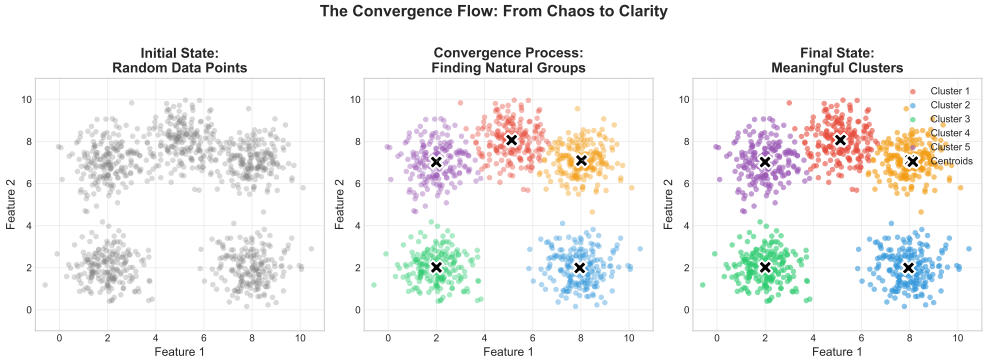
Machine Learning for Smarter Innovation

Week 1: Foundations & Clustering

Augmenting the Empathize Phase with ML

BSc Course in AI-Enhanced Innovation



The Convergence Flow: Order from Chaos

Watch 5000 data points self-organize into meaningful clusters

That visualization shows the end result.

But every innovation journey starts with a problem.

What problem does clustering solve?

Let's discover why traditional design thinking needs ML augmentation.

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

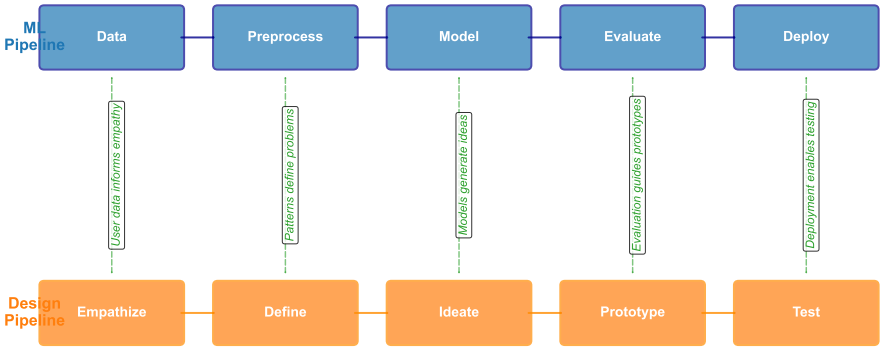
- **Scale**: Can interview 50 users, not 50,000
- **Speed**: Months for insights
- **Bias**: Designer's perspective dominates
- **Patterns**: Miss hidden connections
- **Iteration**: Slow feedback loops

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 Convergence: ML Meets Design Thinking



Each connection point creates innovation opportunities

The Dual Pipeline (Continued)

Understanding Both Worlds

ML Pipeline

Data → Preprocess → Model → Evaluate → Deploy

- Collect user behavior
- Clean and transform
- Train algorithms
- Validate accuracy
- Scale to production

