Teaching Machines to See Patterns

A Neural Networks Primer: Why We Needed Each Piece of the Puzzle

NLP Course 2025

From the 1950s mail sorting crisis to ChatGPT: How humanity taught machines to think

Where We're Going Today - Optimized Flow

Phase 1: The Motivation

- The mail sorting crisis
- Why rules don't work
- First mathematical neurons
- Rosenblatt's learning breakthrough

Phase 2: Understanding Basics

- How neurons calculate
- Activation functions (NEW placement!)
- Hand calculations and examples

Phase 3: Crisis & Solution

- The XOR problem
- Geometric intuition (NEW!)
- Hidden layers solution
- Backpropagation breakthrough

Phase 4: Theory to Practice

- Gradient landscape visualization
- LeNet (1998): First success
- AlexNet (2012): Deep learning explosion
- Modern architectures
- Real-world applications

Phase 5: Your Turn

- Building your first network
- Debugging tips
- Next steps & resources

1950s: The Mail Sorting Crisis

The Challenge:

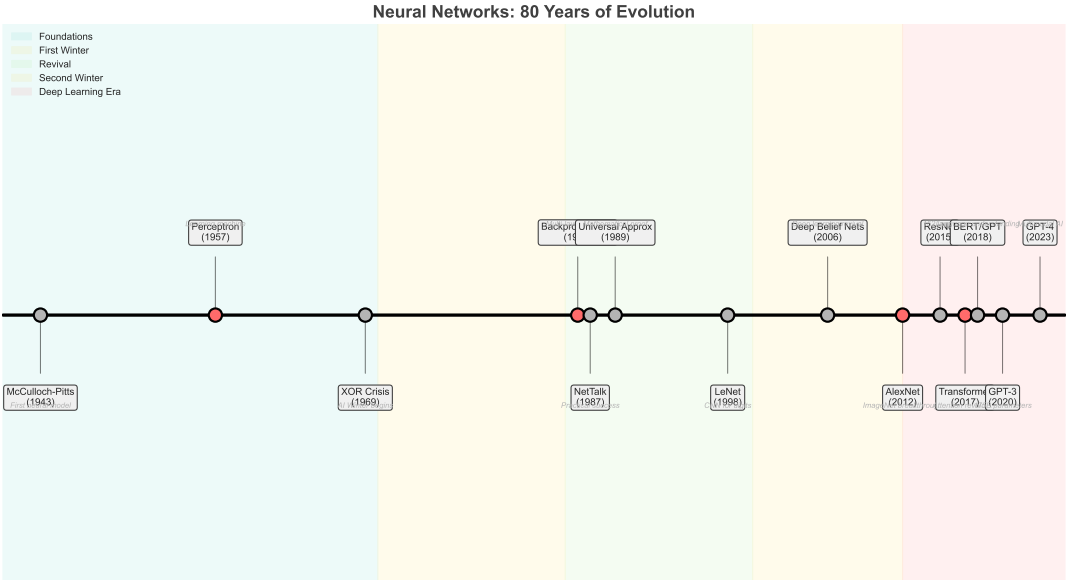
- 150 million letters per day
- Hand-written addresses
- Human sorters: slow, expensive, error-prone
- Traditional programming: useless

Why Traditional Code Failed:

- Can't write rules for every handwriting style
- Too many variations of each letter
- Context matters: "I" vs "l" vs "1"
- This wasn't computation—it was pattern recognition

This problem would take 40 years to solve properly

80 Years of Neural Networks: The Complete Journey



Why Can't We Just Write Rules?

Problem: Recognize the Letter "A"

Traditional Approach (Failed):

```
if (has_triangle_top AND
    has_horizontal_bar AND
    two_diagonal_lines) {
  return "A"
}
```

But what about...

- Handwritten A's?
- Different fonts?
- Rotated A's?
- Partial A's?

The Insight:

- We need pattern recognition, not rules
- System must learn from examples
- Similar to how humans learn

This realization launched the field of machine learning

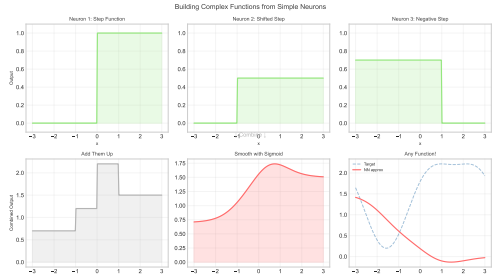
1943: The First Mathematical Neuron

McCulloch & Pitts:

- Neurophysiologists studying brain
- Asked: Can neurons be modeled mathematically?
- Created first artificial neuron

The Model:

- Multiple inputs (dendrites)
- Weighted sum (cell body)
- Threshold activation (axon)
- Binary output (fire or not)



The Limitation:

- Weights were fixed
- No learning mechanism
- Programmer had to set weights manually

Revolutionary idea, but missing the key ingredient: learning

1958: Rosenblatt's Learning Breakthrough

Frank Rosenblatt's Insight:

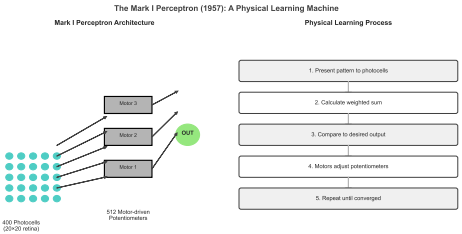
"What if the machine could adjust its own weights based on mistakes?"

The Perceptron Learning Rule:

1. Make a prediction
2. Check if wrong
3. If wrong: adjust weights
4. Repeat until correct

Historic Demo (1958):

- Mark I Perceptron machine
- Learned to recognize simple shapes
- Press coverage: "Thinking machine!"



Why Revolutionary:

- First machine that could learn
- Weights adjusted automatically
- Learned from examples, not rules
- Mathematically proven to converge

This was the birth of machine learning

Let's Understand How This Actually Works

We've Seen the History...

