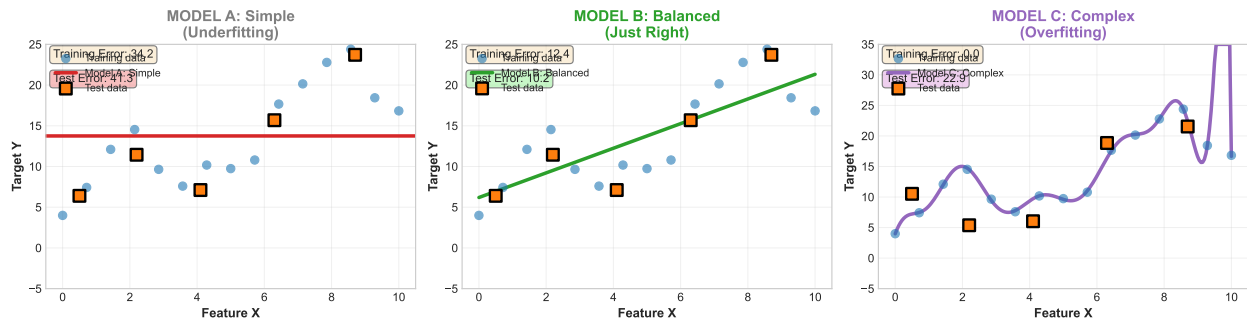# Discovery Worksheet

Introduction to Machine Learning & AI
Pattern Recognition Through Visual Analysis

Machine Learning for Smarter Innovation
Week 0: Pre-Lecture Activity

Chart 1: Model Complexity

MODEL A: Simple (Underfitting) — Training Error: 34.2, Test Error: 41.3, Model A: Simple, Training data, Test data

MODEL B: Balanced (Just Right) — Training Error: 12.4, Test Error: 10.2, Model B: Balanced, Training data, Test data

MODEL C: Complex (Overfitting) — Training Error: 0.0, Test Error: 22.9, Model C: Complex, Training data, Test data

Observation

Three models predict house prices from square footage. Blue dots represent training data. Orange squares represent new test data the models have not seen.

Tasks

Task 1: Rank model complexity

Rank the three models from simplest to most complex:

Simplest: _____ → _____ → Most complex: _____

Task 2: Identify performance pattern

Which model performs worst on the new orange test points?

Answer: _____

Why does this model struggle with new data?

_____

_____

Task 3: Explain the trade-off

Model C fits the training data perfectly (zero error), yet performs poorly on test data. What is the risk of creating a model that fits training data too closely?
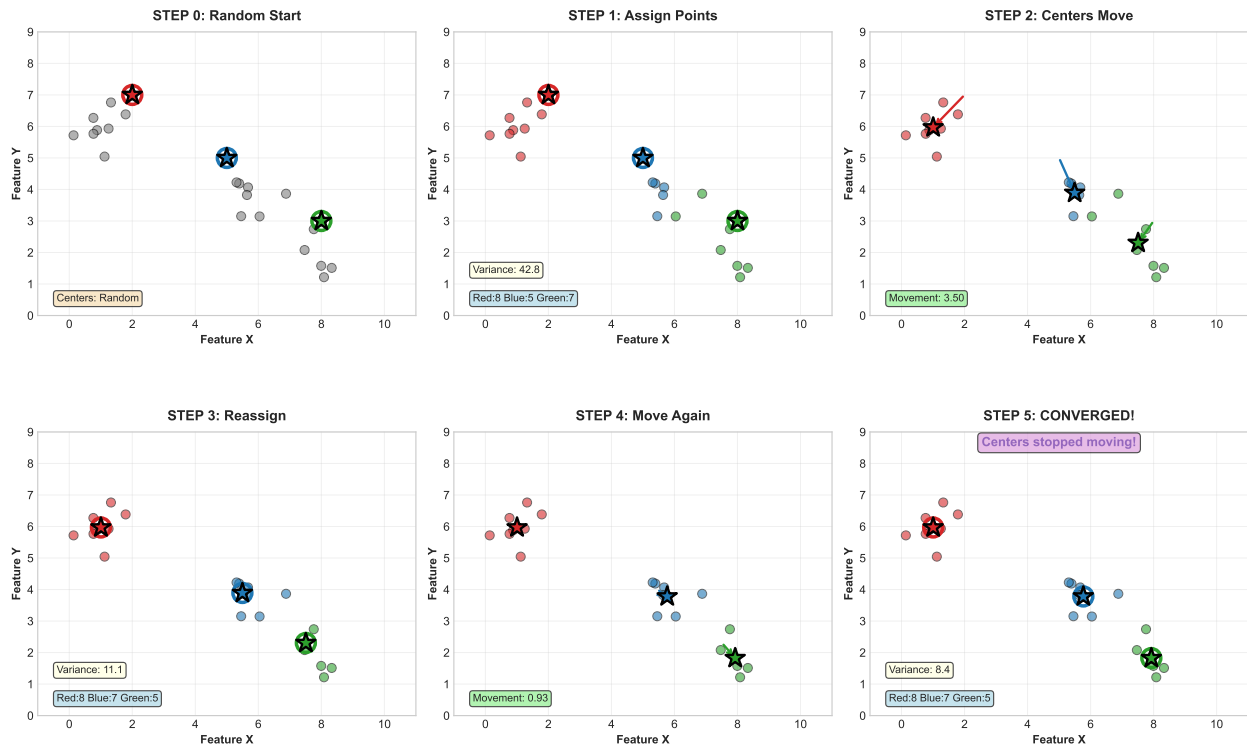
_____

