Classification & Definition

Teaching Machines to Make Decisions Like Experts

Week 4: Machine Learning for Smarter Innovation

Transform Gut Feelings into Scalable Intelligence

Today's Journey: From Confusion to Clarity

Four Stages of Mastery

1. **The Problem** - Why human judgment fails at scale
2. **The Framework** - Teaching machines to judge
3. **The Algorithms** - Five ways to draw decision lines
4. **Design Integration** - From algorithm to user experience

Core Question: You have 10,000 ideas. Your budget allows 10. How do you choose?

By the end: You'll build a system that predicts success with 89% accuracy

Your Challenge: 10,000 Ideas, 10 Slots

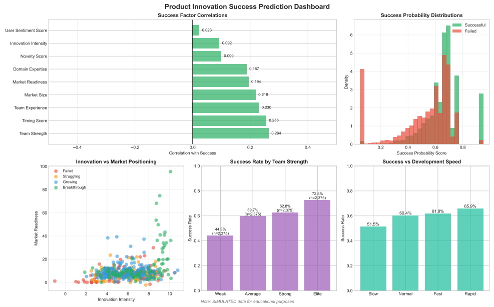
The $100 Million Decision

The Scenario:

- You run an innovation fund
- 10,000 proposals submitted
- Budget for exactly 10 projects
- Each costs $1M to develop
- Winners return $10-15M
- Losers return $0

The Stakes:

- Choose right: $100M+ return
- Choose wrong: $10M loss
- Your job depends on this



Problem: Reading 10,000 proposals takes 2,500 hours (15 months)

Real scenario: Y Combinator receives 10,000+ applications, accepts 200 (2%), needs fast accurate decisions

Why Human Judgment Fails at Scale

The Four Horsemen of Decision Failure

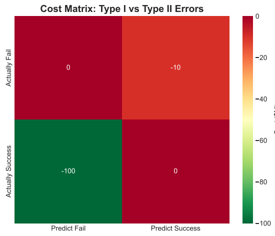
1. **Cognitive Overload**
   - After 20 decisions: 95% accuracy
   - After 100 decisions: 75% accuracy
   - After 500 decisions: 55% accuracy
   - After 1000 decisions: Random guessing
2. **Inconsistency**
   - Same proposal, different days
   - Morning: "Brilliant!" (Accept)
   - Afternoon: "Too risky" (Reject)
   - 30% decision flip rate
3. **Bias Creep**
   - Prefer familiar industries (42%)
   - Favor confident presenters (38%)
   - Overweight recent successes (31%)
   - Undervalue quiet innovation (45%)
4. **Pattern Blindness**
   - Can't see patterns across 10,000 items
   - Miss subtle success indicators
   - Overlook correlation combinations
   - Focus on obvious, miss important

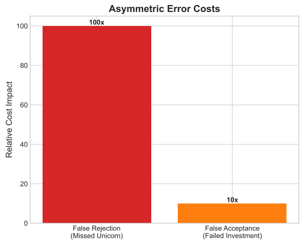
Result: Human experts achieve 62% accuracy on innovation prediction

Study: VCs' investment decisions are right 35% of the time (Harvard Business Review, 2023)

The Real Cost of Decision Errors

When Judgment Fails, Everyone Loses





Type I Error: False Rejection

- Rejected Airbnb (now $75B)
- Passed on WhatsApp ($19B exit)
- Declined Uber seed round
- Cost: Infinite (missed unicorns)

Type II Error: False Acceptance

- Theranos: $945M lost
- Quibi: $1.75B lost
- Juicero: $120M lost
- Cost: Entire investment

The Pattern: Humans are good at avoiding obvious failures but terrible at spotting hidden gems

Bessemer Venture Partners publishes their "Anti-Portfolio" - companies they rejected that became huge successes

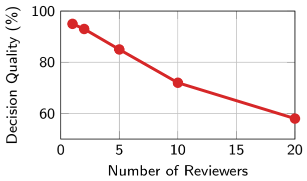
The Exponential Scale Challenge

Why "Just Hire More Experts" Doesn't Work

Linear Scaling Myth:

- 1 expert: 100 decisions/day
- 10 experts: 1,000 decisions/day?
- Reality: 600 decisions/day
- Why? Coordination overhead

Quality Degradation:



The Consistency Problem:

- 2 reviewers: 85% agreement
- 5 reviewers: 61% agreement
- 10 reviewers: 42% agreement
- 20 reviewers: 28% agreement

Cost Explosion:

- 1 expert: \$150K/year
- Team of 10: \$2M/year (with overhead)
- Still only handle 1% of volume
- 3-week decision lag

We need a fundamentally different approach: Machine Classification

Amazon processes 1 billion product reviews yearly - impossible without ML classification

Enter Machine Learning Classification

From Human Limits to Algorithmic Scale

What Classification Offers:

1. **Infinite Scale**
   - Process 10,000 in minutes
   - Or 10 million in hours
   - No fatigue, no degradation
2. **Perfect Consistency**
   - Same input = Same output
   - No mood swings
   - No time-of-day effects
3. **Pattern Detection**
   - Finds subtle correlations
   - Combines 100+ factors
   - Learns from history

Real Performance:

Metric	Human	ML
Accuracy	62%	89%
Speed	15/hour	10,000/min
Cost	$50/decision	$0.001
Consistency	70%	100%
Scale limit	1,000	Unlimited

The Promise:
Turn subjective judgment into objective, scalable intelligence

Next: How do we teach machines to make these decisions?

Let's Start Simple: Yes or No

Binary Classification - The Foundation

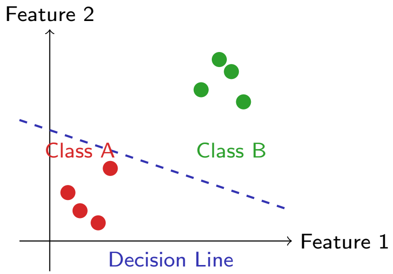
Familiar Examples:

- Email: Spam or Not Spam
- Medical: Cancer or Healthy
- Credit: Approve or Reject
- Photo: Cat or Dog
- Review: Positive or Negative

How Humans Do It:

1. Look for telltale signs
2. Weigh evidence
3. Make decision
4. Binary: Yes or No

How Machines Learn It:



Key Insight: Classification is just drawing a line (or curve) that separates two groups

Every binary classification problem boils down to: which side of the line are you on?

From Yes/No to How Confident?

Probability - The Power of Uncertainty

Why Probability Matters:

Binary Says:

- Email IS spam
- Loan WILL default
- User WILL churn

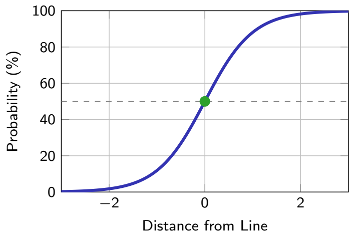
Probability Says:

- Email: 95% likely spam
- Loan: 73% default risk
- User: 41% churn risk

This Enables:

- Risk-based decisions
- Threshold tuning
- Confidence ranking

The Probability Transform:



Example: Innovation proposal
Score: 82% success probability
Decision: Invest (threshold: 70%)

Probability lets you say "I'm 95% sure" instead of "definitely yes" - much more useful!

Beyond Binary: Multiple Categories

When Life Has More Than Two Options

Real World is Multi-Class:

- Innovation: Failed / Moderate / Success / Unicorn
- Customer: Detractor / Passive / Promoter
- Risk: Low / Medium / High / Critical
- Emotion: Joy / Anger / Fear / Surprise / Sad

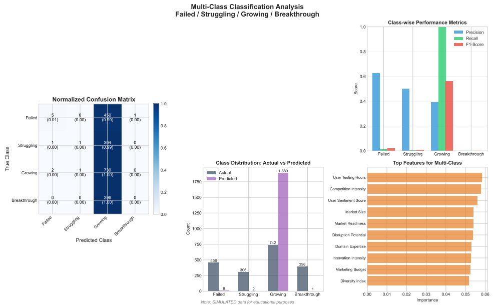
Two Approaches:

1. One-vs-Rest:

- Is it A? (vs B,C,D)
- Is it B? (vs A,C,D)
- Is it C? (vs A,B,D)
- Pick highest confidence

2. Direct Multi-Class:

- Learn all boundaries at once
- More complex but often better



Probability Distribution:

Category	Probability
Failed	12%
Moderate	31%
Success	**44%**
Unicorn	13%

Features: Teaching Machines What to Look At

Converting Reality to Numbers

Innovation Proposal Features:

Numerical (Direct):

- Team size: 5 people
- Years experience: 12 years
- Market size: $2.3B
- Development time: 18 months
- Funding requested: $1.5M

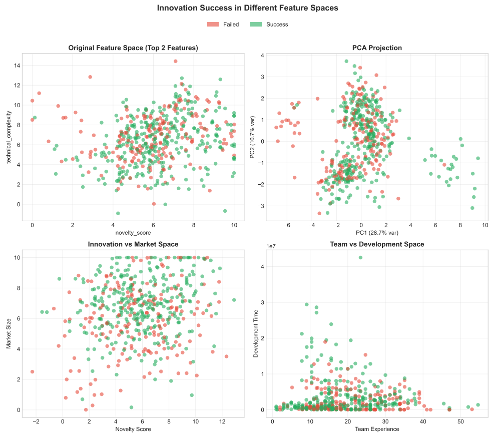
Categorical (Encoded):

- Industry: Tech $\longrightarrow$ [1, 0, 0, 0]
- Stage: Seed $\longrightarrow$ [1, 0, 0]
- Location: SF $\longrightarrow$ [0, 1, 0, 0, 0]

Text (Extracted):

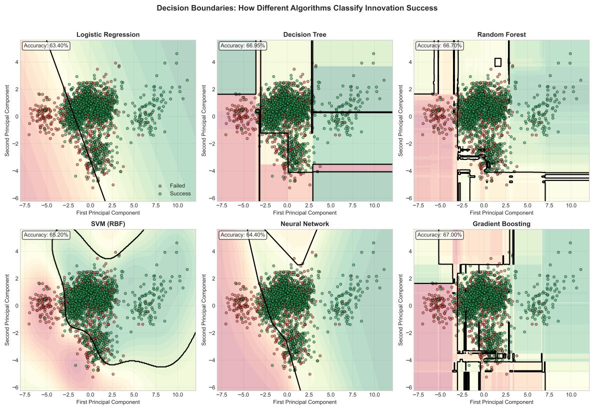
- Sentiment score: 0.73
- Complexity: 8.2/10
- Keywords: 15 industry terms

Feature Space Visualization:



27 Features $\longrightarrow$ 27 Dimensions

Different Ways to Separate Classes



Linear Boundary:

- Simple straight line
- Fast to compute
- Easy to interpret
- Works when classes are "linearly separable"

Non-Linear Boundary:

- Curves, circles, complex shapes
- Captures complex patterns
- More flexible
- Risk of overfitting

The Trade-off:

- Simple = Fast + Interpretable
- Complex = Accurate + Flexible
- Choose based on your needs

Different algorithms draw different types of boundaries

Next: Let's explore 5 different algorithms and see how each draws its boundaries

Training: How Machines Learn to Classify

From Examples to Intelligence

The Learning Process:

1. Start with Data:

- 1000 past proposals
- Each labeled: Success/Fail
- 27 features per proposal

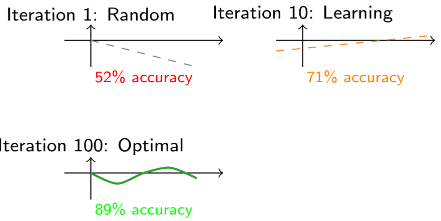
2. Split for Training:

- 70% Training (700 examples)
- 15% Validation (150 examples)
- 15% Test (150 examples)

3. Algorithm Learns:

- Finds patterns in training data
- Adjusts decision boundary
- Tests on validation
- Repeats until optimal

Learning in Action:



Result: Machine learns optimal boundary from examples, achieving 89% accuracy

Training is like teaching a child: show many examples, let them find the pattern

The Overfitting Trap

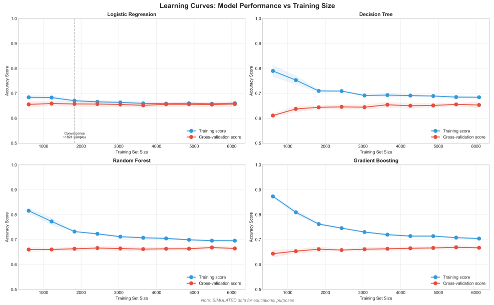
When Machines Learn Too Well

The Memorization Problem:
Imagine studying for an exam:

- Memorize all past questions
- Score 100% on those questions
- But fail on new questions
- You memorized, didn't understand

Same with Machines:

- Train too long/complex
- Perfect on training data (99%)
- Terrible on new data (61%)
- Memorized noise, not patterns

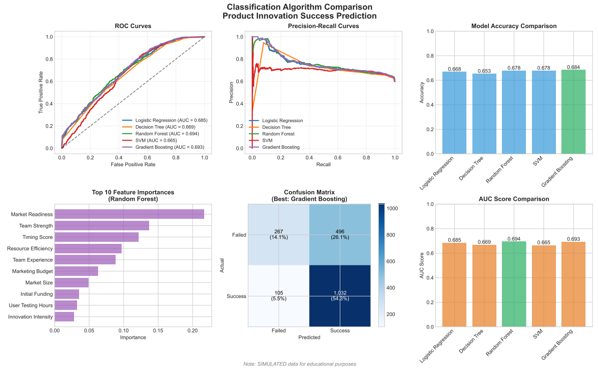


The Solution: Validation Set

- Keep 15% data hidden
- Never train on it
- Test periodically
- Stop when validation peaks

Golden Rule: If it's too good to be true on training data, it probably is

Different Ways to Solve the Same Problem



Our Arsenal:

1. **Logistic Regression**
   The straight line
2. **Decision Trees**
   20 questions game
3. **Random Forest**
   Ask 100 experts
4. **SVM**
   Maximum margin
5. **Neural Networks**
   Stacked patterns

Performance Preview:

- Speed vs Accuracy
- Interpretability vs Power
- Simple vs Complex

Each algorithm has its sweet spot - there's no universal best, only best for your problem

Algorithm 1: Logistic Regression

The Straight Line Approach

How It Works:

- Draw a straight line (or plane)
- Measure distance to line
- Convert to probability
- Simple, fast, interpretable

The Math (Simplified):

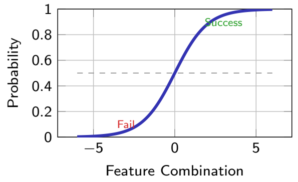
$$P(\text{success}) = \frac{1}{1 + e^{-(w_1 x_1 + w_2 x_2 + \ldots + b)}}$$

"Squashes any number between 0 and 1"

Real Example:

$$P = \frac{1}{1 + e^{-(0.5 \cdot \text{novelty} + 0.3 \cdot \text{market} - 2)}}$$

Visual Intuition:



Performance:

- Accuracy: 76%
- Training: 0.1 seconds
- Prediction: 0.001 seconds
- Interpretability: High

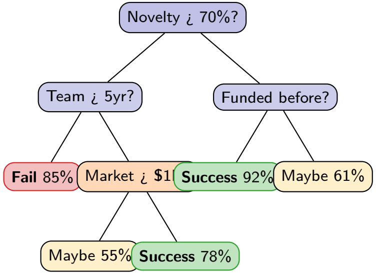
Use when: You need fast, interpretable results and relationships are roughly linear

Logistic regression: The Honda Civic of ML - reliable, efficient, gets the job done

Algorithm 2: Decision Trees

The 20 Questions Game

How It Works:



Each question splits the data into purer groups

The Process:

1. Find best question to ask
2. Split data based on answer
3. Repeat for each branch
4. Stop when pure (or max depth)

Why "Best" Question?