- McCulloch-Pitts invented the neuron
- Rosenblatt made it learn
- The perceptron was born

Now Let's See the Science:

- How does a neuron calculate?
- What does learning mean?
- Why was XOR so hard?

Next 5 slides: Hands-on calculations and exercises
Get your pencil ready - we're going to work through real examples!

Don't worry - we'll return to the story once you understand the basics

Understanding Check: Can You Answer These?

Let's Make Sure We're Together

Quick Questions:

1. Why couldn't traditional programming solve mail sorting?
2. What does a weight represent in simple terms?
3. Why do we need the bias term?
4. What was revolutionary about Rosenblatt's perceptron?

Think About It:

- A weight is like the importance/trust we give to each input
- Bias shifts our decision threshold
- Learning = adjusting these weights
- The perceptron was the first machine that could learn!

Try It Yourself: Draw a simple perceptron with 2 inputs. Label the weights, bias, and output. What would the weights be to compute AND logic?

If any of these are unclear, revisit the previous slides before continuing

Making It Concrete: Teaching OR Logic

Problem: Learn OR function (output 1 if ANY input is 1)

Training Data:

x_1	x_2	Output
0	0	0
0	1	1
1	0	1
1	1	1

The Perceptron:

$$z = w_1 \cdot x_1 + w_2 \cdot x_2 + b$$

$$\text{output} = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{if } z \leq 0 \end{cases}$$

In plain words: Multiply first input by first weight, second input by second weight, add bias, check if positive

Learning Process:

1. Start with random weights
2. For each example:
   - Calculate output
   - If wrong: adjust weights
   - If correct: keep weights
3. Repeat until all correct

Final Solution: $w_1 = 1$, $w_2 = 1$, $b = -0.5$

Success! But this was just the beginning...

Let's Calculate Together: Is This Email Spam?

A Real Perceptron Calculation You Can Follow

The Email:

"FREE money! Click here NOW for amazing offer!!!"

Our Features (Inputs):

- x_1 = Has "FREE"? = 1
- x_2 = Has "money"? = 1
- x_3 = Many "!"? = 1
- x_4 = From friend? = 0

Learned Weights:

- $w_1 = +3$ (FREE is very spammy)
- $w_2 = +2$ (money is suspicious)
- $w_3 = +2$ (!!! is aggressive)
- w_4 = -5 (friends are trusted)
- b = -2 (threshold)

Let's Calculate:

$$\begin{aligned} z &= w_1 \cdot x_1 + w_2 \cdot x_2 + w_3 \cdot x_3 + w_4 \cdot x_4 + b \\ &= 3 \cdot 1 + 2 \cdot 1 + 2 \cdot 1 + (-5) \cdot 0 + (-2) \\ &= 3 + 2 + 2 + 0 - 2 \\ &= 5 \end{aligned}$$

Decision:

- $z = 5 > 0$
- Output = 1 = SPAM!

Try It Yourself: What if this email WAS from a friend ($x_4 = 1$)? Recalculate! Would it still be spam?

Answer: $z = 5 - 5 = 0$, borderline!

This is exactly how early spam filters worked - and why they failed on clever spam

Breaking Down the Math Symbols

Inputs and Weights:

- x_i = input value (what we see)
- w_i = weight (importance/strength)
- b = bias (threshold adjuster)

The Computation:

$$z = \sum_{i=1}^{n} w_i x_i + b$$

This means:

- Multiply each input by its weight
- Add them all up
- Add the bias

Real Example:

Should I go outside?

Factor	Value	Weight
Sunny?	1	+2
Raining?	0	-3
Weekend?	1	+1

$$z = (1 \times 2) + (0 \times -3) + (1 \times 1) = 3$$

Decision: $z > 0$, so YES!

This simple math would evolve into deep learning

Why Linear Doesn't Work: Activation Functions

The Need for Non-Linearity

Problem with Linear:

- Stack of linear layers = still linear!
- $f(g(x)) = (wx + b_1)w' + b_2 = w'wx + ...$
- Can't learn complex patterns

Solution: Activation Functions

- Add non-linearity after each layer
- Allows learning complex boundaries
- Different functions for different needs

Common Activation Functions:

- **Sigmoid:** $\sigma(x) = \frac{1}{1+e^{-x}}$
  - Smooth, outputs 0-1
  - Good for probabilities

  In plain words: Squashes any input to range 0-1. Large positive becomes 1, large negative becomes 0

- **ReLU:** $f(x) = \max(0, x)$
  - Simple, fast
  - Solves vanishing gradient
- **Tanh:** $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
  - Outputs -1 to 1
  - Zero-centered

ReLU's simplicity revolutionized deep learning in 2011

Teaching a Network to Separate Red from Blue Points

The Setup:

- Input: (x, y) coordinates
- Output: Red or Blue class
- Network: 2 → 4 → 2 neurons

Training Process:

1. Epoch 1: Random boundary
2. Epoch 10: Rough separation
3. Epoch 50: Good boundary
4. Epoch 100: Perfect fit

What Each Layer Learns:

- Layer 1: Simple boundaries
- Hidden: Combine boundaries
- Output: Final decision

This same principle scales to millions of parameters

1969: The Problem That Killed AI

The XOR Problem: Why Single Neurons Fail

XOR (Exclusive OR):

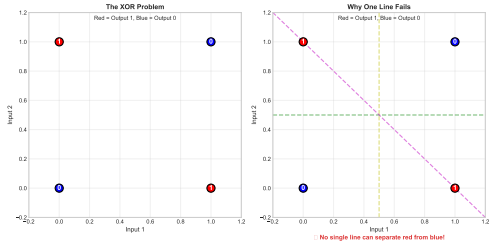
- Output 1 if inputs are different
- Output 0 if inputs are same

Truth Table:

x_1	x_2	Output
0	0	0
0	1	1
1	0	1
1	1	0

The Challenge:

- Try drawing ONE straight line
- That separates 1's from 0's
- Impossible!