_____

Task 4: Optimal complexity

Which model achieves the best balance between simplicity and accuracy?

Answer: _____

What makes this model better than the other two?

_____

> **Summary:** A model that fits training data perfectly may fail on new data. The optimal model balances simplicity with predictive accuracy. This trade-off is fundamental to machine learning.

Chart 2: Clustering Algorithm

Observation

The chart shows six steps of an algorithm that groups data points into clusters. Centers are marked with stars.

Tasks

Task 1: Describe center movement
How do centers move from Step 1 to Step 2?

_____

_____

Task 2: Observe point-to-center distances
From Step 0 to Step 5, what happens to the distance between points and their assigned centers?
Distances: _____ (increasing/decreasing/staying same)
What does this suggest about the algorithm's objective?
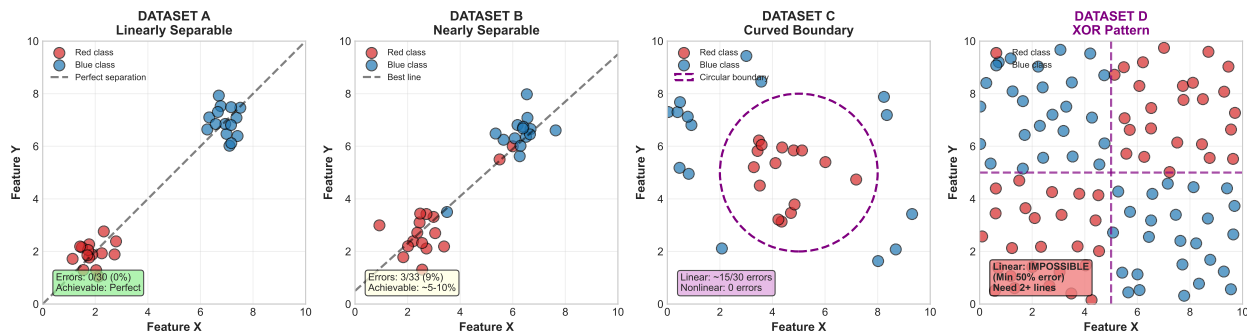
_____

Task 3: Identify assignment rule
How does the algorithm decide which cluster a point belongs to?

_____

_____

Task 4: Detect convergence
How can the algorithm determine when to stop iterating?

_____

Summary: The algorithm alternates between two steps: assigning points to the nearest center, then moving centers to the average position of their assigned points. This process minimizes the total distance from points to their cluster centers.

Chart 3: Classification Boundaries

Observation

Four datasets show red and blue points. The goal is to separate the two colors.

Tasks

Task 1: Attempt linear separation

Using a ruler or mentally, try to draw a straight line that separates red from blue in each dataset. Which datasets allow perfect or near-perfect separation with a straight line?

Possible: _____

Task 2: Identify impossible cases

Which dataset(s) cannot be separated by any straight line?