Design Pipeline

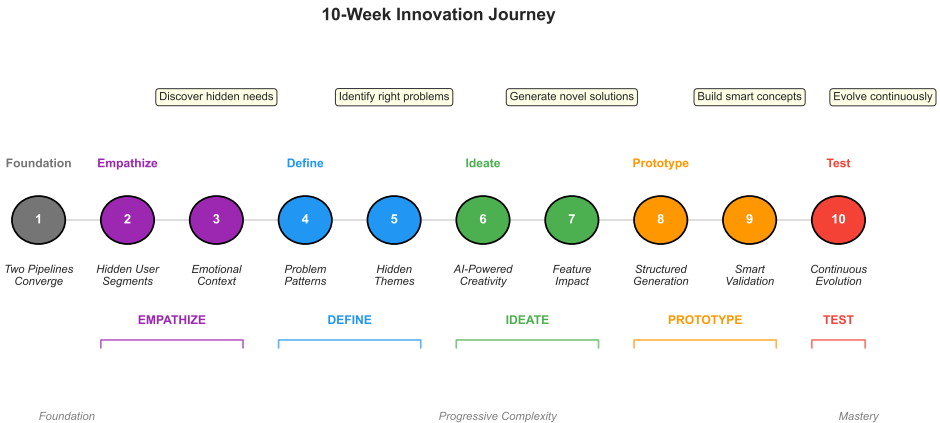
Empathize → Define → Ideate → Prototype → Test

- Understand users
- Frame problems
- Generate solutions
- Build concepts
- Validate with users

Integration = Innovation at Scale

Your Innovation Journey

10 Weeks to AI-Powered Design Mastery



Stage	Weeks	Innovation Unlocked
Empathize	1-2	Discover hidden user needs at scale
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 Deep User Understanding

What We'll Learn:

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

Design Applications:

- Create data-driven personas
- Map user journeys by segment
- Identify pain points systematically
- Prioritize design efforts
- Scale empathy to thousands

Goal: Transform data points into human insights

We've seen the challenge:
Thousands of users with hidden patterns

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 User Segmentation Problem

5000 Users - Are They All the Same?

The Pain

Current Reality:

- One-size-fits-all solutions
- Generic user personas
- Missed opportunities
- Unhappy edge cases

The Cost:

- Majority of users receive generic experiences
- Features with low adoption rates
- Inefficient resource allocation

The Question

What if we could...

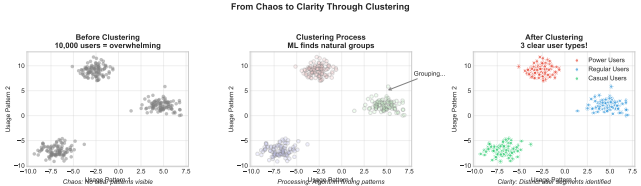
- Find natural user groups?
- Discover hidden segments?
- Personalize at scale?
- Understand real needs?

We can!

Solution: Clustering

What is Clustering?

Finding Natural Groups in Data



Clustering Finds:

- Natural groupings
- Similar behaviors
- Hidden segments
- Pattern relationships

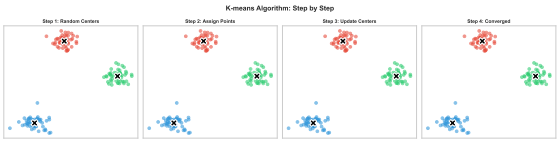
Key Insight:
Users who behave similarly likely have similar needs

K-Means: The Workhorse Algorithm

How It Organizes Your Users

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

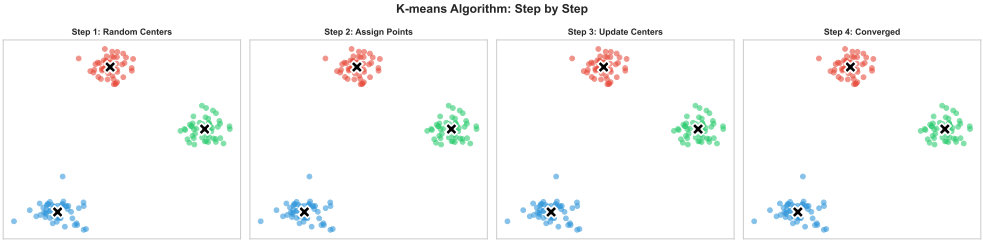


Strengths:

- 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

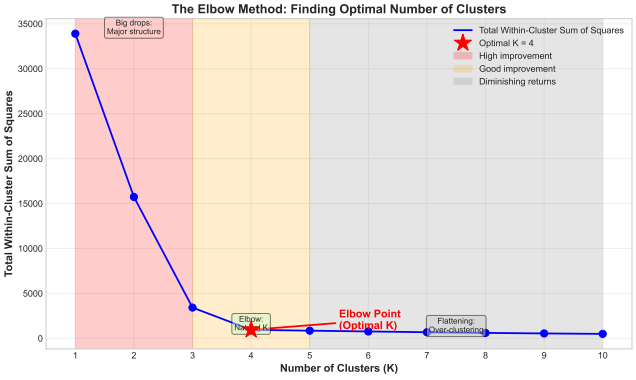
- Clear segments
- Actionable insights
- Manageable complexity

Too Many (K

Analysis Paralysis

- Overfitting
- Tiny segments
- Impossible to act on

How do we find the sweet spot?



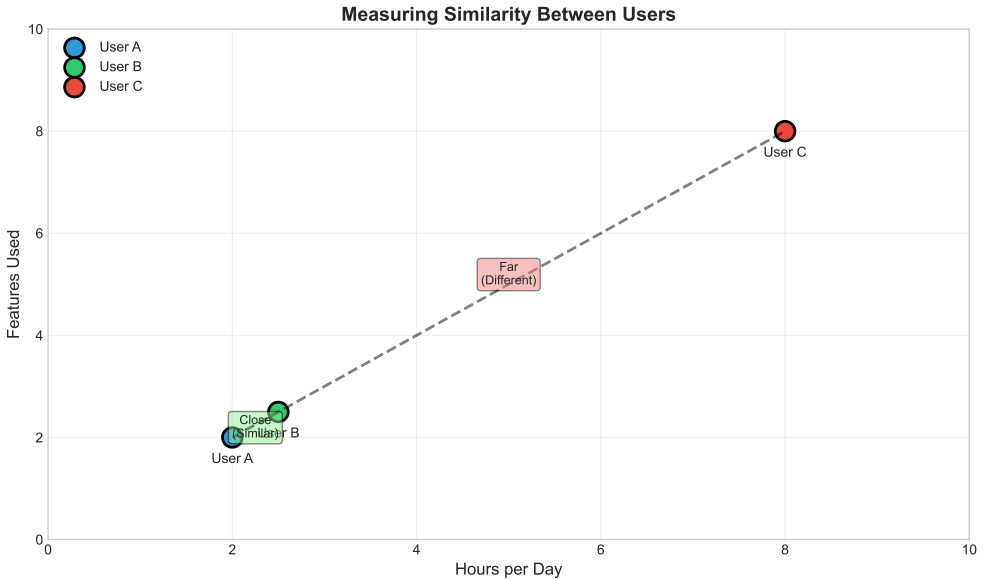
Finding the Elbow:

- 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!

K-Means Assumes Spherical Clusters

But what about:

- Users connected through social networks (chains)
- Geographic clusters (irregular shapes)
- Behavioral patterns (crescents, spirals)
- Outliers and noise points

K-Means Forces Round Pegs into Round Holes

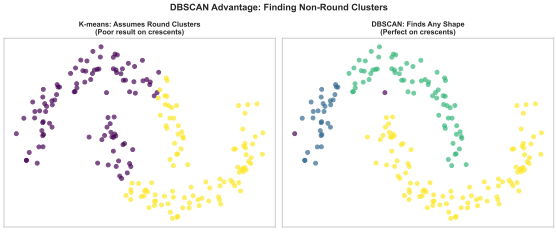
Solution: Density-Based Clustering

DBSCAN Advantages:

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

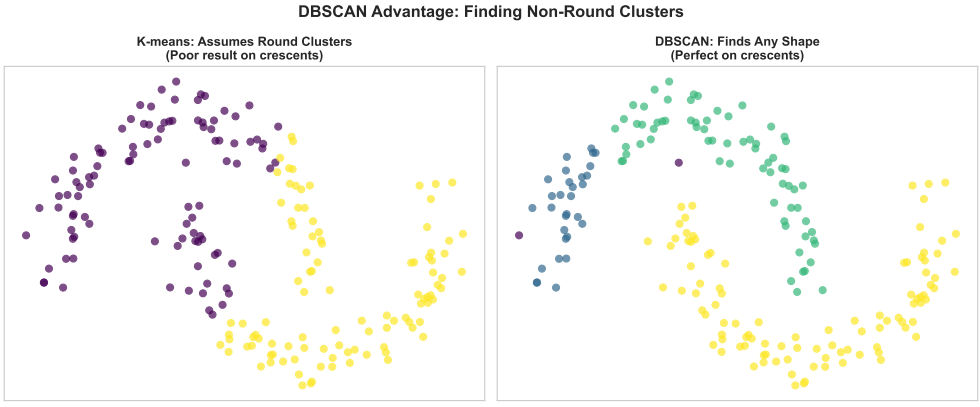
Perfect for:

- 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

Fixed K Gives One View

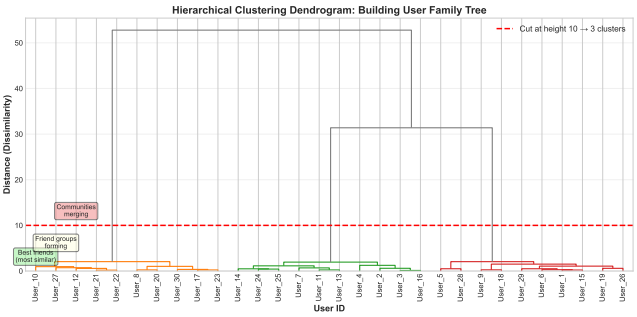
But real relationships are hierarchical:

- Organization: Company → Department → Team → Individual
- Geography: Country → Region → City → Neighborhood
- Products: Category → Subcategory → Brand → SKU
- Users: All → Segments → Sub-segments → Individuals

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

What if we need flexibility?

Solution: See the full hierarchy, cut where needed



Dendrogram Benefits:

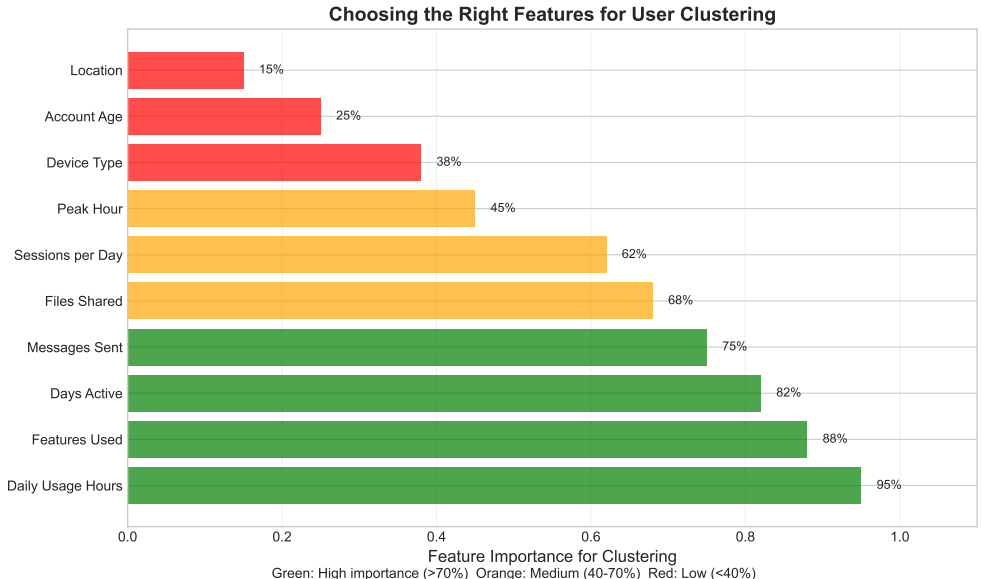
- Shows cluster hierarchy
- Multiple granularities
- Natural relationships
- No preset K needed

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



We've mastered the technical tools:
Clustering, metrics, quality measures

But clusters are just numbers...

