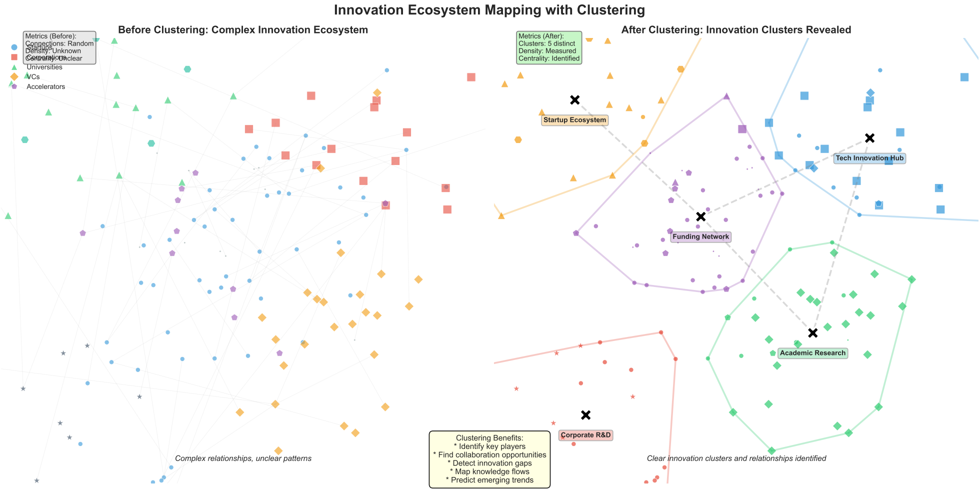
Innovation Lifecycle Stages

How Clustering Reveals Innovation Patterns at Each Stage



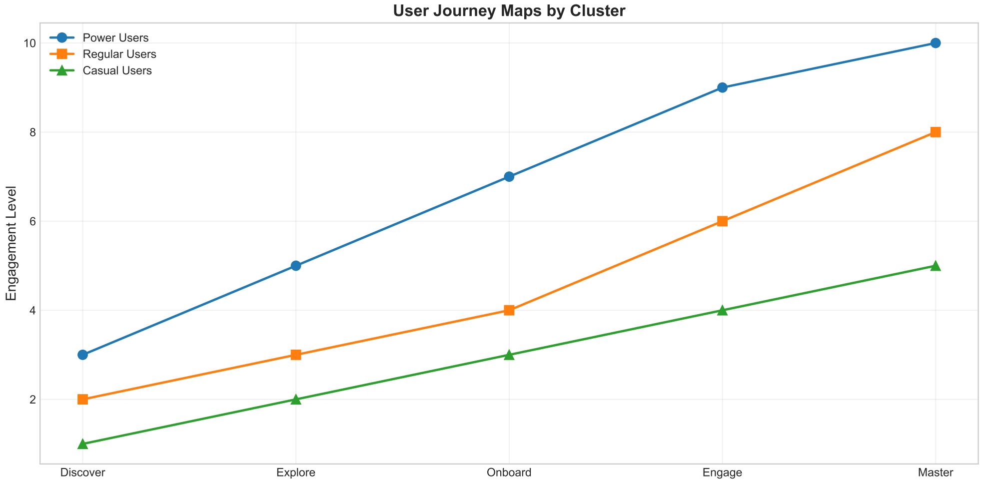
Innovation Ecosystem Mapping

From Complex Networks to Clear Clusters



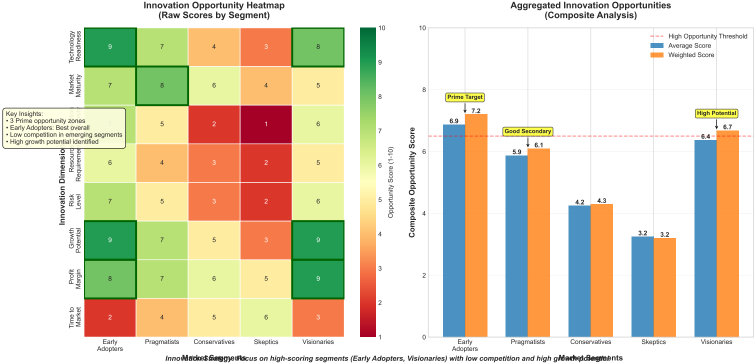
Different Evolution Paths for Innovation Types

