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!

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From Data Points to Innovation Insights

Bridging the Technical-Human Gap

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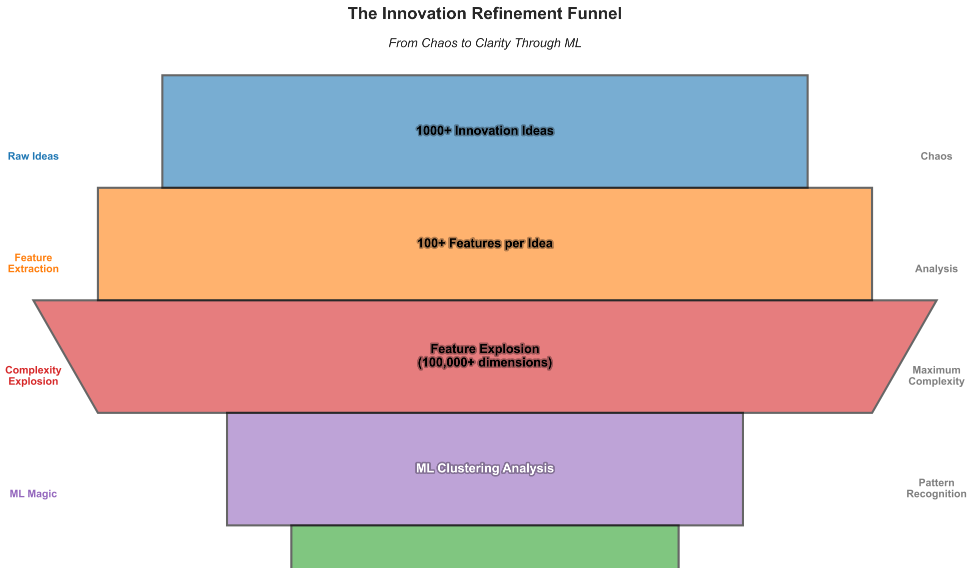
The Innovation Refinement Funnel

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

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The Hidden Complexity

Each Innovation Depends on Hundreds of Features

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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

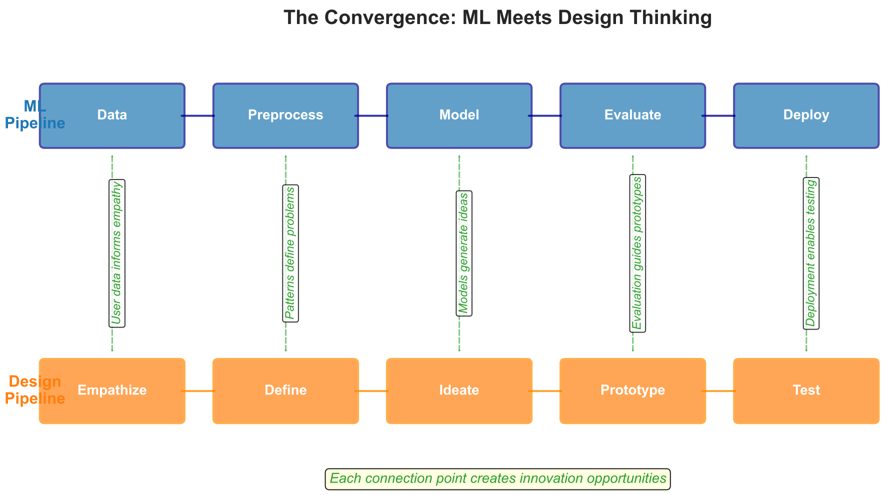
The Promise: 100x more insights, 10x faster innovation

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 Convergence: ML Meets Design Thinking
ML Pipeline
Data
Preprocess
Model
Evaluate
Deploy
User data informs empathy
Patterns define problems
Models generate ideas
Evaluation guides prototypes
Deployment enables testing
Design Pipeline
Empathize
Define
Ideate
Prototype
Test
Each connection point creates innovation opportunities

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

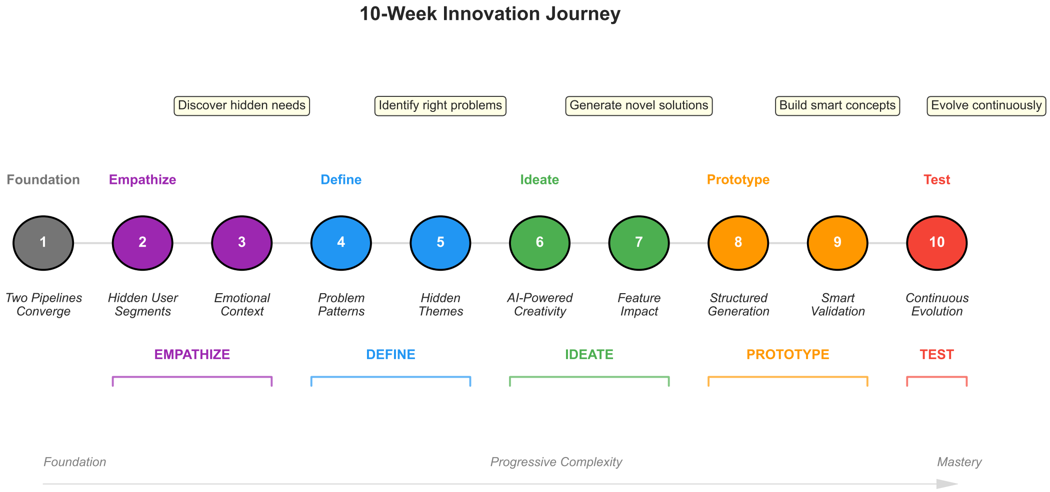
Empathize → Define → Ideate → Prototype → Test

- 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



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

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True or False?

