Classification & Definition

Teaching Machines to Make Decisions Like Experts

Week 4: Machine Learning for Smarter Innovation

Transform Gut Feelings into Scalable Intelligence

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?

Classification systems enable predictive decision-making - supervised learning transforms historical patterns into probabilistic success forecasts

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

charts/innovation_success_dashboard.pdf

The Four Horsemen of Decision Failure

1. Cognitive Overload
Accuracy drops from 95% (20 decisions) to random guessing (1000 decisions)

2. Inconsistency
Same proposal gets opposite decisions on different days; 30% flip rate

3. Bias Creep
Favor familiar industries (42%), confident presenters (38%), recent successes (31%)

4. Pattern Blindness
Cannot see patterns across 10,000 items; miss subtle correlations

Result: Human experts achieve 62% accuracy on innovation prediction

Expert judgment remains probabilistic - domain knowledge improves accuracy but cannot eliminate uncertainty

When Judgment Fails, Everyone Loses

charts/decision_cost_matrix.pdf

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

Why "Just Hire More Experts" Doesn't Work

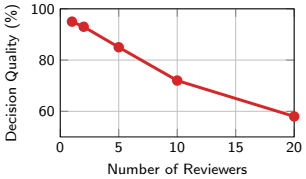
Linear Scaling Myth:

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

The Consistency Problem:

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

Quality Degradation:



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

Classification enables scale - systematic categorization transforms overwhelming volume into manageable decision inputs

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

Supervised learning formalizes decision patterns - explicit examples enable algorithmic generalization of human judgment

Binary Classification - The Foundation

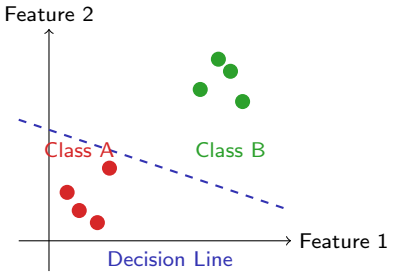
Familiar Examples:

- 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

Geometric partitioning enables decision-making - separating hyperplanes transform multidimensional feature spaces into actionable categories

Probability - The Power of Uncertainty

Why Probability Matters:

Binary Says:

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

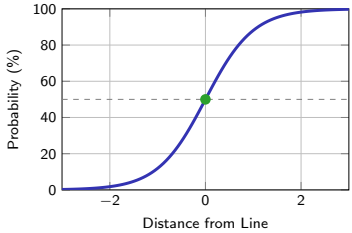
Probability Says:

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

This Enables:

- Risk-based decisions
- Threshold tuning
- Confidence ranking

The Probability Transform:



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

Probabilistic outputs quantify uncertainty - confidence scores enable risk-weighted decisions beyond binary classifications

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

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):

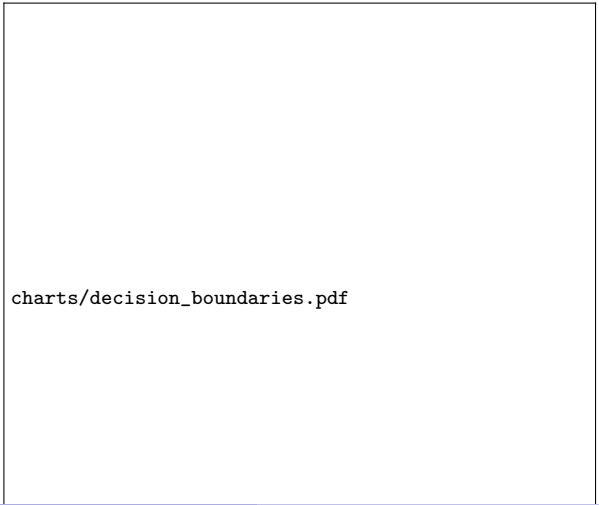
- Industry: Tech → [1, 0, 0, 0]
- Stage: Seed → [1, 0, 0]
- Location: SF → [0, 1, 0, 0, 0]