Innovation Lifecycle Patterns



Innovation Opportunities by Cluster

Where Each Category Has Potential



Key Findings:

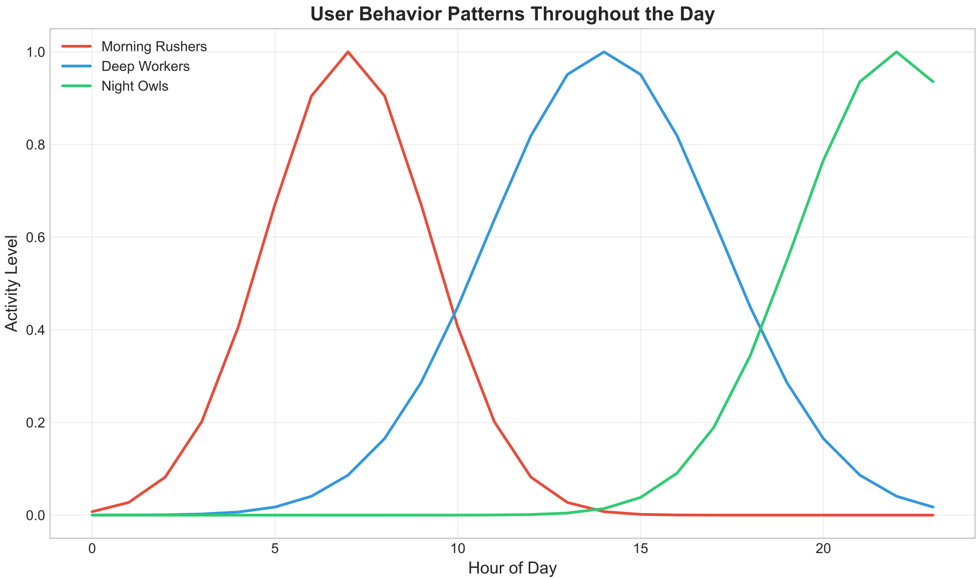
- Emerging tech: Early stage
- Disruptive: Scalability
- Incremental: Integration
- Platform-based: Network effects

Design implication:

One solution won't fit all!

