Topic Modeling & Ideation

Discovering What You Didn't Know You Were Looking For

Week 5: Machine Learning for Smarter Innovation

Transform 1 Million Comments into 10 Innovation Opportunities

Today's Journey: From Chaos to Clarity

Four Stages of Discovery

1. **The Hidden Pattern Problem** - Why we miss what matters most
2. **Understanding Hidden Structure** - How documents mix topics
3. **The Algorithm Arsenal** - Four ways to unmix topics
4. **Innovation Through Discovery** - From patterns to products

Core Question: How do you find themes you didn't know existed in data too large to read?

By the end: You'll discover patterns that lead to breakthrough innovations

Your Challenge: 1 Million Feedback Comments

What Are People Really Saying?

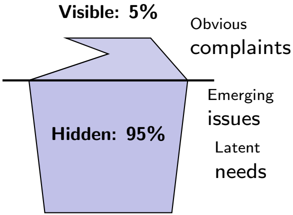
The Scenario:

- Online retailer with 1M reviews
- Need insights by tomorrow
- Competitors analyzing manually
- Missing patterns = lost opportunities

Manual Approach:

- Read 100 reviews/day
- 10,000 days to finish (27 years!)
- Cost: 50 analysts × $50K = $2.5M/year
- Still miss cross-cutting themes

What You're Missing:



Result: You see complaints, miss opportunities

Real case: Amazon processes 1 billion reviews yearly - impossible without topic modeling

The Real Cost of Missing Hidden Patterns

When You Can't See the Forest for the Trees

Blockbuster (2000-2010):

- Had millions of rental records
- Categorized by genre (Action, Drama)
- Missed micro-preferences
- Couldn't see "Films with strong female leads from the 80s"
- Result: Bankruptcy in 2010

Netflix (Same Period):

- Applied topic modeling to viewing data
- Discovered 76,897 micro-genres
- "Critically-acclaimed emotional dramas"
- "Witty foreign thrillers"
- Result: $240B market cap

The Pattern Discovery Gap:

[Chart: Pattern Discovery Comparison]

Netflix found:
- Micro-genres humans never named
- Cross-category preferences
- Time-based viewing patterns
- Mood-driven selections

The difference: Netflix saw patterns invisible to human categorization

Why Human Categorization Breaks Down

Our Brains Aren’t Built for Big Data

Human Limits:

1. Cognitive Capacity

- Can track 7 categories at once
- After 50 items: accuracy drops 40%
- After 500 items: random guessing

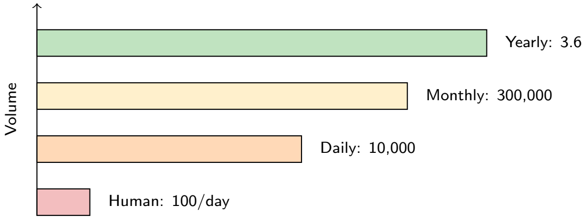
2. Consistency Problem

- Same text, different day = different category
- Two analysts = 60% agreement max
- Fatigue changes decisions

3. Bias Blindness

- See what we expect to see
- Miss emerging trends
- Overlook weak signals

Scale Comparison:



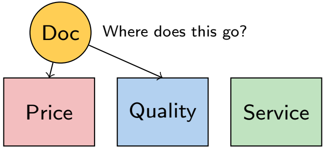
The Gap: Human capacity is linear, data growth is exponential

Spotify processes 4 billion user actions daily - human categorization is impossible

The Cross-Cutting Theme Challenge

When Topics Don't Fit in Boxes

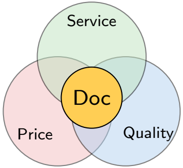
Traditional Categories:



Real Review: "Great value for money, though shipping was slow. Product quality exceeded expectations given the price point."

Problem: Mentions price, quality, AND service - which box?