Answer: _____

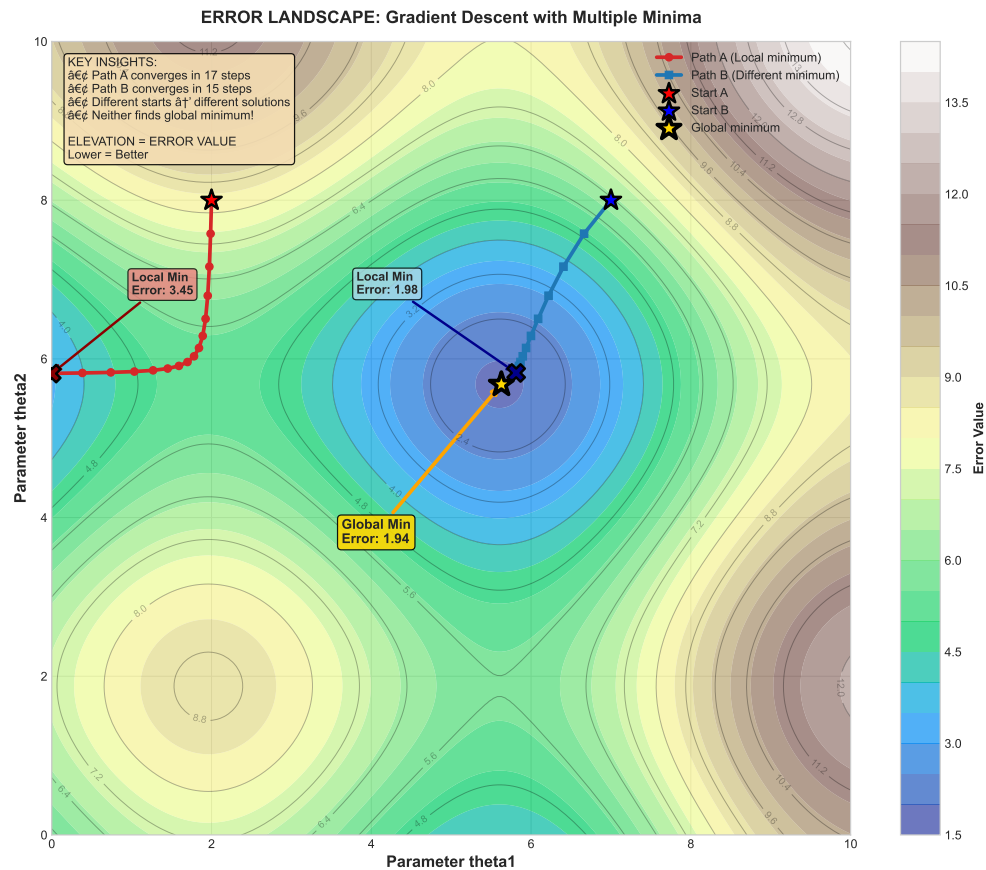What pattern in the data makes linear separation impossible?

_____

_____

Task 3: Propose alternative solutions

For Dataset D (the impossible case), what alternative approach could work?

_____

_____

Optional challenge: Can you prove mathematically that Dataset D is impossible for a single line?

Summary: Linear models work when data classes can be separated by a straight line or plane. Some patterns require more complex decision boundaries. This limitation motivates the development of nonlinear models such as neural networks.

Chart 4: Optimization Paths

ERROR LANDSCAPE: Gradient Descent with Multiple Minima

KEY INSIGHTS:
• Path A converges in 17 steps
• Path B converges in 15 steps
• Different starts → different solutions
• Neither finds global minimum!

ELEVATION = ERROR VALUE
Lower = Better

- Path A (Local minimum)
- Path B (Different minimum)
- Start A
- Start B
- Global minimum

Local Min
Error: 3.45

Local Min
Error: 1.98

Global Min
Error: 1.94

Observation

This topographic map shows an error landscape where elevation represents error value. Two paths descend from different starting points.

Tasks

Task 1: Compare final destinations
Do Path A (red) and Path B (blue) end in the same valley?
Answer: _____
What does this tell us about the importance of starting position?