Why It Matters:

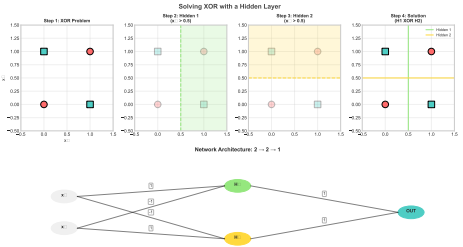
- Perceptrons can only draw straight lines
- XOR requires curved boundary
- This is the simplest non-linear problem
- Minsky & Papert proved this mathematically

This proof triggered the first AI Winter (1970-1980)

NEW: Geometric Intuition - Why We Need Two Boundaries

The Key Insight: XOR Needs TWO Lines, Not One

Visualization:



What We See:

- Red line: Separates (0,0) from others
- Blue line: Separates (1,1) from others
- Green region: Intersection of both
- Points (0,1) and (1,0) in green = Output 1!

This geometric intuition explains WHY hidden layers work

The Breakthrough Idea:

1. Use TWO neurons (not one)
2. Each neuron creates one boundary
3. Combine their outputs
4. Intersection solves XOR!

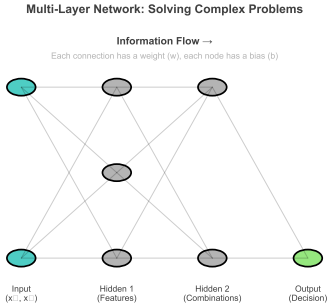
This Requires:

- Hidden layer with 2 neurons
- Output layer combines results
- This is a 2-layer network
- First layer: create boundaries
- Second layer: find intersection

Key Insight: Hidden layers let us combine simple boundaries into complex decision regions!

The Solution: Hidden Layers

Architecture with Hidden Layer:



How It Works:

- Input layer: 2 neurons (x_1, x_2)
- Hidden layer: 2 neurons (two boundaries)
- Output layer: 1 neuron (combines)

Forward Pass for XOR:
Given weights:

- Hidden 1: $w = [1, 1], b = -0.5$
- Hidden 2: $w = [1, 1], b = -1.5$
- Output: $w = [1, -1], b = 0$

For input $(1, 0)$:

$$\begin{aligned} h_1 &= \sigma(1 \cdot 1 + 1 \cdot 0 - 0.5) \\ &= \sigma(0.5) \approx 0.62 \\ h_2 &= \sigma(1 \cdot 1 + 1 \cdot 0 - 1.5) \\ &= \sigma(-0.5) \approx 0.38 \\ y &= \sigma(1 \cdot 0.62 - 1 \cdot 0.38) \\ &= \sigma(0.24) \approx 0.56 \text{ (close to 1!)} \end{aligned}$$

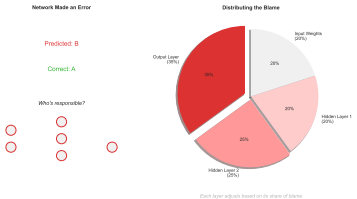
Hidden layers unlock non-linear patterns

The New Challenge: How to Train Hidden Layers?

The Credit Assignment Problem:

- Output is wrong - we know the error
- But which hidden neuron caused it?
- How much should each weight change?
- Perceptron rule only works for output layer

Why It's Hard:



Early Failed Attempts (1970s):

- Random weight adjustment
- Genetic algorithms
- Simulated annealing
- All too slow or unreliable

What We Needed:

- Systematic way to assign blame
- Efficient computation
- Guaranteed to improve
- Works for many layers

The solution would come from calculus...

This problem was solved in 1986 with backpropagation

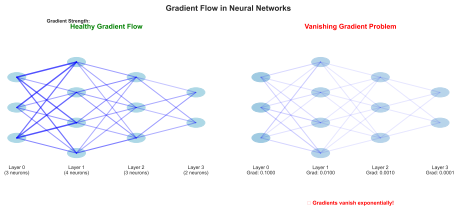
1986: Backpropagation - The Breakthrough Algorithm

The Algorithm (Rumelhart et al.):

1. **Forward pass**: Compute output
2. **Compute error**: Compare to target
3. **Backward pass**: Use chain rule to compute gradients
4. **Update weights**: Gradient descent

The Key Insight:

- Use calculus (chain rule)
- Error flows backward through network
- Each layer gets its share of blame
- Weights adjusted proportionally



Mathematical Foundation:

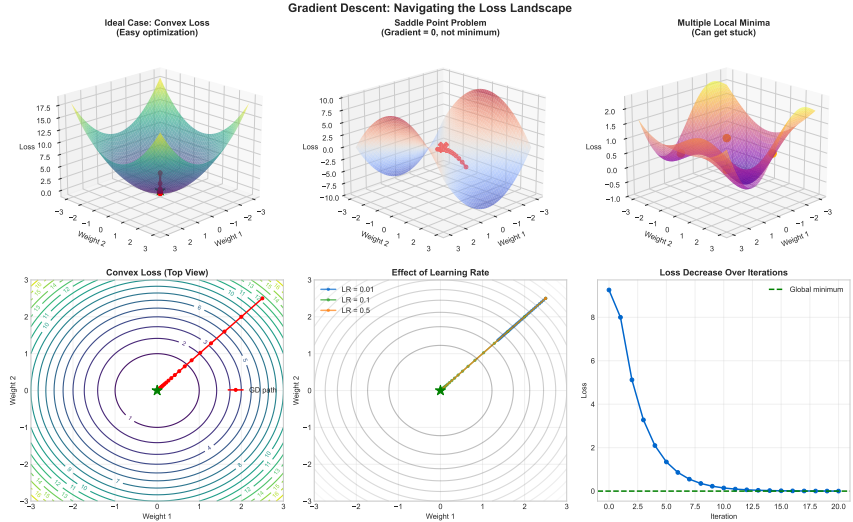
$$\frac{\partial L}{\partial w_{ij}} = \frac{\partial L}{\partial a_j} \cdot \frac{\partial a_j}{\partial z_j} \cdot \frac{\partial z_j}{\partial w_{ij}}$$
$$= \delta_j \cdot a_i$$