Until we connect them to human needs

Let's transform data into empathy

Each cluster represents real people with real problems

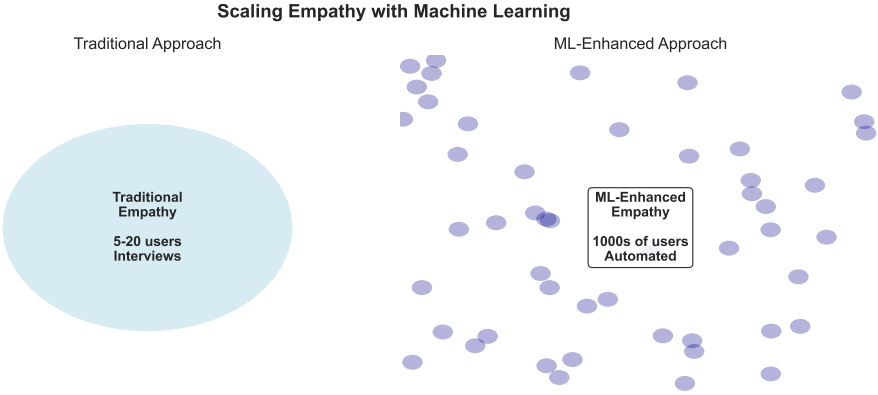
PART 3

Design Integration

What we'll create:

- Data-driven personas
- Empathy maps per segment
- Cluster-specific journeys
- Pain point heat maps
- Design priority matrices

