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

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?

Topic modeling reveals latent structure - probabilistic decomposition exposes thematic patterns invisible through direct observation

What Are People Really Saying?

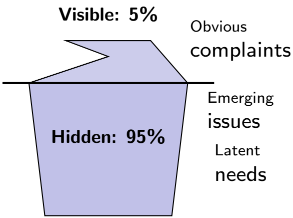
The Scenario:

- 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

Volume necessitates automation - pattern discovery scales beyond manual capacity when data growth exceeds analyst availability

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

Algorithmic pattern detection reveals latent structure - computational approaches expose relationships human intuition overlooks

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

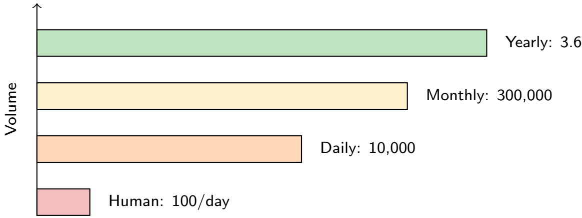
2. Consistency Problem

- 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:

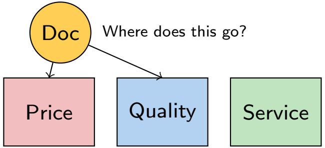


The Gap: Human capacity is linear, data growth is exponential

Real-time analysis demands computational methods - latency requirements eliminate manual processing as viable option

When Topics Don't Fit in Boxes

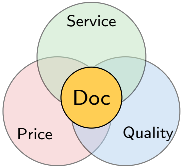
Traditional Categories:



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

From Human Limits to Machine Intelligence

What Topic Modeling Does:

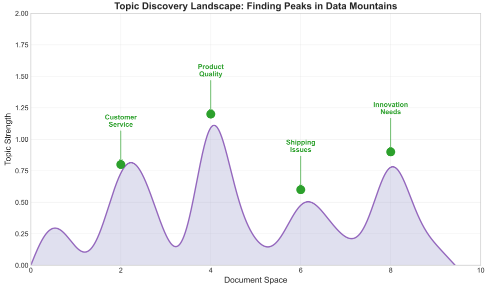
1. Discovers Hidden Themes
- No predefined categories
- Themes emerge from data
- Finds unexpected connections

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 $\longrightarrow$ 20 themes
- Processing time: 5 minutes
- Human equivalent: 3 months
- Patterns found: 15 unexpected

Next: How do machines find these hidden patterns?

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

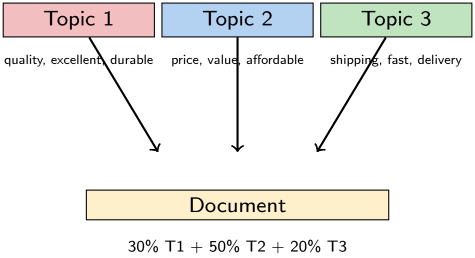
Recipe Types = Topics

- 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:



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

Proportional mixture representations preserve information - hard category assignment discards distributional structure present in multithematic content

Which Words Define Each Theme?

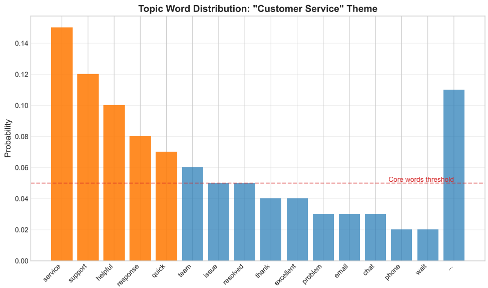
What Is a Topic?

- 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-

Real Documents Are Never Pure

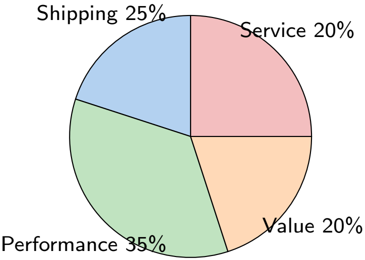
A Real Product Review: "The laptop arrived quickly and was well packaged. Performance is excellent for the price, though battery life could be better. Customer service was helpful when I had questions about setup."