1. Clustering requires labeled data (F)
2. ML can process more data than humans (T)
3. Design thinking has 5 stages (T)
4. 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

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

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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

Innovation Archetypes

Common Patterns We'll Discover

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

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

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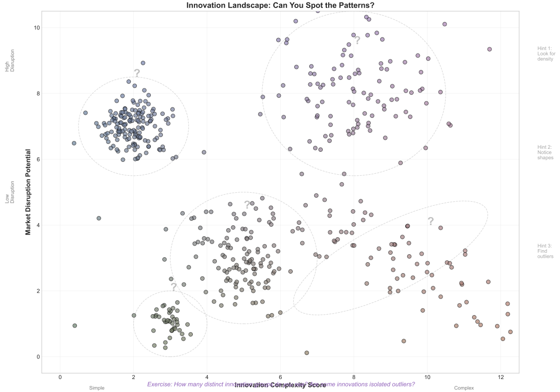
Discovery: How Many Groups Do You See?

Visual Pattern Recognition Exercise

Look at this innovation data:



Questions:

- How many distinct groups?

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.

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: _________

How ML Would Cluster:

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 50+ hidden features you might miss!

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

Initial Setup - Like Choosing City Centers

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

Iteration Process - Finding Natural Groups

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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)

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Distance Metrics

Different Ways to Measure "How Close" Things Are

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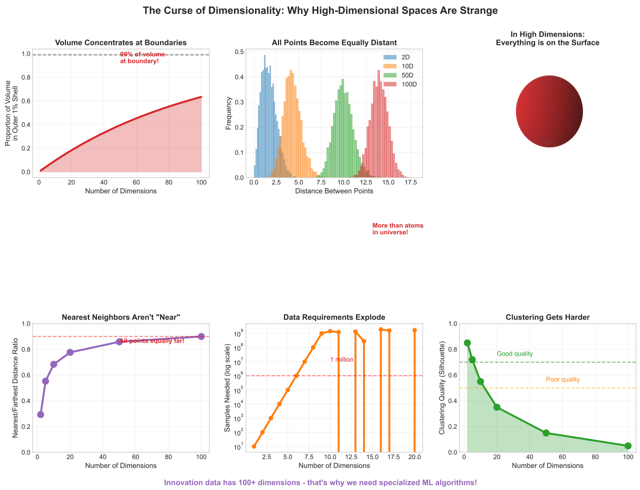
Sidestep: The Curse of Dimensionality

Why High-Dimensional Spaces Are Strange and Empty



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)

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Evaluation Metric 1: Silhouette Score

Measuring Cluster Cohesion and Separation

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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

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Evaluation Metric 3: Davies-Bouldin Index

Balancing Within and Between Cluster Distances

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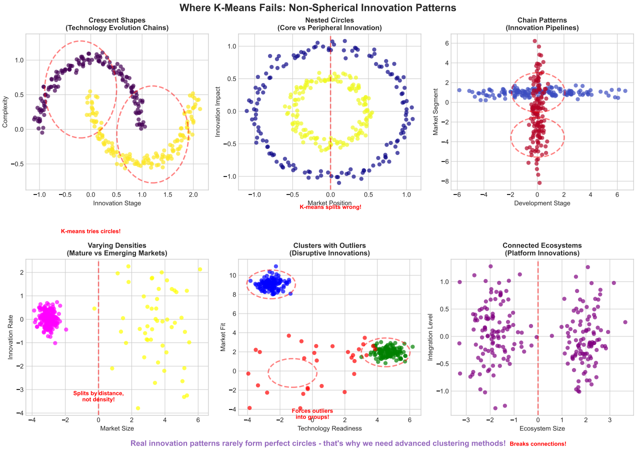
K-Means Assumes Spherical Clusters

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



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 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

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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: MinPts $= 2 \times$ dimensions

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

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Gaussian Mixture Models (GMM)

Soft Clustering for Overlapping Innovation Categories

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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

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What Drives the Clusters?

Feature Importance Analysis

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Data Preprocessing Pipeline

From Raw Data to Clustering-Ready Features

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Common Mistakes & Troubleshooting

Learn from These Pitfalls

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Parameter Tuning Guidelines

Recommended Ranges and Best Practices

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Check Your Understanding - Part 2

Technical Concepts Review

Progress: 2/3

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

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AI-Generated Innovation Archetypes

Data-Driven Character Development

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Innovation Pattern Maps

Cluster-Specific Insights

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Innovation Framework

Taxonomy and Lifecycle Stages

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charts/innovation_lifecycle.pdf

Innovation Ecosystem & Journey Mapping

From Networks to Evolution Paths

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Innovation Opportunities by Cluster

Where Each Category Has Potential

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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

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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

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Check Your Understanding - Part 3

Application Knowledge Check

Progress: 3/3

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