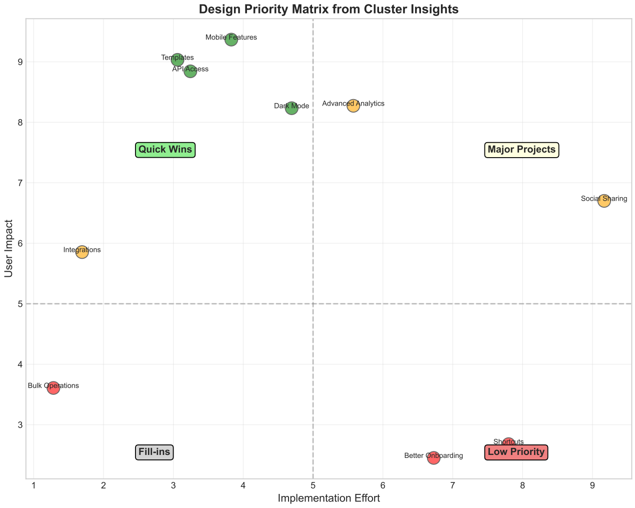
Innovation Patterns Revealed

What Clusters Tell Us About Evolution



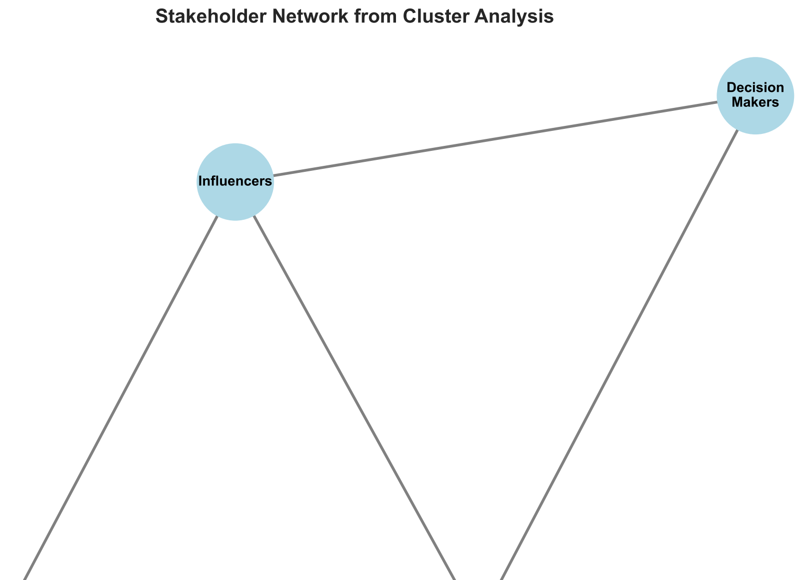
Design Priority Matrix

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


Stakeholder Network from Cluster Analysis
Decision Makers
Influencers

You've learned:

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

Now let's see it in action

Real companies using these exact techniques
to drive innovation breakthroughs

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

Real-World Clustering Patterns

Common Applications and Success Metrics

Common Applications:

- Innovation portfolio management
- Technology trend clustering
- Opportunity space mapping
- Anomaly detection

Typical Results:

- Engagement: +35-45%
- Retention: +20-30%
- Conversion: +15-25%
- Processing time: -60%

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

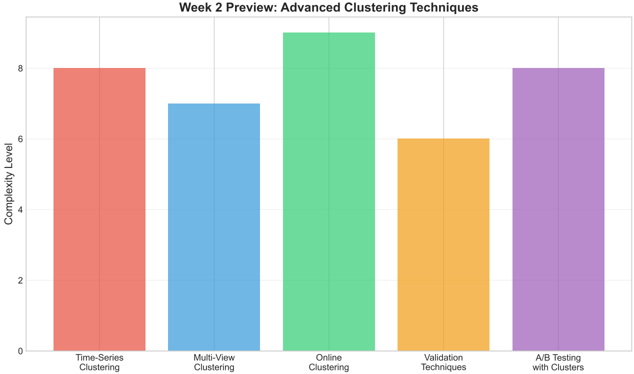
- ☐ Choose distance metric
- ☐ Select clustering method
- ☐ Determine optimal K
- ☐ Validate with metrics

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 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

Resources & Further Reading

Deepen Your Understanding

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!

Objective Function (Inertia):

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

Where:

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

Update Rules:

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

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:

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

Silhouette Score for point i:

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

Where:

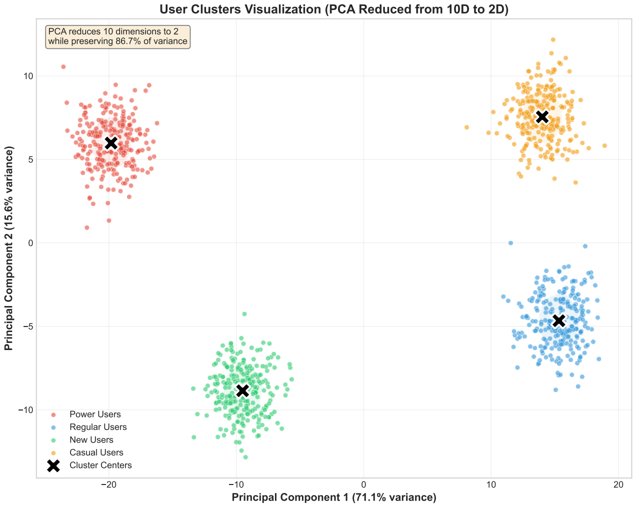
- $a(i)$ = average distance to points in same cluster
- $b(i)$ = average distance to points in nearest neighbor cluster

Interpretation:

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

Overall Score:

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



PCA Process:

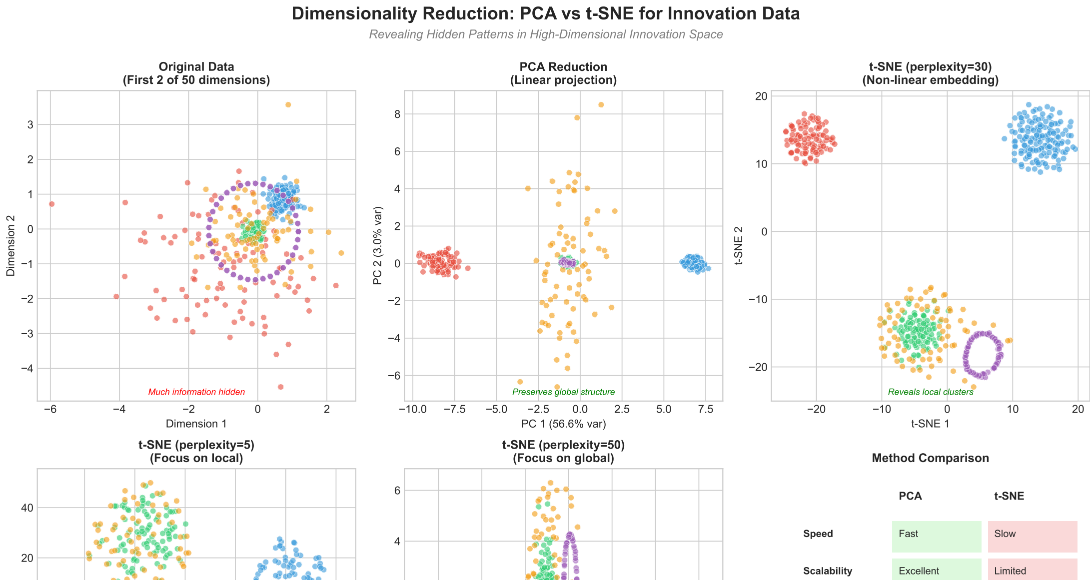
1. Standardize data
2. Compute covariance matrix
3. Find eigenvectors/values
4. Select top 2 components
5. Transform data

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



Key Parameters:

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

Point Classification:

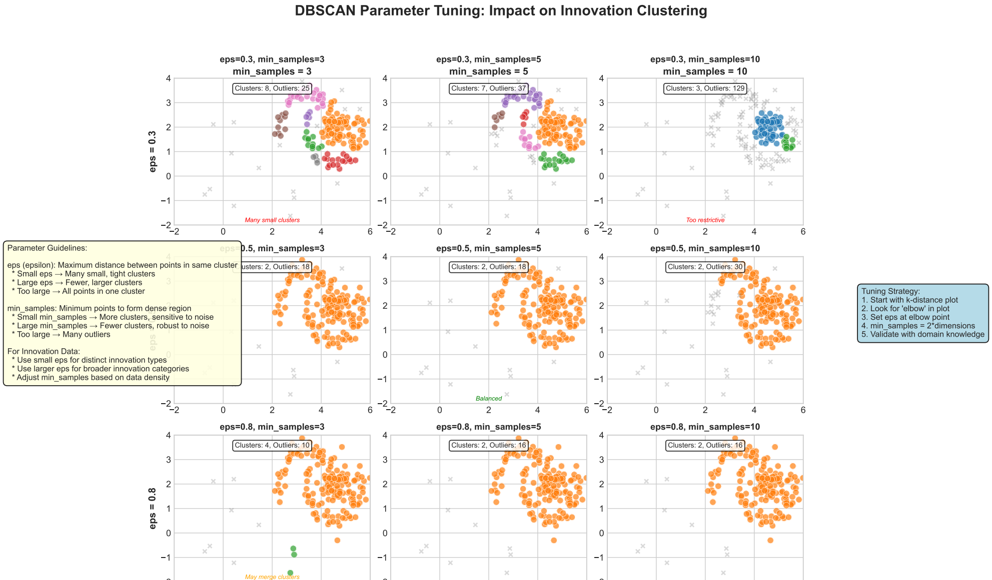
- **Core point**: Has $\geq$ MinPts within ϵ
- **Border point**: Within ϵ of core point
- **Noise point**: Neither core nor border

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



K-Means Example:

```
from sklearn.cluster import KMeans
import numpy as np

# Generate data
X = np.random.randn(1000, 2)

# Fit K-means
kmeans = KMeans(n_clusters=3,
                random_state=42)
labels = kmeans.fit_predict(X)

# Get centroids
centroids = kmeans.cluster_centers_
```

DBSCAN Example:

```
from sklearn.cluster import DBSCAN

# Fit DBSCAN
dbscan = DBSCAN(eps=0.3,
                min_samples=5)
labels = dbscan.fit_predict(X)

# Identify outliers
outliers = labels == -1
n_clusters = len(set(labels)) - 1

print(f"Clusters: {n_clusters}")
print(f"Outliers: {sum(outliers)}")
```

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