Why Revolutionary:

- Efficient: One backward pass
- General: Works for any architecture
- Automatic: No manual tuning

This paper revived neural networks and enabled modern deep learning

Visualizing Learning: The Gradient Landscape



Gradient descent finds the valley where error is minimized

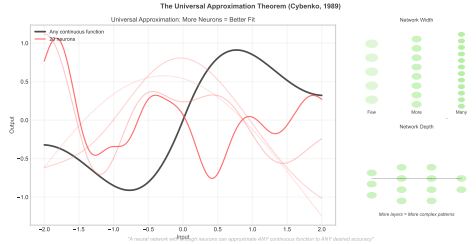
1989: The Theoretical Guarantee

Cybenko's Universal Approximation Theorem:

A neural network with one hidden layer and finite neurons can approximate ANY continuous function to ANY desired accuracy

What This Means:

- Mathematical proof
- Not just XOR - ANY pattern!
- Theoretical justification
- Explains why NNs are so powerful



Caveats:

- Guarantees existence, not learning
- May need exponential neurons
- Deep networks often more efficient
- Still need good training algorithm

Theory meets practice: NNs CAN learn any pattern, backprop shows us HOW

The Core Idea: Neural Networks are Function Approximators

What does this actually mean?

The Problem:

- We have inputs (x)
- We want outputs (y)
- But we don't know the formula!
- Examples:
  - Size → Price
  - Image → Label
  - Text → Sentiment

Traditional Approach:

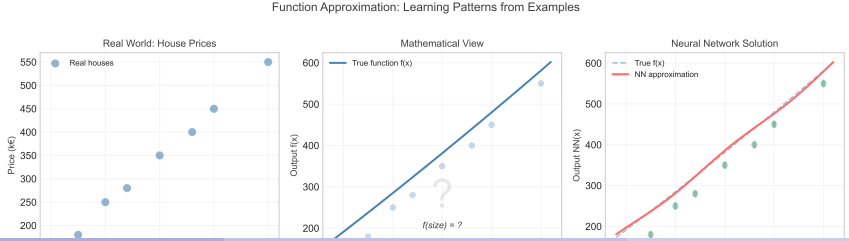
- Guess the formula
- Write explicit rules
- Hope it works
- Problem: Real world is too complex!

Example:
Price = a × Size + b
(Too simple for real data!)

Neural Network Approach:

- Learn from examples
- Build the formula automatically
- Adjust until it fits
- Works for ANY pattern!

Magic:
NN learns: f(x) ≈ y
No formula needed!



The LEGO Principle: Combine Simple Parts to Build Anything

The Building Blocks:

1. **Individual Neurons:** Simple decisions
   - "Is input ¿ threshold?"
   - Outputs: on/off (smooth version)
2. **Combine Neurons:** Weight and add
   - Create complex shapes
3. **Stack Layers:** Build hierarchy
   - Each layer adds abstraction

Real-World Analogy:

Making a Cake from Ingredients:

- Flour + Sugar + Eggs
- Mix right amounts
- → Perfect cake!

In Neural Networks:

- Edges + Curves + Colors
- Combine with weights
- → Recognize faces!

The Universal Approximation Theorem: Why This Always Works

The Most Important Theorem in Deep Learning (Cybenko, 1989)

The Theorem (Plain English):

> *"A neural network with enough neurons can approximate* **ANY** *continuous function to* **ANY** *desired accuracy"*

What This Means:

- Universal: Works for any smooth pattern
- Guaranteed: Not hoping, but proving
- Practical: Just add more neurons!

The Catch:

- How many neurons? Could be millions
- How to train? That's the art

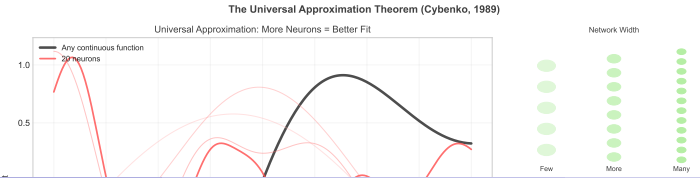
Intuitive Proof:

Pixel art analogy:

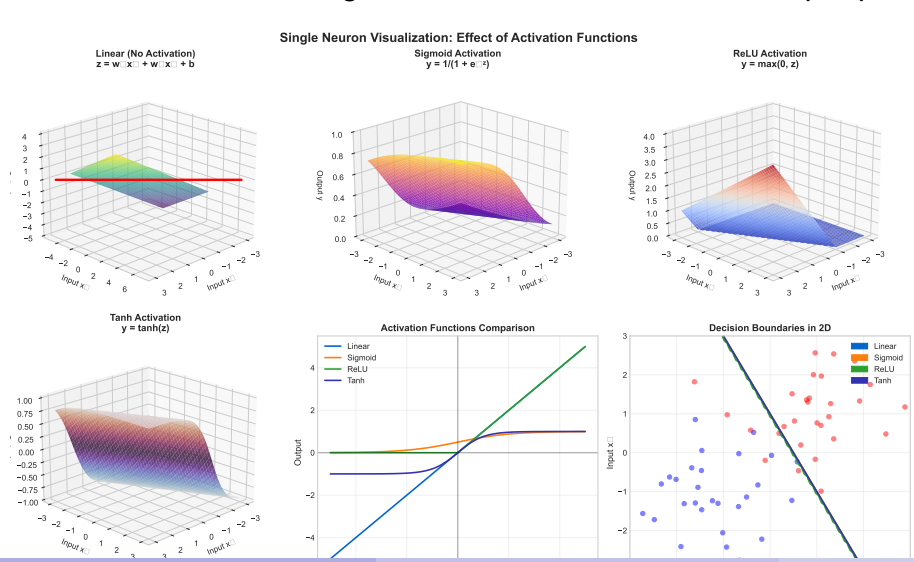
- 4 pixels: Blocky
- 100 pixels: Recognizable
- 10,000 pixels: Photo-realistic