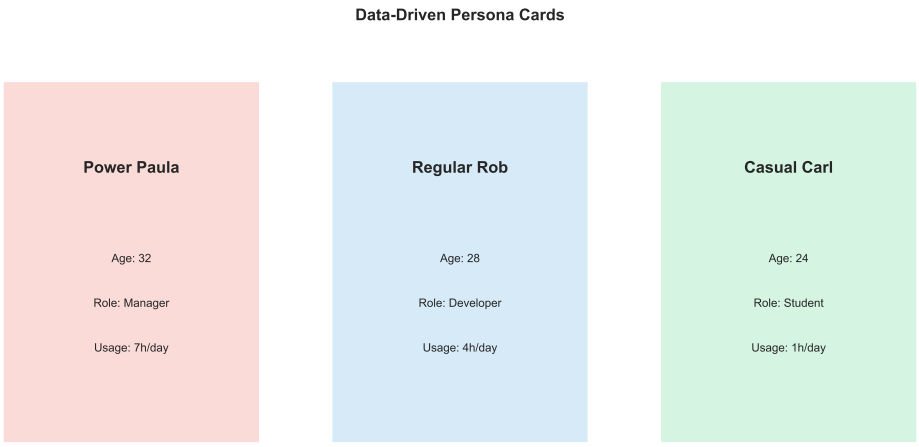
Where ML meets human-centered design



Each cluster represents real human needs

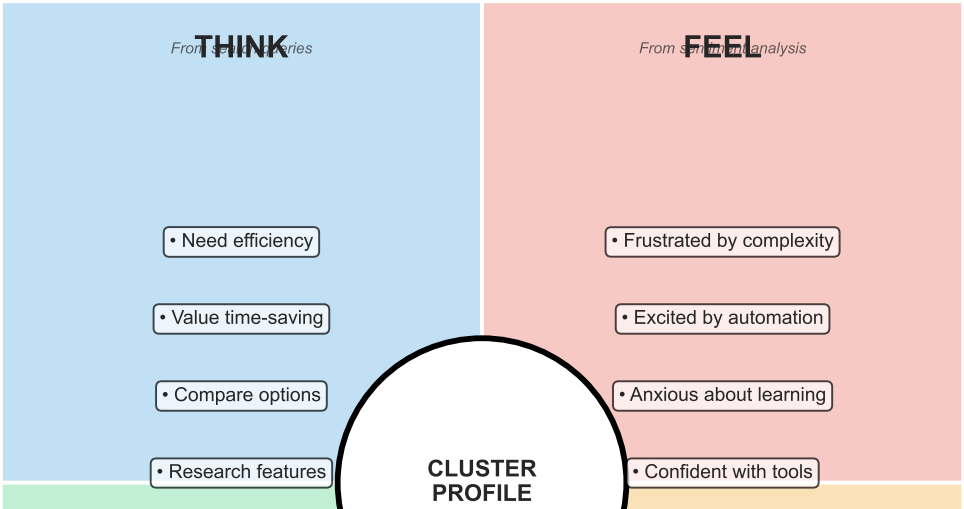
AI-Generated User Personas

Data-Driven Character Development



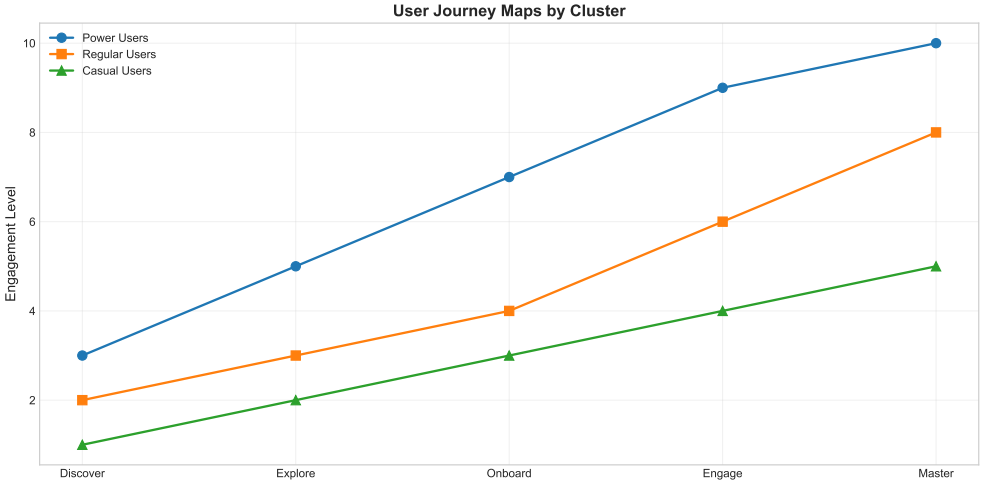
Power Users — Casual Browsers — Price-Conscious — Feature Seekers — New Users

Empathy Map: Data-Driven User Understanding



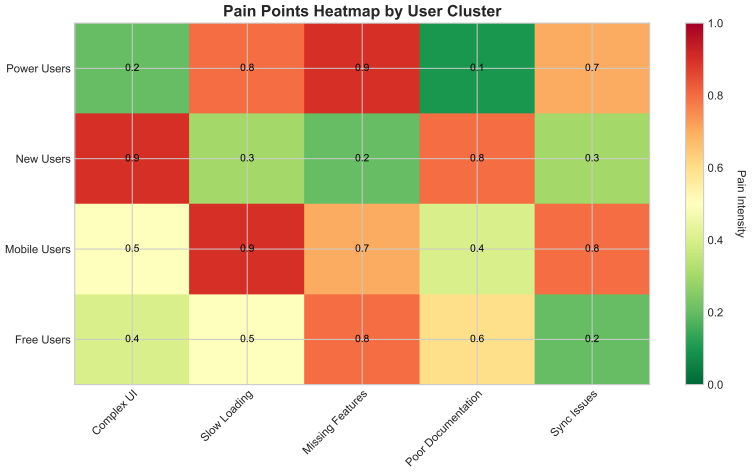
Different Journeys for Different Clusters