Topic Modeling Solution:



Document Mixture:

- 40% about price/value
- 35% about quality
- 25% about service

Benefit: Captures full meaning, not forced choice

Every document is a unique mixture of topics - forcing single categories loses information

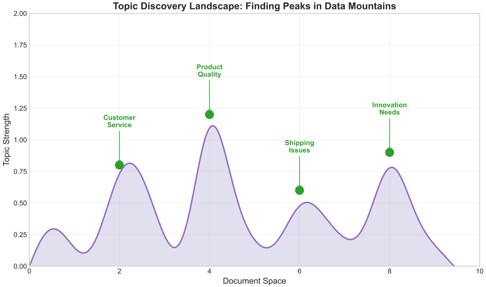
Enter Topic Modeling: Pattern Discovery at Scale

From Human Limits to Machine Intelligence

What Topic Modeling Does:

1. **Discovers Hidden Themes**
   - No predefined categories
   - Themes emerge from data
   - Finds unexpected connections
2. **Handles Scale**
   - 1M documents in hours
   - Consistent analysis
   - Never gets tired
3. **Captures Nuance**
   - Documents as topic mixtures
   - Probabilistic understanding
   - Cross-cutting themes
4. **Evolves with Data**
   - Detects emerging trends
   - Tracks topic evolution
   - Adapts to new patterns

The Transformation:



Real Impact:

- 10,000 documents → 20 themes
- Processing time: 5 minutes
- Human equivalent: 3 months
- Patterns found: 15 unexpected

Next: How do machines find these hidden patterns?

Documents Are Like Recipes

A Simple Way to Think About Topics

Think of Cooking:

Ingredients = Words

- Tomato, cheese, basil, pasta...
- Each has different uses
- Can appear in many dishes

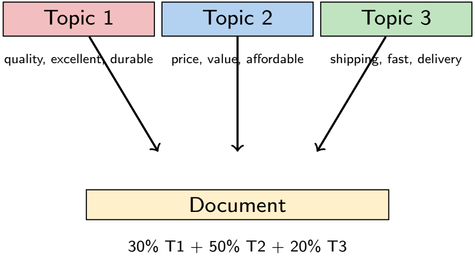
Recipe Types = Topics

- Italian: pasta, tomato, basil, olive oil
- Mexican: beans, corn, chili, lime
- Asian: rice, soy, ginger, sesame

Actual Dish = Document

- Fusion pasta: 60% Italian, 40% Asian
- Uses ingredients from both
- Mixed in specific proportions

The Document Recipe:



Topic 1

quality, excellent, durable

Topic 2

price, value, affordable

Topic 3

shipping, fast, delivery

Document

30% T1 + 50% T2 + 20% T3

Key Insight: Every document mixes multiple topics, just like fusion cuisine mixes cooking styles

This mixing is why forcing documents into single categories loses so much information

Topics Are Word Probabilities

Which Words Define Each Theme?

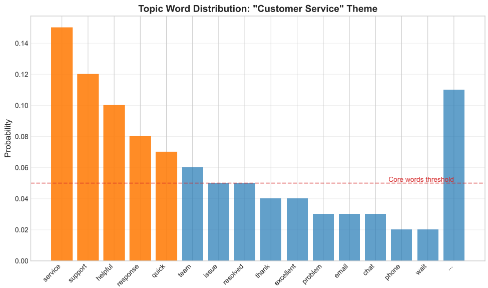
What Is a Topic?

- A list of words with probabilities
- High probability = core to topic
- Low probability = rarely appears
- All probabilities sum to 100%

Example: "Customer Service" Topic

Word	Probability
service	15%
support	12%
helpful	10%
response	8%
quick	7%
team	6%
...	...

Visual Distribution:



Reading the Chart:

- Tall bars = defining words
- Many small bars = common words
- Pattern = topic signature

Computers find these patterns by analyzing millions of word co-

Every Document Mixes Multiple Topics

Real Documents Are Never Pure

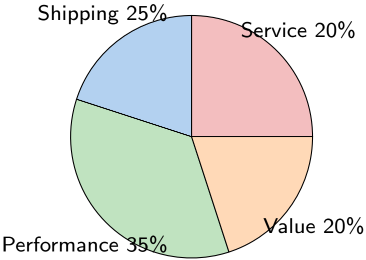
A Real Product Review: ”The laptop arrived quickly and was well packaged. Performance is excellent for the price, though battery life could be better. Customer service was helpful when I had questions about setup.”