_____

Task 2: Identify the better solution
Which path finds the valley with lower error?
Answer: _____
Is this the global minimum (lowest point on the entire landscape)?
Answer: _____

Task 3: Analyze step size effects
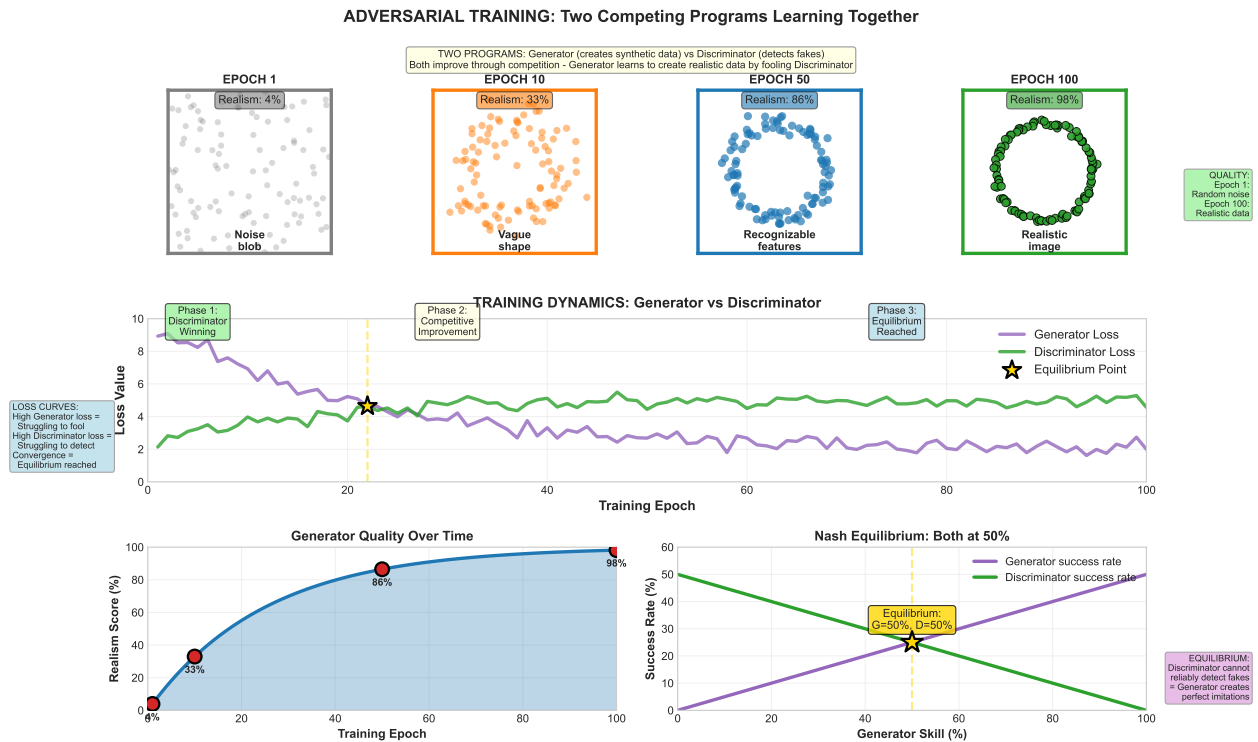What would happen if steps were too large?

_____

What would happen if steps were too small?

_____

Task 4: Propose improvement strategies
How might the algorithm escape from a suboptimal local minimum?

_____

5

Summary: Optimization algorithms follow the gradient downhill to find error minima. Different starting points can lead to different solutions. The learning rate (step size) must balance speed with stability. Complex landscapes may contain multiple local minima.

Chart 5: Adversarial Training

ADVERSARIAL TRAINING: Two Competing Programs Learning Together

Observation

The chart shows two programs competing over 100 training epochs. The Generator creates synthetic data while the Discriminator attempts to detect fakes.

Tasks

Task 1: Track quality progression

Describe how generated samples change from Epoch 1 to Epoch 100.

_____

_____

Task 2: Analyze competitive dynamics

Examine the middle training dynamics panel showing loss curves.

In Phase 1 (Epochs 1-10), which program has the advantage?

Answer: _____

In Phase 3 (Epochs 50-100), what happens to both loss curves?