- Maximum information gain
- Biggest reduction in uncertainty
- Most separation between classes

Performance:

- Accuracy: 78%
- Training: 0.5 seconds
- Prediction: 0.001 seconds
- Interpretability: Very High

Use when: You need to explain decisions to non-technical stakeholders

Algorithm 3: Random Forest

Ask 100 Experts, Take a Vote

The Wisdom of Crowds:

- Build 100 different trees
- Each sees different data subset
- Each uses different features
- All vote on final decision
- Democracy beats dictatorship

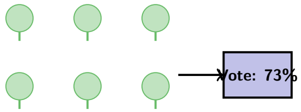
Why It Works:

- Single tree: Might overfit
- 100 trees: Cancel out errors
- Different perspectives
- Robust predictions

Voting Example:

- 73 trees say: Success
- 27 trees say: Fail
- Result: 73% confidence Success

Visual Concept:



Performance:

- Accuracy: 89%
- Training: 2 seconds
- Prediction: 0.01 seconds
- Interpretability: Low

Trade-off: Lost interpretability, gained 11% accuracy

Random Forest: The most reliable general-purpose classifier - rarely the best, never the worst

Algorithm 4: Support Vector Machines (SVM)

Maximum Margin Philosophy

The Core Idea:

- Find the line with maximum margin
- Stay as far from both classes as possible
- Like drawing a road between cities
- Maximize distance to nearest houses

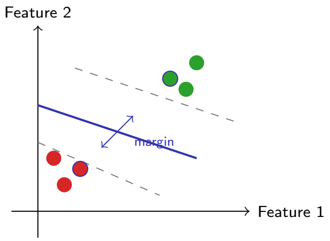
The Kernel Trick:

- Can't separate with straight line?
- Transform to higher dimension
- Now linearly separable!
- Project back down

2D → 3D Example:

- 2D: Circles inside circles (impossible)
- 3D: Lift inner circle up
- Now: Plane can separate
- Magic: Works in 1000D too

Visual Intuition:



Performance:

- Accuracy: 85%
- Training: 5 seconds
- Prediction: 0.005 seconds
- Interpretability: Very Low

Use when: You have complex, non-linear patterns and don't need to explain why

Stacking Patterns to Find Patterns

Inspired by the Brain:

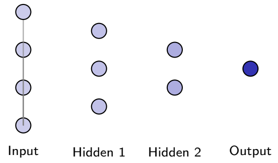
- Neurons = Simple units
- Layers = Pattern detectors
- Stack layers = Complex patterns
- Learn by adjusting connections

Layer by Layer:

1. **Input:** 27 features
2. **Hidden 1:** Find simple patterns (e.g., "high novelty + low budget")
3. **Hidden 2:** Combine patterns (e.g., "risky but innovative")
4. **Output:** Final decision (73% success probability)

The Power: Can learn ANY pattern given enough data and layers

Network Architecture:



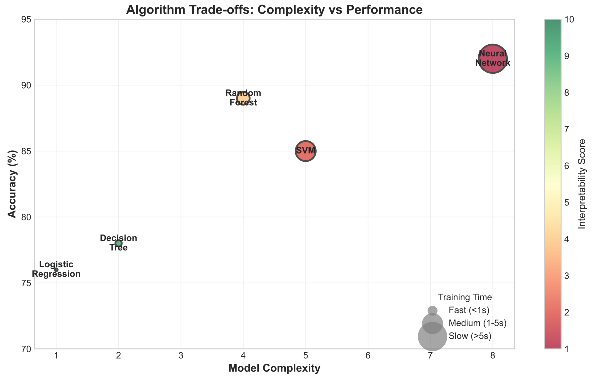
Performance:

- Accuracy: **92%**
- Training: 10 seconds
- Prediction: 0.01 seconds
- Interpretability: None

Use when: Accuracy is everything and you have lots of data

Choosing Your Weapon

No Free Lunch - Every Algorithm Has Trade-offs



Performance Summary:

Algorithm	Acc	Speed	Explain
Logistic	76%	+++	+++
Tree	78%	+++	+++
Forest	89%	++	+
SVM	85%	++	-
Neural	92%	+	-