Same with neurons:

- Few: Rough
- More: Better
- Many: Nearly perfect

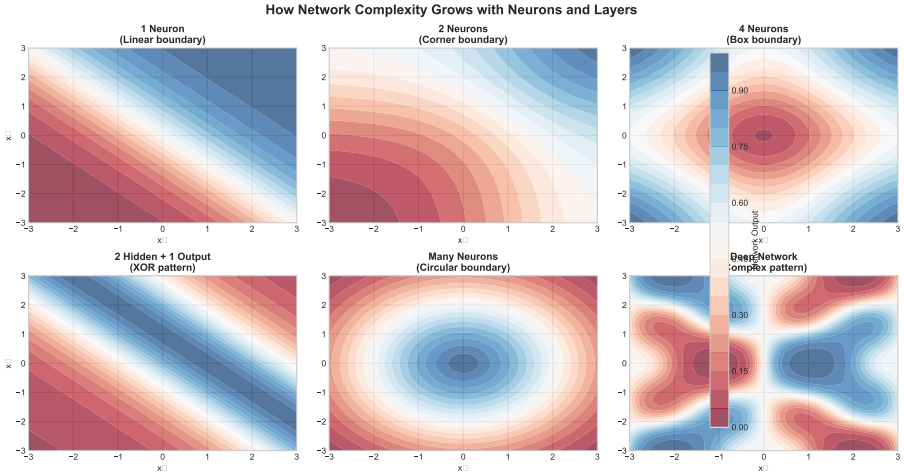


The Neuron as a 3D Function



From Simple to Complex: Network Depth Creates Complexity

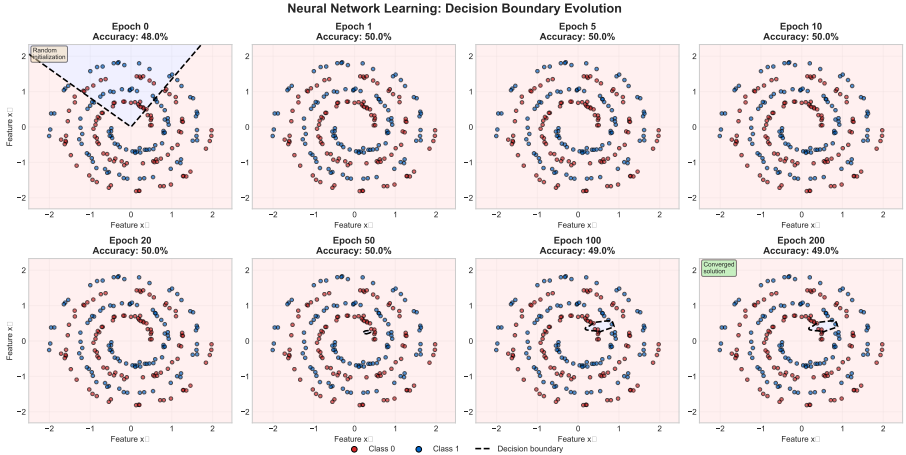
How More Neurons Enable More Complex Decision Boundaries



Each neuron adds a new "dimension" to what the network can learn

The Learning Process: Frame by Frame

Watching Decision Boundaries Evolve During Training

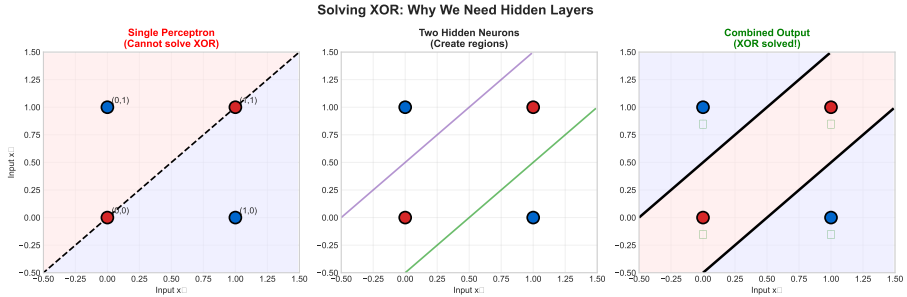


Try It Yourself: Notice how the boundary starts random and gradually fits the data pattern!

This is what "learning" looks like - not magic, just systematic improvement

XOR Problem Solved Visually

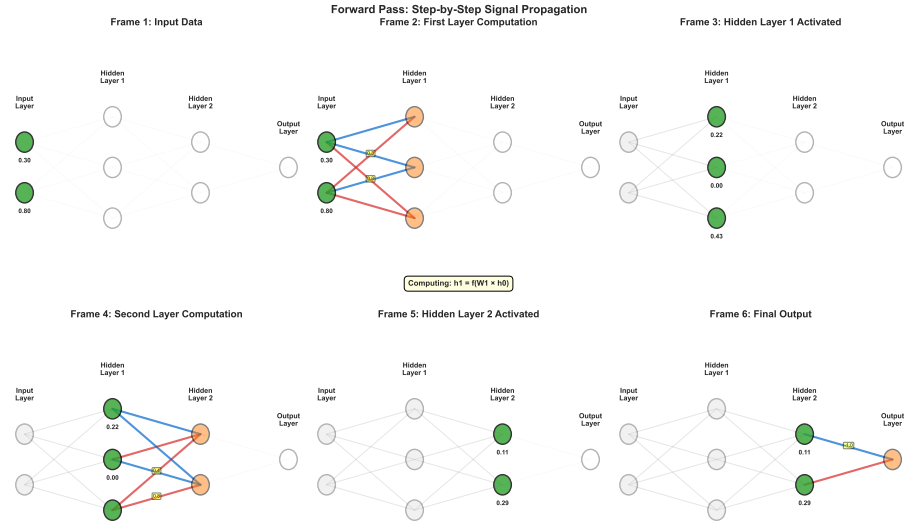
Why We Need Hidden Layers: The XOR Solution