Personalized Path Understanding



Pain Points by Cluster

Where Each Segment Struggles



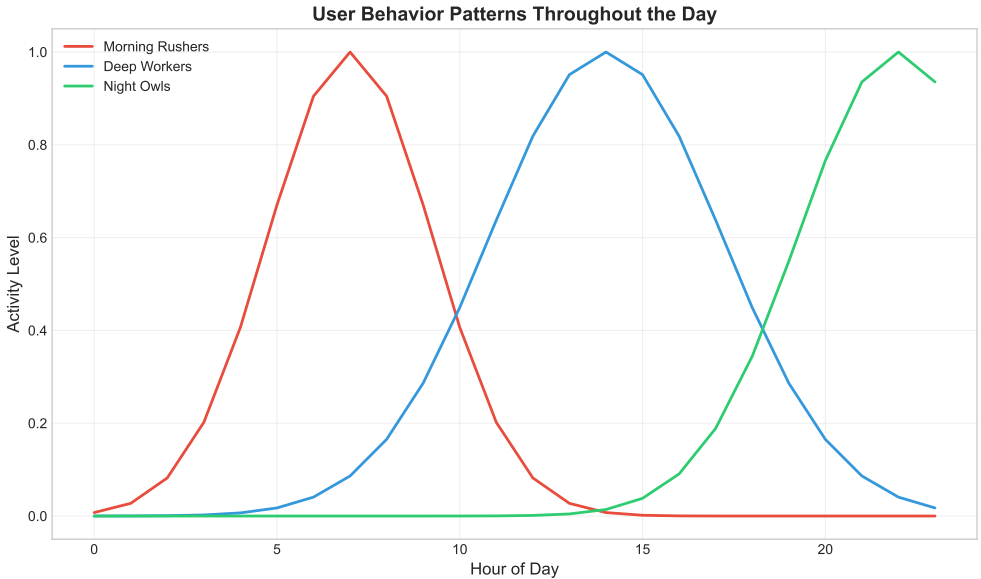
Key Findings:

- New users: Onboarding
- Power users: Speed
- Casual: Complexity
- Price-conscious: Value

Design implication:
One solution won't fit all!