Text (Extracted):

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

Feature Space Visualization:

Different Ways to Separate Classes



Linear Boundary:
Simple, fast, interpretable; works when classes are linearly separable

Non-Linear Boundary:
Curves and complex shapes; captures patterns but risks overfitting

The Trade-off:
Simple = Fast + Interpretable; Complex = Accurate + Flexible

From Examples to Intelligence

The Learning Process:

1. Start with Data:

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

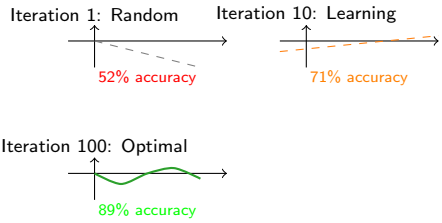
2. Split for Training:

- 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

Example-based learning generalizes patterns - sufficient representative instances enable algorithms to infer underlying decision rules

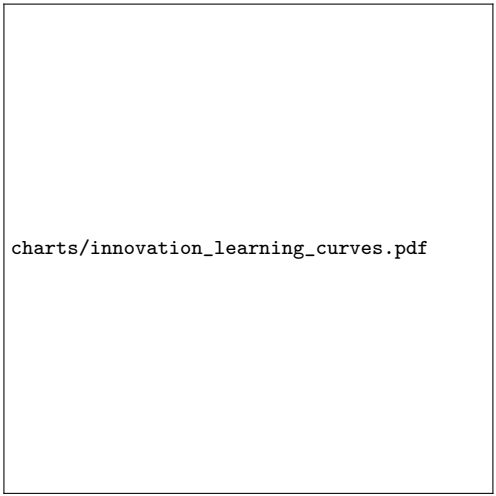
When Machines Learn Too Well

The Memorization Problem:
Imagine studying for an exam:

- Memorize all past questions
- Score 100% on those questions
- But fail on new questions

Same with Machines:

- Train too long: 99% training, 61% test
- Memorized noise, not patterns



Different Ways to Solve the Same Problem

charts/innovation_algorithm_comparison.pdf

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

The Straight Line Approach

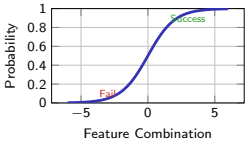
How It Works:
Draw line, measure distance, convert to probability via sigmoid function

The Math:

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

"Squashes any number between 0 and 1"

Sigmoid Curve:

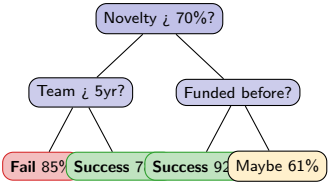


Performance: 76% acc, 0.1s train, high interpretability

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

Linear simplicity enables interpretability - coefficient-based models provide transparent feature importance attribution

The 20 Questions Game



Each question splits data into purer groups

The Process:
Find best question (max information gain), split, repeat until pure or max depth

Why It Works:
Sequential yes/no questions mirror human reasoning; fully interpretable decision paths

Performance:
78% accuracy, 0.5s train, very high interpretability

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

Hierarchical partitioning mirrors human reasoning - sequential decision rules create interpretable classification paths

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

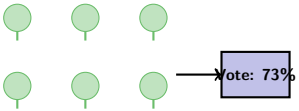
Why It Works:

- 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

Ensemble averaging reduces variance - aggregating diverse models improves robustness over single estimator predictions

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

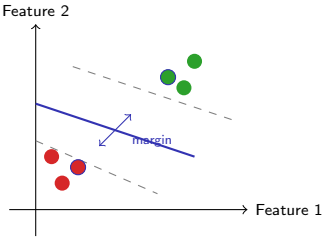
The Kernel Trick:

- 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:

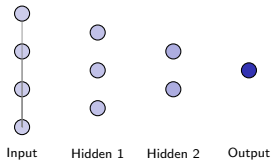
- Neurons = Simple units
- Layers = Pattern detectors
- Stack layers = Complex patterns
- Learn by adjusting connections

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

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? → Tree
- Need speed? → Logistic
- Need accuracy? → Neural
- Good all-around? → Forest
- Complex patterns? → SVM

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

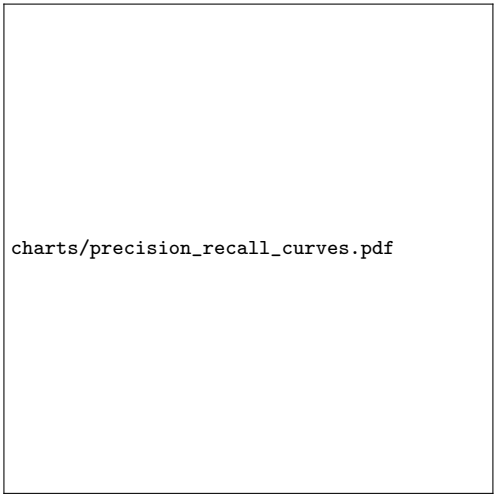
Accuracy Isn't Everything

The Accuracy Trap:
Imagine: 95% innovations fail

- Algorithm: "Always predict fail"
- Accuracy: 95% - great!
- Usefulness: Zero - useless!
- 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



Combining Algorithms for Super Performance

The Ensemble Idea:

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

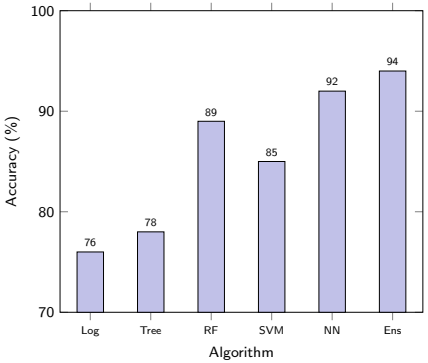
Combination Methods:

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

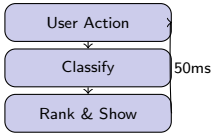
The Cost:

Classification Powers Personalization

Netflix's Challenge:
200M users, 15K titles, 90 seconds to capture interest

Classification Pipeline:
Binary (will watch?) → Multi-class (genre) → Probability score → Rank top 10 → Display

Update Cycle:
Real-time after views, nightly retraining, continuous A/B testing



Impact:
80% views from recommendations, $1B saved, 75% churn reduction

Design Principle: Classification invisible to user, value visible immediately

Ensemble deployment scales complexity - parallel model execution delivers diverse predictions within strict latency constraints

Let Classification Judge Your Experiments

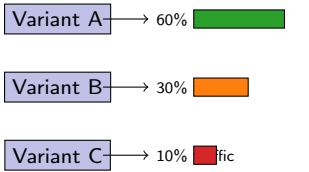
Traditional A/B Testing:

- Run 2 weeks, collect metrics
- Statistical test + human interpretation
- 3-week cycle time

ML-Powered Testing:

- Real-time monitoring, predict winner early
- Auto-stop losing, allocate to winners
- 3-day cycle time (10x faster)

Multi-Armed Bandit:



Adaptive allocation

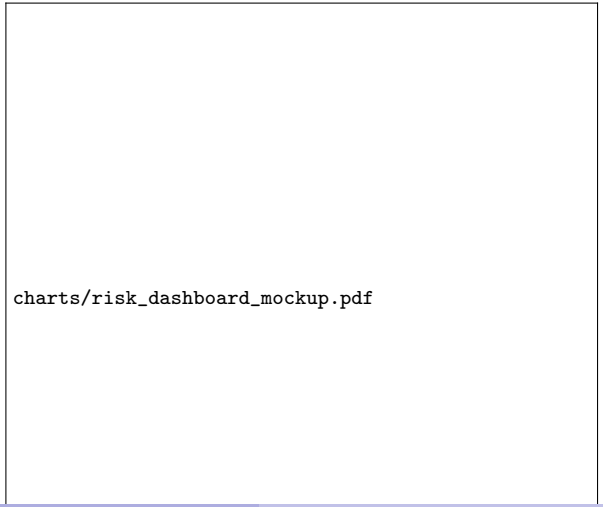
Classification Decides:

- 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

Automated experimentation enables continuous optimization - classification directs traffic allocation based on predicted outcomes

Making ML Predictions Actionable



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

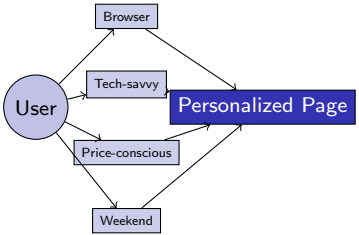
Classification Layers:

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

Classification Optimizes Billions in Revenue

The Problem:
7M+ listings; hosts don't know optimal price; too high = no bookings, too low = lost revenue

Classification Solution:
Classify listing type → demand level → booking probability at each price → recommend optimal

Features:
Location, amenities, photos, season, events, historical bookings, competitor performance

Impact:

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

Algorithm: Random Forest, 500 trees, 67 features, daily retrain, 89% accuracy

UX: Simple toggle, confidence level, factor explanations, override option

Dynamic classification drives pricing optimization - predicting booking probability enables revenue maximization through rate adjustment

From Prototype to Production

Phase 1: Prototype
Define metrics, gather data, try 3-5 algorithms, validate on test set

Phase 2: Pilot
Build API + dashboard, run with 1% traffic, monitor and iterate

Phase 3: Scale
Optimize speed, add monitoring, gradual rollout (1% $\rightarrow$ 100%), A/B test

Avoid:
Starting too complex, ignoring data quality, no baseline, overfitting, no monitoring

Do:
Start simple, focus on data quality, human fallback, monitor everything, retrain regularly

Remember: Perfect is the enemy of good - ship at 80%, improve to 95%

Incremental deployment reduces risk - simple baseline models enable production learning before investing in complex approaches

When to Use Which Classification Algorithm: Judgment Criteria

charts/classification_algorithm_decision.pdf

Three Skill Levels, Same Dataset

Exercise 1: Basic Success Predictor

Time: 30 minutes
Difficulty: Beginner

Task:

- Load dataset, train logistic
- Evaluate accuracy
- Make predictions

Goal: First classifier
Output: 76% accuracy

Exercise 2: Intermediate Algorithm Comparison

Time: 60 minutes
Difficulty: Medium

Task:

- Compare 5 algorithms
- Cross-validation + ROC
- Build ensemble

Goal: Best algorithm
Output: 89%+ accuracy

Exercise 3: Advanced Production System

Time: 2 hours
Difficulty: Challenging

Task:

- Build REST API
- Real-time + confidence
- Monitoring dashboard

Goal: Production-ready
Output: ¡50ms response

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

Differentiated learning paths serve diverse backgrounds - identical data across complexity levels enables progression while maintaining relevance

From Intuition to Intelligence

Conceptual Understanding:

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

Practical Skills:

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

Core Insight: Probability outputs enable risk-weighted decisions beyond binary classifications

Classification formalizes judgment - systematic pattern recognition scales human decision-making beyond individual cognitive limits

Design Integration

Design Applications:

- Recommendation systems
- Risk assessment dashboards
- Personalization engines
- A/B test automation

Algorithm Selection:

- **Start Simple:** Logistic regression
- **Default:** Random Forest
- **Max Accuracy:** Neural nets
- **Explainability:** Decision trees

Next Week: Topic Modeling - Finding Hidden Themes

Production deployment requires monitoring - continuous validation ensures model performance remains aligned with business objectives

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