Two hidden neurons working together can solve what one neuron cannot

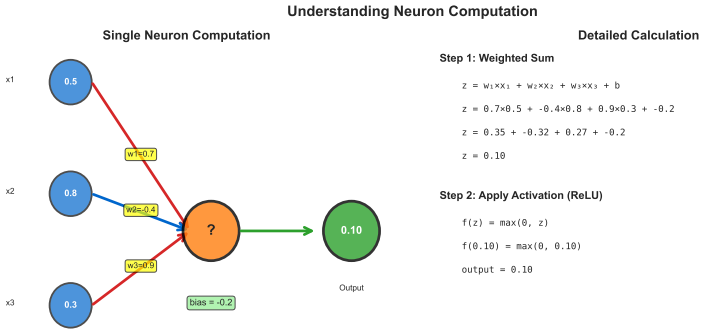
Forward Pass: Signal Propagation Step-by-Step

Following Data as it Flows Through the Network



Detailed Computation: Inside One Neuron

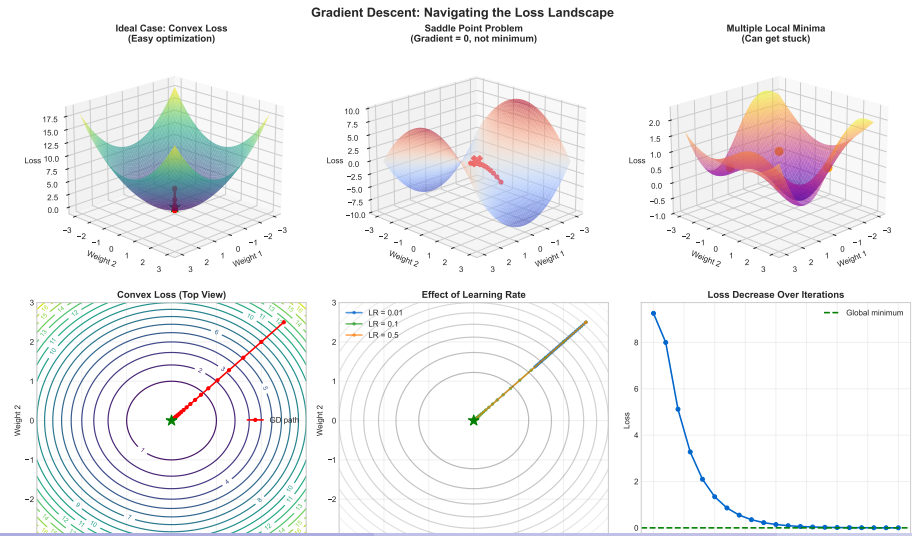
The Math Behind a Single Neuron's Calculation



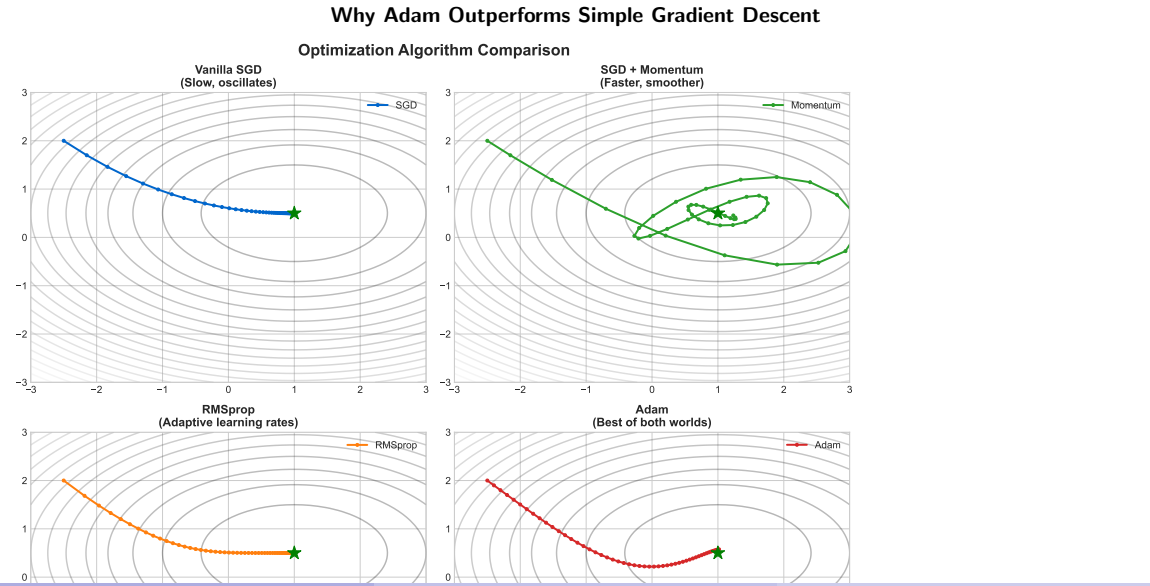
Try It Yourself: Follow along: multiply each input by its weight, add them up, add bias, apply activation!