Topic Breakdown:

- Shipping (25%): arrived, quickly, packaged
- Performance (35%): excellent, battery, performance
- Value (20%): price, worth
- Service (20%): customer, helpful, questions

The Math: P(word—doc) = $\sum$ P(word—topic) × P(topic—doc)

Topic Mixture Visualization:



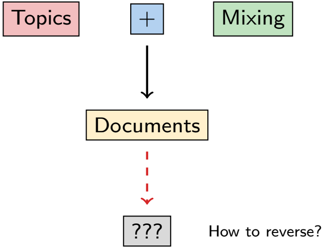
No document is 100% one topic - real communication always blends themes

This mixture approach captures how humans actually write - we naturally blend topics

The Challenge: Unmixing the Smoothie

Reverse Engineering the Recipe

The Problem:



Given: Mixed documents
Find: Original topics
Challenge: Many valid solutions!

Like Having a Smoothie:

- Taste the final blend
- Need to identify ingredients
- Determine proportions
- Without the recipe!

How Algorithms Solve It:

1. Pattern Recognition

- Words that appear together
- Consistent co-occurrences
- Statistical regularities

2. Iterative Refinement

- Start with random guess
- Improve topic definitions
- Adjust document mixtures
- Repeat until stable

3. Optimization

- Maximize topic coherence
- Minimize reconstruction error
- Balance specificity/coverage

The Magic: Algorithms find patterns humans can't see in millions of documents

Topic modeling is essentially sophisticated pattern recognition at massive scale

The Matrix View: Documents × Words

Organizing Text as Numbers

Step 1: Count Words

	quality	price	service
Review 1	3	1	0
Review 2	0	2	4
Review 3	2	3	1
Review 4	1	0	5

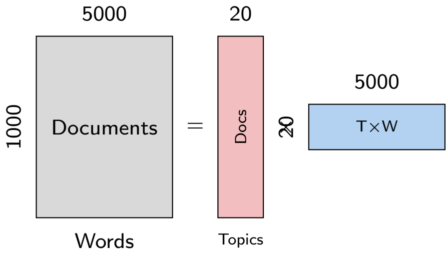
Step 2: Find Patterns

- Reviews 1,3: quality + price
- Reviews 2,4: service-focused
- Hidden structure emerges

Step 3: Decompose

- Original = Topics × Mixtures
- 1000×5000 = (1000×20) × (20×5000)
- Huge matrix → Two smaller ones

Visual Decomposition:



Benefit: Compress millions of words into 20 meaningful topics

Matrix decomposition: Like compressing a huge spreadsheet into its essential patterns

How Do We Know Topics Are Good?

Measuring Quality Without Ground Truth

Good Topics Are:

1. Coherent

- Words belong together
- Make semantic sense
- Tell a clear story

Example: [GOOD] {pizza, pasta, Italian, restaurant}

2. Distinctive

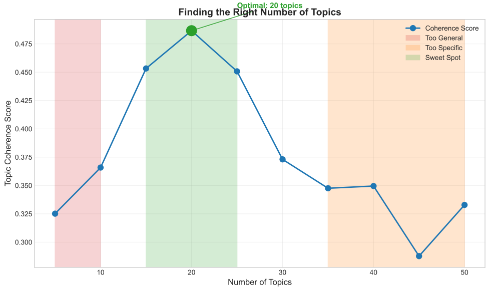
- Different from other topics
- Not overlapping
- Clear boundaries

Example: [BAD] Topic 1 and 2 both about "food"

3. Interpretable

- Humans understand them
- Can be labeled easily
- Actionable insights

Quality Metrics:



Choosing Number of Topics:

- Too few (5): Too general
- Just right (20): Clear themes
- Too many (100): Redundant

Rule of thumb: 20-50 topics for most datasets, check coherence

Ready to Learn the Algorithms

What You Now Understand

Core Concepts:

- Documents mix multiple topics
- Topics are word probabilities
- Goal: unmix the smoothie
- Matrix decomposition helps
- Quality matters more than quantity

The Challenge:

- Given: Mixed documents
- Find: Hidden topics
- Make: Useful for innovation

Next: Four Approaches

LDA: Probabilistic

NMF: Parts-based

LSA: Semantic

BERT: Context

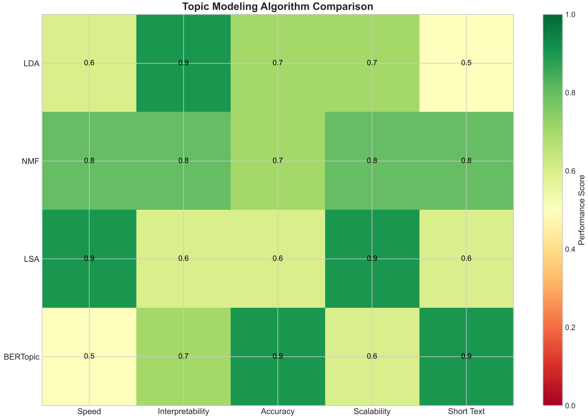
Each algorithm unmixes topics differently - like different chefs approaching the same ingredients

Next: Deep dive into each algorithm

You now understand the problem - let's see how different algorithms solve it

Four Algorithms, Four Philosophies

Different Ways to Find Hidden Themes



Our Toolkit:

1. **LDA**
   The probabilistic chef
   "What's the recipe probability?"
2. **NMF**
   The LEGO builder
   "What parts combine?"
3. **LSA**
   The meaning compressor
   "What's the essence?"
4. **BERTopic**
   The context reader
   "What's the full meaning?"

Trade-offs:

- Speed vs Quality
- Interpretability vs Accuracy
- Simple vs Complex

Each algorithm has its sweet spot - choose based on your specific needs

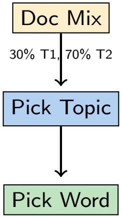
Algorithm 1: LDA (Latent Dirichlet Allocation)

The Probabilistic Recipe Finder

How LDA Thinks:

- Documents are recipe cards
- Topics are ingredient lists
- Each word is randomly picked:
  1. Pick a topic (from document's mix)
  2. Pick a word (from that topic)
- Work backwards from words to topics

The Process:



Real Example:

Input: 1000 restaurant reviews
Output: 5 topics discovered

Topic	Top Words
Food	pizza, pasta, taste
Service	waiter, friendly, quick
Ambiance	cozy, music, romantic
Price	expensive, value, worth
Location	parking, convenient

Performance:

- Speed: Medium (5 min/1000 docs)
- Quality: High
- Interpretability: Excellent

Use LDA when: You need interpretable topics with probability estimates

LDA: The Math (Made Simple)

Probability All the Way Down

The Generative Story:

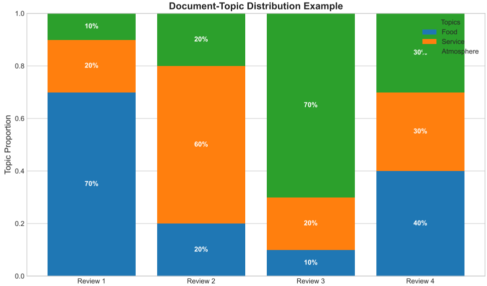
1. **For each document:**
   Draw topic proportions
   e.g., [0.3, 0.5, 0.2] for 3 topics
2. **For each word position:**
   Pick a topic from proportions
   Pick a word from that topic

The Math (Simplified):

$$\text{P(word—doc)} = \sum \text{P(word—topic)} \times \text{P(topic—doc)}$$

"Word probability = Sum of (word in topic × topic in document)"

Visual Process:



Parameters to Set:

- **K**: Number of topics (try 20)
- α: Document focus (small = focused)
- β: Topic focus (small = specific)

Don't worry about the Greek letters - most tools set them automatically

Algorithm 2: NMF (Non-negative Matrix Factorization)

The LEGO Block Builder

How NMF Thinks:

- Topics are LEGO sets
- Documents are built from blocks
- Only adding, never subtracting
- Each part contributes positively

The Decomposition:

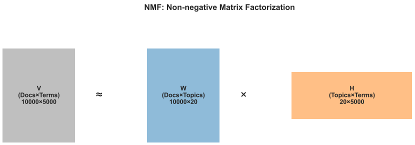
$$V = W \times H$$

- V: Your documents (1000×5000)
- W: Document-topics (1000×20)
- H: Topic-words (20×5000)
- All values ≥ 0 (non-negative)

Why "Parts-Based"?

- Face = eyes + nose + mouth
- Review = quality + price + service
- Only additive components

Visual Decomposition:



Real Example Output:

Part/Topic	Components
Battery	life, hours, charge
Screen	display, bright, clear
Speed	fast, quick, responsive
Build	quality, solid, durable

Performance:

- Speed: Fast (2 min/1000 docs)
- Quality: Good
- Interpretability: Very High

Algorithm 3: LSA (Latent Semantic Analysis)

The Meaning Compressor

How LSA Thinks:

- Words have hidden meanings
- "Car" ≈ "Automobile" ≈ "Vehicle"
- Compress to essential concepts
- Like MP3 for text

The Math Tool: SVD

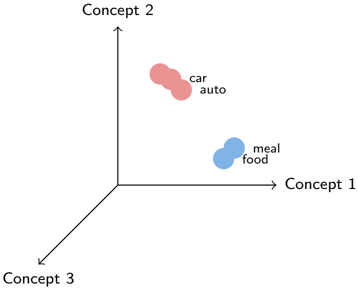
$$A = U \times \Sigma \times V^T$$

- A: Document-term matrix
- U: Document concepts
- Σ: Concept importance
- V: Term concepts

Dimension Reduction:

- 5000 words → 100 concepts
- Keep most important patterns
- Lose noise, keep signal

Semantic Space:



What It Finds:

- Synonyms automatically grouped
- Related concepts connected
- Hidden relationships revealed

Performance:

- Speed: Very Fast (30 sec/1000)

Algorithm 4: BERTopic

The Modern Context Master

How BERTopic Thinks:

- Uses BERT's language understanding
- ”Bank” (money) ”Bank” (river)
- Context determines meaning
- Clusters similar meanings

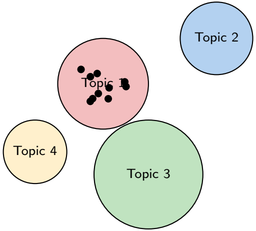
The Process:

1. Embed documents with BERT
2. Reduce dimensions (UMAP)
3. Cluster embeddings (HDBSCAN)
4. Extract topics with TF-IDF

Why It's Better:

- Understands context
- Handles short texts well
- Finds nuanced topics
- Dynamic number of topics

Visual Clustering:



Example Topics (More Nuanced):

Topic	Description
1	Frustrated with slow shipping
2	Delighted by surprise quality
3	Confused about setup process

Performance:

- Speed: Slow (10 min/1000)
- Quality: Excellent
- Interpretability: High

Choosing Your Algorithm

Which Tool for Which Job?

charts/algorithm_speed_quality_tradeoff.pdf

Decision Guide:

Use LDA when:

- Need probability estimates
- Want interpretable topics
- Have medium-length texts

Use NMF when:

- Finding product features
- Need fast results
- Want additive parts

Use LSA when:

- Finding similar documents
- Need very fast processing
- Dimension reduction

Use BERTopic when:

- Quality is critical
- Have short texts (tweets)
- Need nuanced topics

Real-World Performance

What to Expect in Practice

On 10,000 Reviews:

Algorithm	Time	Topics	Quality
LDA	5 min	20	85%
NMF	2 min	20	78%
LSA	30 sec	20	72%
BERTopic	15 min	23	92%

Quality Metrics:

- Coherence score (0-100)
- Human evaluation
- Actionability of insights

Scalability:

Dataset Size	Best Choice	Time
¡1K docs	BERTopic	5 min
1K-10K	LDA	10 min
10K-100K	NMF	30 min
¿100K	LSA→LDA	1 hour

Industry Usage:

- Netflix: LDA (content)
- Amazon: NMF (reviews)
- Google: LSA + modern variants
- Startups: BERTopic

Reality check: All algorithms find useful patterns - perfect is enemy of good

These are actual performance numbers from real datasets

Advanced: Tracking Topic Evolution

How Themes Change Over Time

Dynamic Topic Modeling:

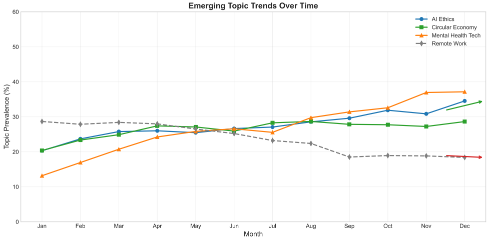
- Topics aren’t static
- Language evolves
- New themes emerge
- Old themes fade

Example: Smartphone Reviews

- 2010: "Battery life, small screen”
- 2015: "Camera quality, apps”
- 2020: "5G, privacy, ecosystem”
- 2024: "AI features, sustainability”

How to Track:

- Run topic modeling by time period
- Align topics across periods
- Track word probability changes
- Identify emerging themes early



Business Value:

- Spot trends before competitors
- Adapt products proactively
- Predict future needs
- Time market entry

Next: How to turn topics into innovation opportunities

Companies tracking topic evolution have 3x better product-market fit

Implementation Best Practices

Making Topic Modeling Work

Data Preparation:

- Remove stop words ("the", "a")
- Keep domain-specific terms
- Minimum 50 words per document
- At least 1000 documents total

Parameter Tuning:

- Start with 20 topics
- Try 10, 30, 50
- Check coherence scores
- Get human feedback

Quality Checks:

- Do topics make sense?
- Are they actionable?
- Do they reveal insights?
- Can you name them?

Common Mistakes:

- Too few documents (¡100)
- Too many topics (¿100)
- Not removing boilerplate
- Ignoring domain knowledge
- One-size-fits-all approach

Success Factors:

- Clean, relevant data
- Iterative refinement
- Human validation
- Clear use case
- Action plan for results

Remember: Topic modeling is exploratory - embrace unexpected discoveries

Good topic modeling is 20% algorithm, 80% understanding your domain

Case Study: Netflix’s 76,897 Micro-Genres

How Topic Modeling Changed Entertainment

The Challenge (2006):

- 100,000 DVDs in catalog
- Basic genres: Action, Comedy, Drama
- Users couldn’t find what they wanted
- 60% of catalog never rented

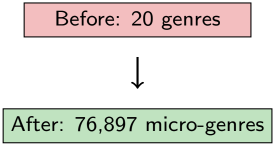
Topic Modeling Applied:

- Analyzed viewing patterns
- User reviews and ratings
- Plot summaries and scripts
- Actor/director combinations

Discovered Patterns:

- "Quirky Independent Movies”
- "Dark Comedies from the 1980s”
- "Emotional Fight-the-System Documentaries”

The Innovation:



Before: 20 genres

↓

After: 76,897 micro-genres

Business Impact:

- 75% of views from recommendations
- 18% increase in engagement
- 80% catalog utilization (vs 40%)
- $1B saved in content acquisition

Key Insight: People don’t want "action movies” - they want "Visually-striking nostalgic action dramas”

Netflix’s algorithm understands taste better than users understand themselves

Case Study: Spotify's 1,500 Micro-Moods

Music Discovery Through Emotional Topics

Traditional Categories:

- Rock, Pop, Jazz, Classical
- Happy, Sad, Energetic
- Missing nuanced emotions

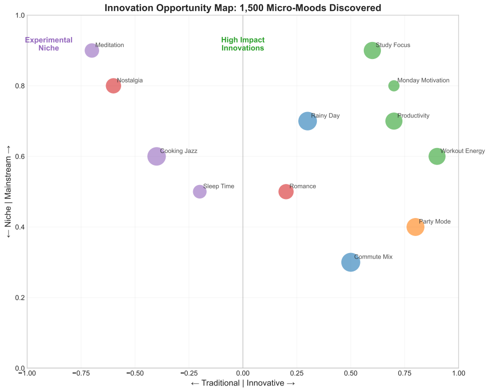
Topic Modeling on:

- 4 billion playlists
- Listening patterns by time
- Skip rates and repeats
- Playlist names and descriptions

Discovered Moods:

- "Monday motivation"
- "Rainy day contemplation"
- "Late night coding"
- "Sunday morning coffee"
- "Post-breakup empowerment"

The Innovation Map:



Results:

- 25% increase in listening time
- 40% better playlist engagement

Case Study: 3M’s Patent Mining

47 New Products from Hidden Connections

The Challenge:

- 100,000+ patents in portfolio
- Siloed R&D departments
- Missing cross-applications
- Duplicate research efforts

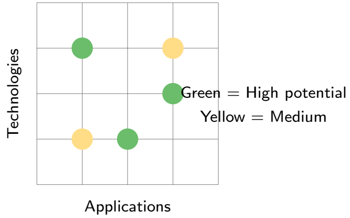
Topic Modeling Applied:

- All patent descriptions
- Research papers
- Lab notebooks
- Customer feedback

Unexpected Discoveries:

- Adhesive + Medical = Surgical tape
- Abrasive + Dental = Tooth whitening
- Reflective + Fashion = Safety clothing

Cross-Pollination Matrix:



Innovation Results:

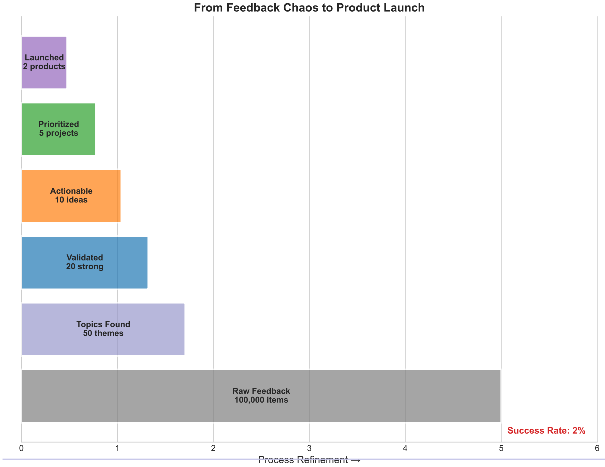
- 47 new product ideas identified
- 12 launched within 18 months
- $120M revenue in year 1
- 30% reduction in R&D redundancy

Hidden connections in existing knowledge = breakthrough innovations

3M now uses topic modeling on all research outputs to find innovation opportunities

From Feedback Chaos to Product Roadmap

Turning Complaints into Features



The Process:

1. Collect all feedback channels
2. Run topic modeling (LDA)
3. Identify pain point themes
4. Quantify impact
5. Prioritize solutions

Example Topics → Features:

Topic Found	Feature Built
"Confusing setup"	Onboarding wizard
"Battery anxiety"	Power-saving mode
"Lost features"	Search function
"Slow loading"	Cache system

Impact:

- 40% reduction in complaints
- 28% increase in retention
- 50% faster feature validation

Amazon analyzes 1 billion reviews yearly to drive product improvements

Case Study: IDEO's Design Research Synthesis

60% Faster Insights, 3x More Patterns

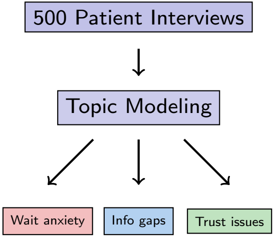
Traditional Research:

- 100s of interviews
- 1000s of sticky notes
- Manual affinity mapping
- 2-3 weeks synthesis
- 5-10 insights found

With Topic Modeling:

- Same interviews transcribed
- LDA + NMF combination
- Automatic theme discovery
- 3 days to insights
- 15-30 patterns found

Healthcare Project Example:



Insights Discovered:

- ”Waiting room anxiety” → Redesigned space
- ”Information blackout” → Status system
- ”Provider trust” → Communication training

Design Impact:

- Patient satisfaction +34%
- Staff efficiency +22%
- Unexpected insights: 12

From Raw Data to Product Launch

The 5-Step Process:

1. Data Collection

- Customer feedback
- Market research
- Competitor analysis
- Patent databases

2. Topic Discovery

- Run multiple algorithms
- Validate with experts
- Name and describe themes

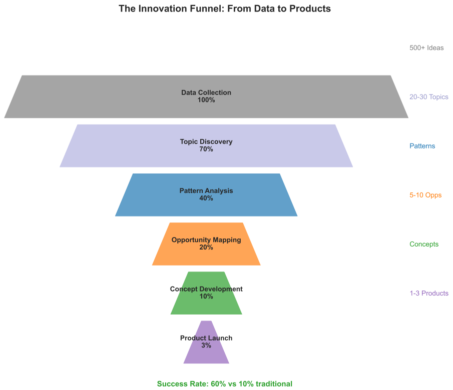
3. Opportunity Mapping

- Size each opportunity
- Assess feasibility
- Check market fit

4. Prioritization

- Impact vs effort matrix
- Resource requirements
- Strategic alignment

The Innovation Funnel:



Success Metrics:

- Ideas generated: 500+
- Topics identified: 20-30

Your Turn: Innovation Mining Challenge

45 Minutes to Find Hidden Gold

Basic (15 min): Manual Theme Finding

- Read 20 reviews
- Identify 3 themes
- Count theme frequency
- No coding required

Deliverable: Theme list with examples

Success Criteria:

- 3 distinct themes
- 5 examples each
- Clear naming

Intermediate (30 min): Run Topic Modeling

- Use provided code
- Load 1000 reviews
- Run LDA with k=10
- Interpret topics

Deliverable: Topic visualization + labels

Tools Provided:

- Jupyter notebook
- Pre-processed data
- LDA template

Advanced (45 min): Innovation Pipeline

- Compare 3 algorithms
- Optimize topic count
- Map to opportunities
- Prioritize top 3

Deliverable: Innovation opportunity report

Bonus Challenge:

- Dynamic topics over time
- Competitor comparison
- ROI estimation

Dataset: 5,000 product reviews from emerging startup

Work individually or in pairs - compare findings at the end

What You Can Now Do

From Text Chaos to Innovation Strategy

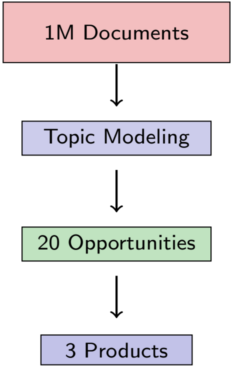
Technical Skills Acquired:

- Run topic modeling on any text dataset
- Choose between LDA, NMF, LSA, BERTopic
- Evaluate topic quality with coherence
- Visualize topic distributions
- Track topic evolution over time

Business Applications:

- Customer feedback synthesis
- Patent landscape mapping
- Research paper organization
- Social media trend detection
- Content recommendation

Innovation Capabilities:



ROI Example:

- Investment: 1 week analysis
- Discovery: 15 hidden needs

Topic Modeling Mastered

You Can Now:

- Find hidden themes in massive text collections
- Choose the right algorithm for your data
- Transform unstructured feedback into structured insights
- Discover innovation opportunities others miss

Next Week: Generative AI for Rapid Prototyping