Answer: _____
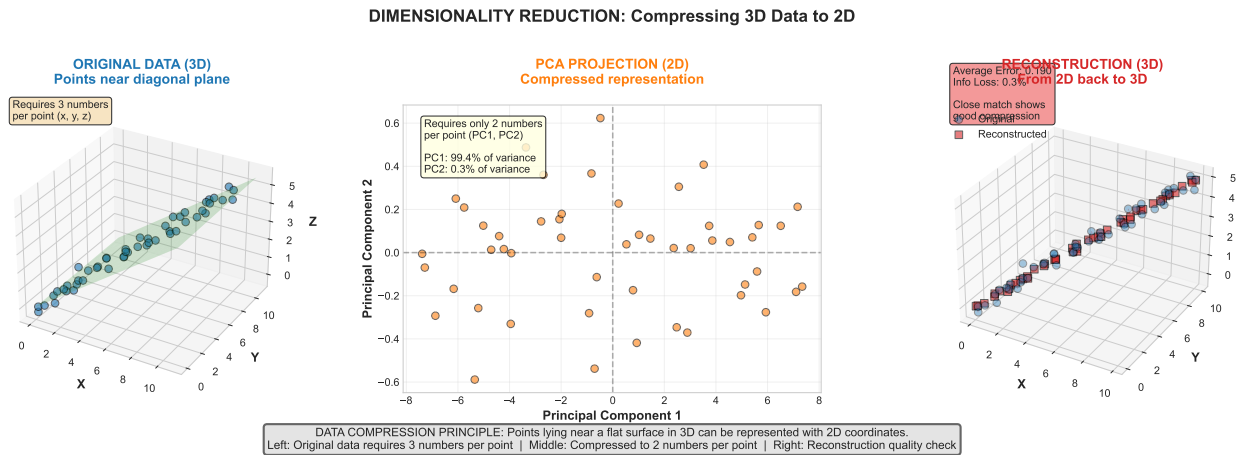
Task 3: Explain mutual improvement

Both programs are competing, yet both improve. How is this possible?

_____

_____

Task 4: Predict equilibrium outcome

When both programs reach equilibrium, the Discriminator cannot reliably distinguish real from fake data. What does this imply about the Generator's performance?

_____

Summary: Adversarial training uses competition between two programs to drive improvement. The Generator learns to create realistic data by attempting to fool the Discriminator. The Discriminator improves its detection ability, which forces the Generator to improve further. At equilibrium, the Generator produces data indistinguishable from real examples.

Chart 6: Dimensionality Reduction

DIMENSIONALITY REDUCTION: Compressing 3D Data to 2D

ORIGINAL DATA (3D)
Points near diagonal plane

Requires 3 numbers per point (x, y, z)

PCA PROJECTION (2D)
Compressed representation

Requires only 2 numbers per point (PC1, PC2)

PC1: 99.4% of variance
PC2: 0.3% of variance

RECONSTRUCTION (3D)
from 2D back to 3D

Average Error: 0.190
Info Loss: 0.3%

Close match shows good compression

Reconstructed

DATA COMPRESSION PRINCIPLE: Points lying near a flat surface in 3D can be represented with 2D coordinates.
Left: Original data requires 3 numbers per point | Middle: Compressed to 2 numbers per point | Right: Reconstruction quality check

Observation

The chart shows data transformation from three dimensions to two dimensions, then reconstruction back to three dimensions.

Tasks

Task 1: Assess data structure

Examine the left panel showing 3D data.

Do the points fill the entire 3D space, or do they lie near a flat surface?

Answer: _____

Task 2: Evaluate compression feasibility

The middle panel shows the same data represented with only 2 numbers per point instead of 3.

Is this compression possible without major information loss?

Answer: _____

Why or why not?

_____

Task 3: Analyze reconstruction quality

The right panel overlays original points (blue) with reconstructed points (red).

Are the reconstructed points close to the original positions?

Answer: _____

What does this indicate about the quality of the 2D representation?

_____

Task 4: Generalize the principle

Under what conditions can high-dimensional data be compressed to fewer dimensions?

_____

_____

Summary: Data lying near a lower-dimensional structure can be compressed by projecting onto principal directions of variance. This reduces storage requirements and computational complexity while preserving most information. The technique is particularly effective when original dimensions are correlated.

Connections Across Charts

Recurring Patterns

Examine the six charts and identify common themes:

1. Optimization objectives

Multiple charts show algorithms minimizing some quantity:

- Chart 1: Minimizing _____

- Chart 2: Minimizing _____

- Chart 4: Minimizing _____

2. Complexity trade-offs

Several charts illustrate balancing competing objectives:

- Chart 1: Simple models vs complex models

- Chart 3: Linear boundaries vs nonlinear boundaries

- Chart 6: Full dimensions vs compressed dimensions

What general principle connects these trade-offs?

_____

3. Iterative improvement

Which charts show algorithms that improve through repeated steps?
Charts: _____

Key Insights

What are the three most important patterns observed across all charts?

1. _____

   _____

2. _____

   _____

3. _____

   _____

Questions for Lecture

List 2-3 questions to ask during the lecture:

1. _____

2. _____

3. _____