This calculation happens millions of times per second in modern networks

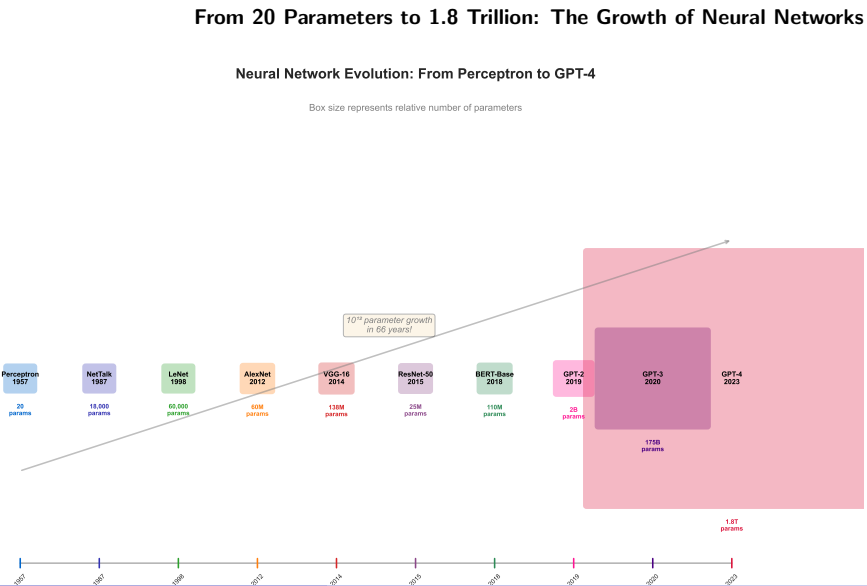
Gradient Descent: Finding the Valley in 3D Space



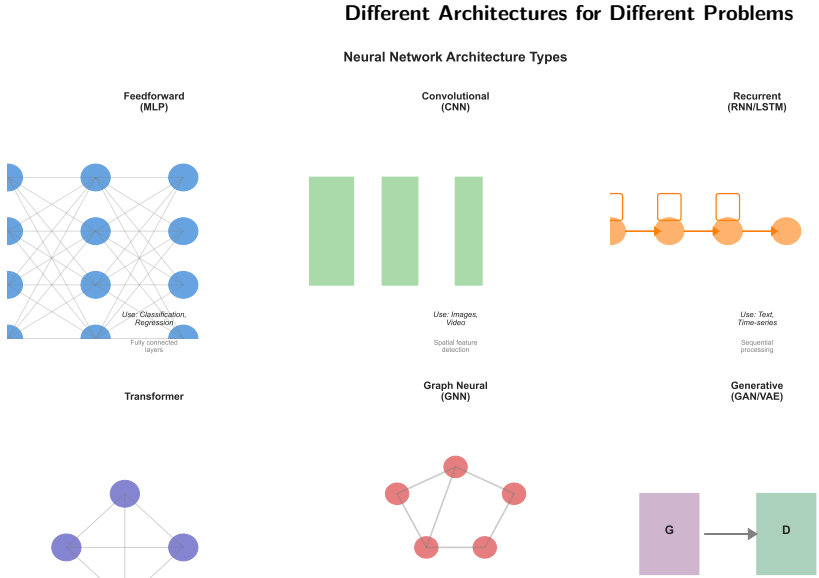
Comparing Optimization Algorithms



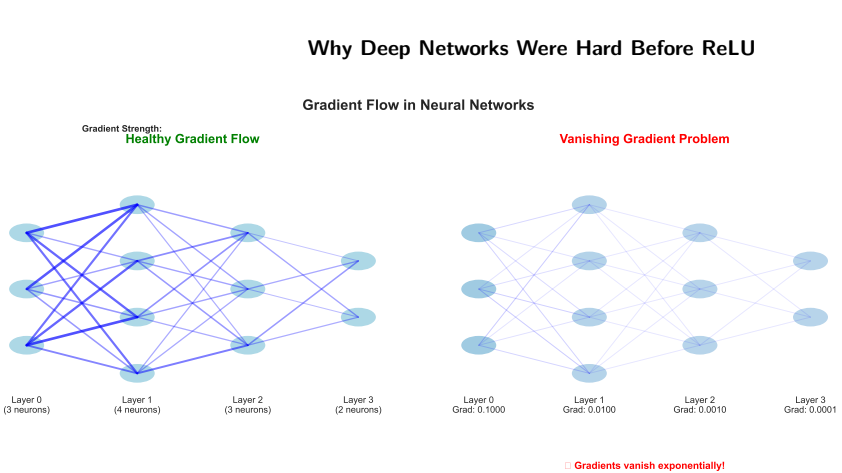
Architecture Evolution Over Time



Architecture Types Comparison



Gradient Flow: Healthy vs Vanishing



Left: Healthy gradient flow, Right: Vanishing gradients - this problem limited networks to 2-3 layers for decades

From Theory to Working Systems

1998-2012: From Digits to ImageNet

1998 - LeNet: First Success

- Yann LeCun's CNN for digits
- 32×32 pixels $\rightarrow$ 10 classes
- 60,000 parameters
- Banks adopt for check reading

Key Innovation: Convolutions

- Share weights across image
- Detect features anywhere
- Build complexity layer by layer

2012 - AlexNet: The Revolution

- 1000 ImageNet classes
- 60 million parameters
- GPUs enable training
- Error rate: 26% $\rightarrow$ 16%

What Changed:

- Big Data (millions of images)
- GPU computing (100x faster)
- ReLU activation
- Dropout regularization

This victory ended the second AI winter permanently

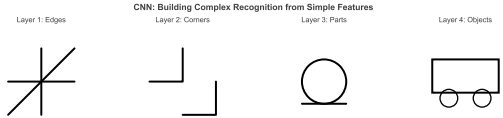
How We Actually Recognize Objects

Human Vision Process:

1. Detect edges
2. Find shapes
3. Identify parts
4. Recognize object

CNN Mimics This:

- Layer 1: Edge detectors
- Layer 2: Corner/curve detectors
- Layer 3: Part detectors
- Layer 4: Object detectors



Key Insight:

- A "wheel detector" works anywhere in image
- Share the same detector across positions
- Reduces parameters dramatically
- Makes network translation-invariant