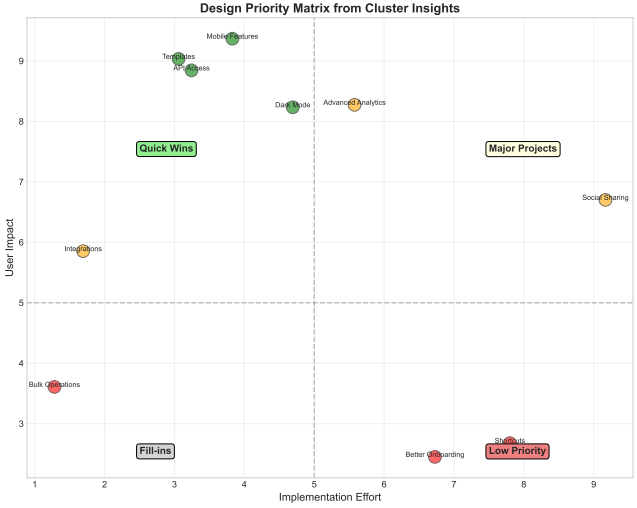
Behavioral Patterns Revealed

What Clusters Tell Us About Usage



Design Priority Matrix

Where to Focus Your Efforts

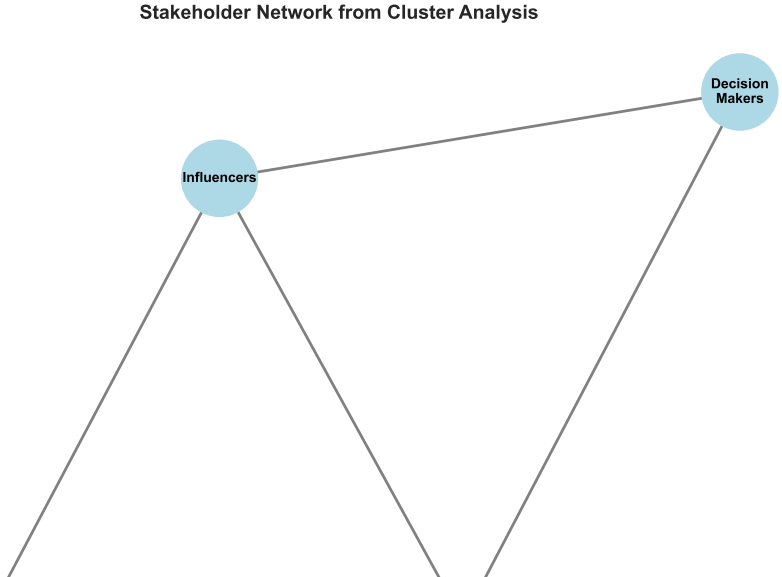


Priority Quadrants:

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

Understanding Stakeholder Connections

Network Analysis of User Relationships



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 transform their user experience

PART 4

Summary & Practice

What we'll do:

- See real-world success (Spotify)
- 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:

- Content recommendation systems
- User behavior segmentation
- Product categorization
- 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 personas
- Segment-specific journeys
- Pain point identification
- Priority matrices
- Scaled empathy

Clustering transforms data into actionable user 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

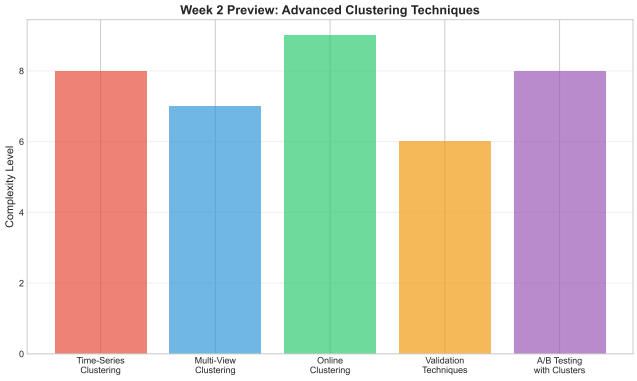
- ☐ Choose distance metric
- ☐ Select clustering method
- ☐ Determine optimal K
- ☐ Validate with metrics

Common Pitfalls

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

Next Week: Advanced Clustering

Going Deeper into User Understanding



Week 2 Topics:

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

Design Focus:

- Dynamic personas
- Evolving segments
- Predictive empathy
- Micro-segmentation

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 (persona 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
- 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

Mathematical Definitions

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:

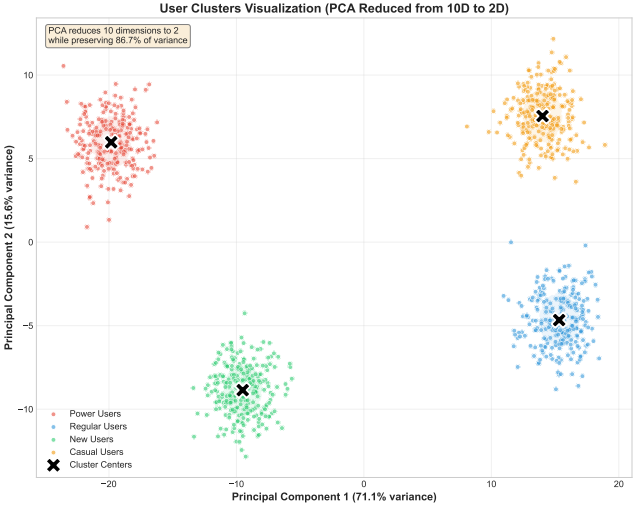
- $s(i) \approx 1$: Well clustered
- $s(i) \approx 0$: On border between clusters
- $s(i) \approx -1$: Misclassified

Overall Score:

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

Appendix: PCA for Cluster Visualization

Dimensionality Reduction



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%

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

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