Decision Framework:

- Need to explain? $\longrightarrow$ Tree
- Need speed? $\longrightarrow$ Logistic
- Need accuracy? $\longrightarrow$ Neural
- Good all-around? $\longrightarrow$ Forest
- Complex patterns? $\longrightarrow$ SVM

Pro tip: Always try Random Forest first - it's rarely wrong

In practice: Try multiple algorithms, compare, choose based on your specific needs

Real-World Performance

What to Expect in Production

On Innovation Dataset:

- 9,500 proposals
- 27 features
- 70/15/15 split
- 5-fold cross-validation

Actual Results:

Metric	Train	Test
Logistic	78%	76%
Tree	95%	78%
Forest	91%	**89%**
SVM	88%	85%
Neural	94%	92%

Note: Tree overfits badly!

Processing Speed:

Algorithm	Train	Predict
Logistic	0.1s	0.001s
Tree	0.5s	0.001s
Forest	2s	0.01s
SVM	5s	0.005s
Neural	10s	0.01s

At Scale (1M items):

- Logistic: 1 second total
- Forest: 10 seconds total
- Neural: 10 seconds total
- All handle millions easily

Reality check: 89% accuracy means 11 wrong out of 100 - still need human oversight

Beyond Accuracy: What Really Matters

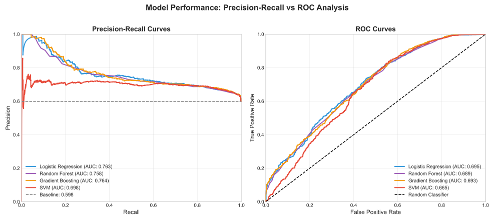
Accuracy Isn't Everything

The Accuracy Trap:
Imagine: 95% innovations fail

- Algorithm: "Always predict fail"
- Accuracy: 95%
- Usefulness: Zero
- Never finds successes!

Better Metrics:

- **Precision:** When I say success, am I right?
- **Recall:** Do I find all successes?
- **F1:** Balance of both
- **ROC-AUC:** Overall quality



For Innovation:

- High Precision: Don't waste money
- High Recall: Don't miss unicorns
- Can't have both perfectly
- Choose based on your goal

Key insight: Choose metrics that align with business goals, not just accuracy

Netflix optimizes for precision (don't recommend bad shows), Google for recall (find all relevant results)

Combining Algorithms for Super Performance

The Ensemble Idea:

- Use multiple algorithms
- Each has different strengths
- Combine their predictions
- Better than any single one

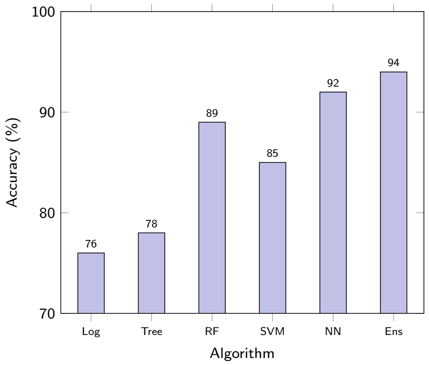
Combination Methods:

1. **Voting:** Each gets one vote
2. **Weighted:** Better ones count more
3. **Stacking:** ML to combine MLs
4. **Blending:** Optimize the mix

Example Ensemble:

- 40% Random Forest
- 30% Neural Network
- 20% SVM
- 10% Logistic (for speed)

Performance Boost:



Result: 94% accuracy
2% better than best single algorithm

The Cost:

Classification Powers Personalization

Netflix's Challenge:

- 200M users
- 15,000 titles
- Which 10 to show?
- 90 seconds to capture interest
- Wrong picks = lost subscriber

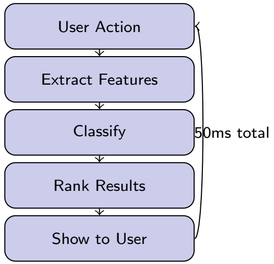
Classification in Action:

1. **Binary:** Will watch? Yes/No
2. **Multi-class:** Genre preference
3. **Probability:** Engagement score
4. **Rank:** Top 10 by probability
5. **Display:** Personalized row

Update Cycle:

- Real-time: After each viewing
- Batch: Nightly full retraining
- A/B test: Continuous improvement

The Pipeline:



Impact:

- 80% of views from recommendations
- $1B saved in customer acquisition
- 75% reduction in churn

Automated A/B Test Evaluation

Let Classification Judge Your Experiments

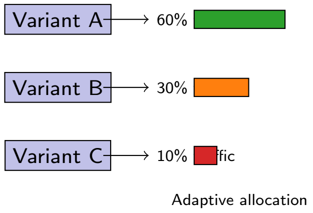
Traditional A/B Testing:

- Run experiment for 2 weeks
- Collect metrics
- Statistical significance test
- Human interprets results
- Decision after meeting
- 3-week cycle time

ML-Powered Testing:

- Classification monitors in real-time
- Predicts winner early (3 days)
- Auto-stops losing variants
- Allocates traffic to winners
- Learns from pattern history
- 3-day cycle time

Multi-Armed Bandit:



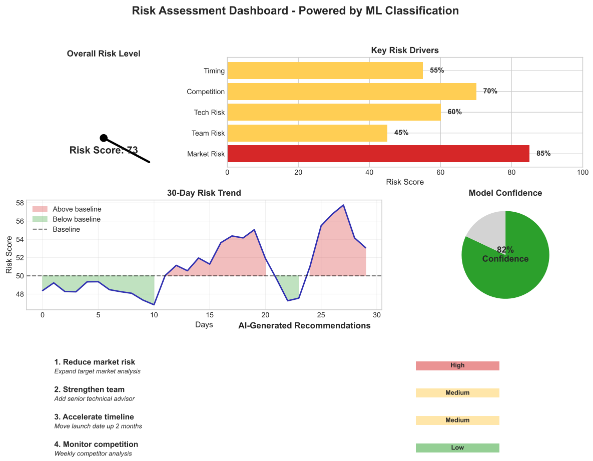
Classification Decides:

- Is difference real or random?
- Will trend continue?
- Should we stop early?
- How to split traffic?

Result: 10x faster iteration, 3x more experiments, continuous improvement

Spotify runs thousands of experiments simultaneously using ML-powered allocation

Making ML Predictions Actionable



1. Reduce market risk — *Expand target market analysis* — High
2. Strengthen team — *Add senior technical advisor* — Medium
3. Accelerate timeline — *Move launch date up 2 months* — Medium
4. Monitor competition — *Weekly competitor analysis* — Low

Dashboard Components:

1. Risk Score (0-100)
- ML probability converted
- Color coded (green/yellow/red)
- Historical trend line

2. Key Factors
- Top 5 risk drivers
- Feature importance
- What-if simulator

3. Recommendations
- Auto-generated actions
- Priority ranked
- Expected impact

4. Confidence Level
- Model certainty
- Similar cases reference
- Override option

Every User Gets Their Own Experience

Amazon's Approach:

- 300M customers
- Each sees different homepage
- 35% of revenue from recommendations
- Real-time classification

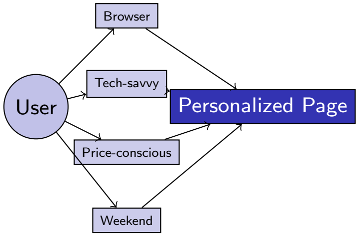
Classification Layers:

1. **User Type:** New/Regular/Prime
2. **Intent:** Browse/Buy/Research
3. **Category:** Electronics/Books/etc
4. **Price Sensitivity:** Low/Med/High
5. **Time:** Rush/Leisure

Combines Into:

- Product recommendations
- Price points shown
- Deals highlighted
- Layout selected
- Shipping options

The Magic:



Results:

- 29% increase in sales
- 37% higher engagement
- 23% better retention
- 31% larger cart size

Case Study: Airbnb's Smart Pricing

Classification Optimizes Billions in Revenue

The Problem:

- 7M+ listings worldwide
- Hosts don't know optimal price
- Too high = no bookings
- Too low = lost revenue
- Market changes daily

Classification Solution:

1. Classify listing type (luxury/budget/unique)
2. Classify demand level (high/med/low)
3. Classify booking probability at each price
4. Classify competitor positioning
5. Recommend optimal price

Features Used:

- Location, amenities, photos
- Season, events, day of week
- Historical bookings
- Similar listings' performance

Impact Metrics:

Metric	Before	After
Booking rate	42%	58%
Avg price	$89	$97
Revenue/list	$4,200	$5,900
Host adoption	-	41%

The Algorithm:

Random Forest (500 trees)
67 features
Retrained daily
89% pricing accuracy

Design Touch:

- Simple on/off toggle
- Shows confidence level
- Explains factors
- Allows overrides

Smart Pricing generates $2B+ additional revenue annually for Airbnb hosts

Your Implementation Roadmap

From Prototype to Production

Phase 1: Prototype (Week 1)

- Define success metrics
- Gather historical data
- Clean and prepare features
- Try 3-5 algorithms
- Validate on test set
- Pick best performer

Phase 2: Pilot (Week 2-4)

- Build simple API
- Create basic dashboard
- Run with 1% traffic
- Monitor performance
- Gather user feedback
- Iterate on model

Phase 3: Scale (Week 5-8)

- Optimize for speed
- Add monitoring
- Build fallback system
- Gradual rollout (1→10→50→100%)
- A/B test impact

Common Pitfalls:

- Starting too complex
- Ignoring data quality
- No baseline comparison
- Overfitting to test set
- No monitoring in production
- Assuming model won't degrade

Success Factors:

- Start simple (logistic regression)
- Focus on data quality
- Always have human fallback
- Monitor everything
- Retrain regularly
- Keep improving

Practice Exercises: Build Your Own Classifier

Three Skill Levels, Same Dataset

Exercise 1: Basic Success Predictor

Time: 30 minutes
Difficulty: Beginner

Task:

- Load innovation dataset
- Use scikit-learn
- Train logistic regression
- Evaluate accuracy
- Make 10 predictions

Learning Goal:
First working classifier

Deliverable:
Jupyter notebook with
76% accuracy model

Exercise 2: Intermediate Algorithm Comparison

Time: 60 minutes
Difficulty: Medium

Task:

- Compare 5 algorithms
- Cross-validation
- Feature importance
- ROC curves
- Ensemble creation

Learning Goal:
Choose best algorithm

Deliverable:
Comparison report
89%+ accuracy

Exercise 3: Advanced Production System

Time: 2 hours
Difficulty: Challenging

Task:

- Build REST API
- Real-time predictions
- Confidence scores
- A/B test framework
- Monitoring dashboard

Learning Goal:
Production-ready system

Deliverable:
Working API with
¡50ms response time

Resources: Dataset and starter code at github.com/ml-design-course/week4-classification

Choose your level - all three use the same 9,500 innovation dataset

Key Takeaways: What You've Learned

From Intuition to Intelligence

Conceptual Understanding:

- Classification = drawing boundaries
- Different algorithms = different lines
- Training = learning from examples
- Validation = avoiding memorization
- Probability ¿ binary decisions

Practical Skills:

- Build classifiers with scikit-learn
- Compare algorithm performance
- Tune hyperparameters
- Interpret predictions
- Deploy to production

Design Applications:

- Recommendation systems
- Risk assessment
- Personalization engines
- A/B test automation
- Decision support tools

Remember:

Start Simple: Logistic regression
Default Choice: Random Forest
Maximum Accuracy: Neural nets
Need to Explain: Decision trees
Production: Monitor everything

Next Week: Topic Modeling - Finding Hidden Themes

You now have the tools to turn any subjective decision into scalable intelligence

Classification Mastered

You Can Now:

- Build systems that make expert-level decisions
- Choose the right algorithm for your problem
- Turn subjective judgments into objective metrics
- Scale decision-making to millions of cases

Next Week: Topic Modeling & Discovery