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) $\times$ P(topic—doc)

Topic Mixture Visualization:



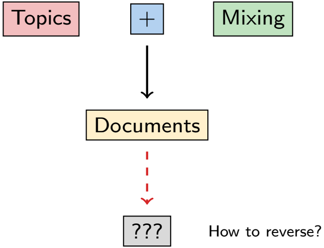
No document is 100% one topic - real communication always blends themes

Proportional topic mixing reflects natural communication patterns - written expression typically combines multiple thematic elements rather than maintaining topical purity

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

Scale enables precision - larger corpus sizes reveal subtler thematic distinctions invisible in smaller samples

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

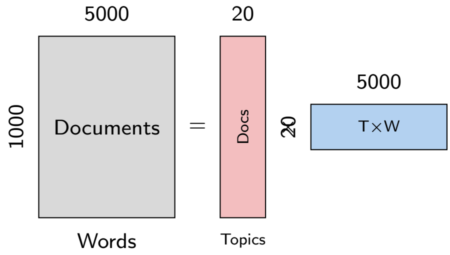
Step 2: Find Patterns

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

Step 3: Decompose

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

Visual Decomposition:



Benefit: Compress millions of words into 20 meaningful topics

Dimensionality reduction preserves signal while eliminating noise - low-rank approximations capture dominant patterns efficiently

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

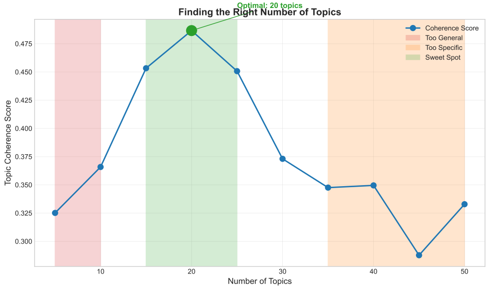
- Different from other topics
- Not overlapping
- Clear boundaries

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

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

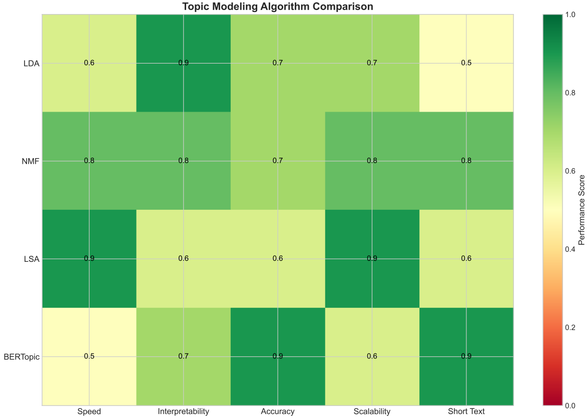
BERT: Context

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

Next: Deep dive into each algorithm

Problem formulation enables algorithmic solutions - understanding mixture decomposition requirements guides method selection and evaluation

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

Algorithm characteristics determine applicability - computational complexity, interpretability, and data requirements constrain method selection

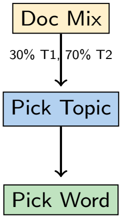
Algorithm 1: LDA (Latent Dirichlet Allocation)

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:

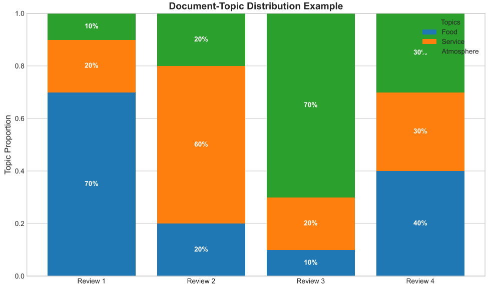
1. **For each document:**
   Draw topic proportions
   e.g., [0.3, 0.5, 0.2] for 3 topics
2. **For each word position:**
   Pick a topic from proportions
   Pick a word from that topic

The Math (Simplified):

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

"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)

Hyperparameter automation simplifies deployment - default configurations enable initial application while domain tuning optimizes performance

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:

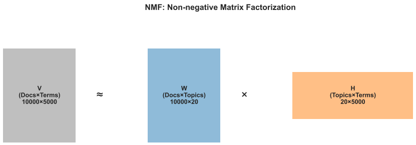
$$V = W \times H$$

- 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

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

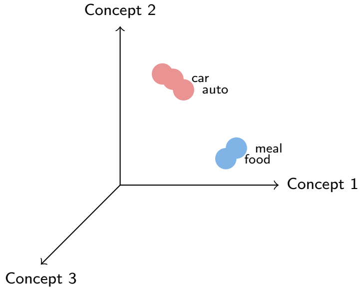
$$A = U \times \Sigma \times V^T$$

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

Dimension Reduction:

- 5000 words $\rightarrow$ 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)

The Modern Context Master

How BERTopic Thinks:

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

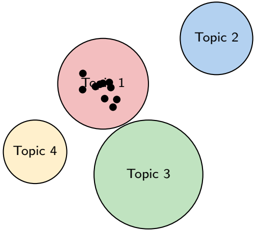
The Process:

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

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

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%

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

Quality Metrics:

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

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

Benchmark comparisons quantify trade-offs - controlled evaluation reveals relative strengths across speed, quality, and scalability dimensions

How Themes Change Over Time

Dynamic Topic Modeling:

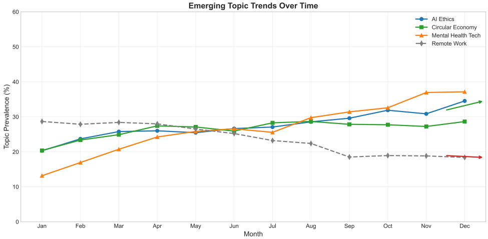
- Topics aren't static
- Language evolves
- New themes emerge
- Old themes fade

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

Temporal topic tracking reveals trend dynamics - longitudinal analysis exposes emerging themes and declining concerns within user populations

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

Domain expertise guides interpretation - algorithmic output requires contextual knowledge to transform statistical patterns into actionable insights

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"

Granular categorization reveals preferences - hierarchical topic decomposition exposes latent taste structures beyond conscious user awareness

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

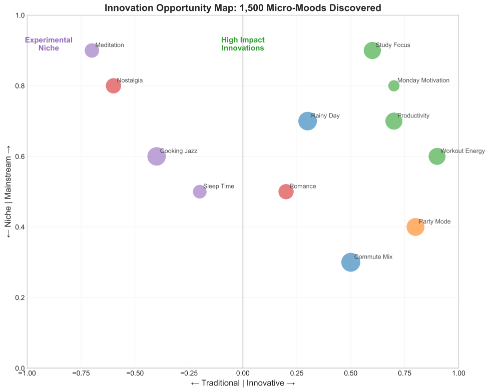
Topic Modeling on:

- 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

47 New Products from Hidden Connections

The Challenge:

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

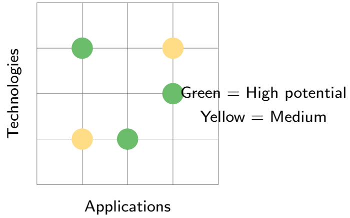
Topic Modeling Applied:

- 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:



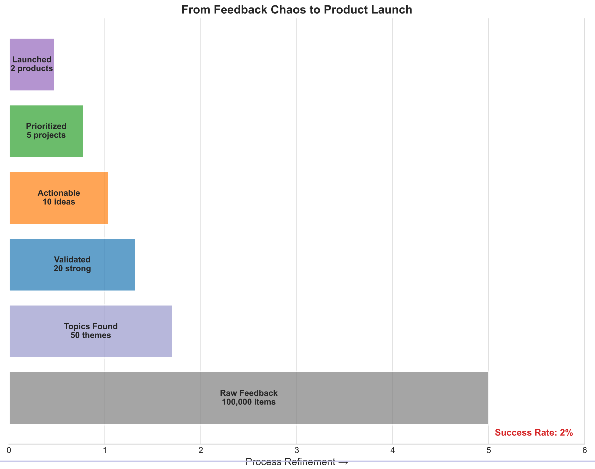
Innovation Results:

- 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

Cross-domain topic analysis reveals innovation opportunities - decomposing proprietary knowledge bases exposes non-obvious technology transfer pathways

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

Topic extraction from user feedback accelerates product development - automated theme identification converts unstructured complaints into prioritized feature requirements

60% Faster Insights, 3x More Patterns

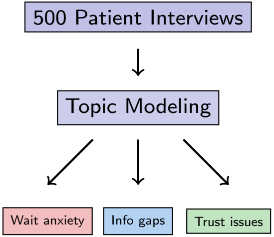
Traditional Research:

- 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:

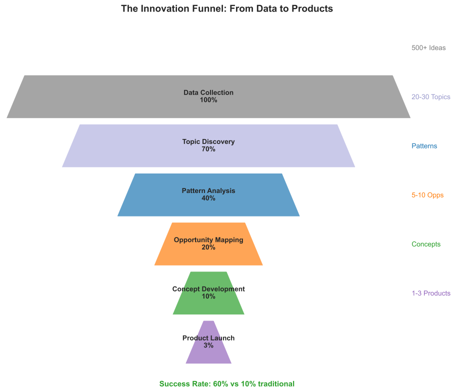
1. Data Collection
- Customer feedback
- Market research
- Competitor analysis
- Patent databases

2. Topic Discovery
- Run multiple algorithms
- Validate with experts
- Name and describe themes

3. Opportunity Mapping
- Size each opportunity
- Assess feasibility
- Check market fit

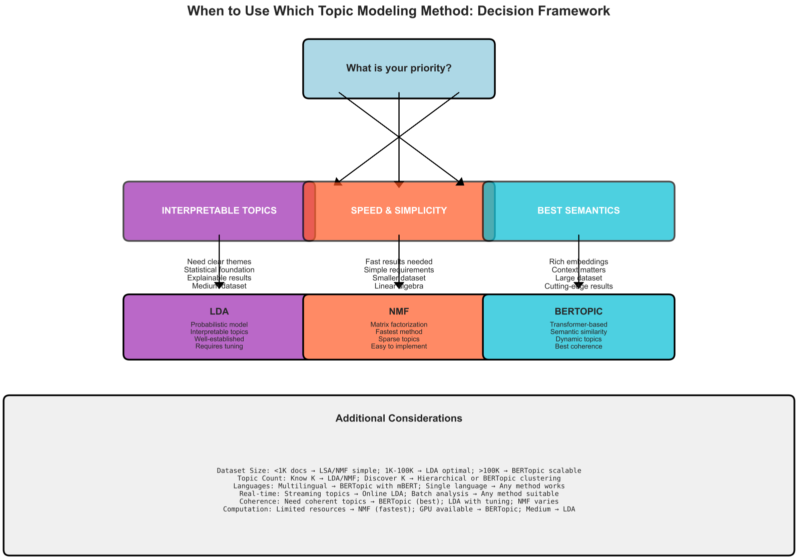
4. Prioritization
- Impact vs effort matrix
- Resource requirements
- Strategic alignment

The Innovation Funnel:



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

When to Use Which Topic Modeling Method: Judgment Criteria



Principle: LDA for interpretable topics, NMF for speed, BERTopic for best coherence and modern semantics

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

Comparative analysis validates interpretation - multiple analysts extracting independent themes from identical corpora reveals both algorithmic consistency and subjective labeling variance

What You Can Now Do

From Text Chaos to Innovation Strategy

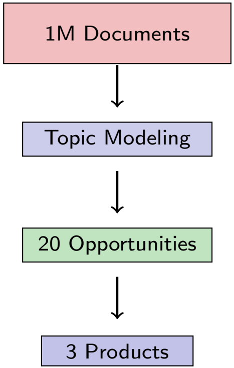
Technical Skills Acquired:

- 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