This is why CNNs dominate computer vision

Finding the Best Weights: Like Hiking Down a Mountain

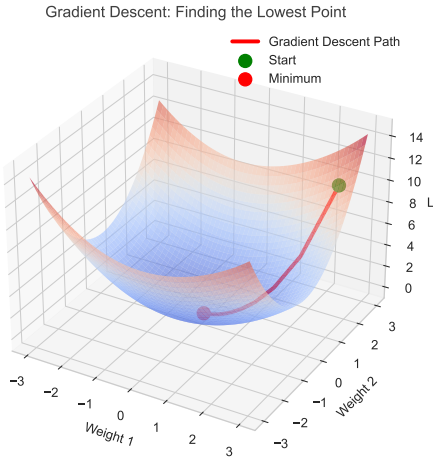
The Optimization Problem:

- Millions of weights to adjust
- Each affects the error
- Need to find best combination

Gradient Descent:

1. Calculate error (loss)
2. Find slope (gradient) for each weight
3. Step downhill: $w = w - \alpha \cdot \nabla L$

   In plain words: New weight = old weight - (step size times slope)
4. Repeat until bottom



Learning Rate (α):

Types of Learning: Different Problems, Different Approaches

Supervised Learning:

- Have input-output pairs
- Learn mapping function
- Examples: Classification, Regression

Unsupervised Learning:

- Only have inputs
- Find patterns/structure
- Examples: Clustering, Compression

Reinforcement Learning:

- Learn through trial/error
- Maximize reward signal
- Examples: Games, Robotics

Self-Supervised (Modern):

- Create labels from data itself
- Predict next word, masked words
- Examples: GPT, BERT

Self-supervised learning powers all modern language models

Check Your Understanding: Learning Types

Can You Match These Examples?

Try It Yourself: Match each scenario to a learning type: Supervised, Unsupervised, Reinforcement, Self-Supervised

Scenarios:

1. Teaching a robot to walk by giving rewards for standing
2. Showing 1000 cat photos labeled "cat"
3. Giving GPT text with words masked out
4. Finding groups in customer data

Answers:

1. Reinforcement (trial and error)
2. Supervised (labeled examples)
3. Self-supervised (creates own labels)
4. Unsupervised (finds patterns)

Common Confusion: Self-supervised IS supervised learning - we just create the labels automatically from the data itself!

Understanding these differences helps you choose the right approach

The Overfitting Problem: When Learning Goes Too Far

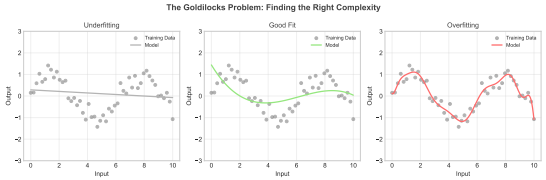
Memorization vs. Understanding

The Problem:

- Network memorizes training data
- Fails on new, unseen data
- Like student memorizing answers

Signs of Overfitting:

- Training accuracy: 99%
- Test accuracy: 60%
- Complex decision boundaries
- High variance

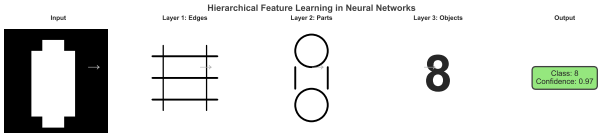


Solutions:

- **More data:** Can't memorize everything
- **Dropout:** Randomly disable neurons
- **Regularization:** Penalize complexity
- **Early stopping:** Stop before overfitting

"With four parameters I can fit an elephant, with five I can make him wiggle his trunk" - von Neumann

From Pixels to Concepts: The Hierarchy of Understanding



What Each Layer Learns:

- **Layer 1:** Edges, colors, gradients
- **Layer 2:** Corners, textures, curves
- **Layer 3:** Parts (eyes, wheels, patterns)
- **Layer 4:** Objects (faces, cars, scenes)
- **Layer 5:** Concepts (identity, style, context)

Why Hierarchy Matters:

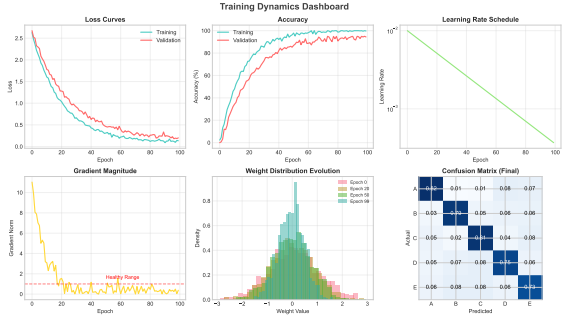
- Reusable features
- Efficient representation
- Transfer learning works
- Mimics visual cortex

Discovered Automatically:

- No manual feature engineering
- Emerges from data
- Different tasks, same hierarchy
- Universal pattern

Each layer combines features from the previous layer into more abstract concepts

Real-Time Monitoring: The Training Dashboard



Key Metrics to Track:

- **Loss Curves:** Training vs validation
- **Accuracy:** How often we're right
- **Learning Rate:** Speed of updates
- **Gradient Norm:** Update magnitude

Warning Signs:

- Gap = Overfitting
- Flat = Learning stopped
- Spikes = Instability
- NaN = Numerical issues

Healthy Training:

- Smooth decrease
- Val follows train
- Gradients stable
- LR decays properly

When to Stop:

- Validation plateaus
- Gap increasing
- Diminishing returns

Modern training requires constant monitoring - it's more art than science

The Explosion of Modern AI

2014-Present: Networks That Changed the World

The Depth Revolution:

- 2014 - VGGNet: 19 layers
- 2015 - ResNet: 152 layers
- 2017 - Transformers: Attention
- 2020 - GPT-3: 175B parameters

Why Depth Matters:

- Each layer = abstraction level
- Deep = complex reasoning
- Hierarchical feature learning

Real-World Impact:

- **Vision:** Self-driving cars
- **Language:** Google Translate
- **Speech:** Siri, Alexa
- **Medicine:** Disease diagnosis
- **Science:** Protein folding

The Scale:

- Billions of parameters
- Trained on internet-scale data
- Months of GPU time
- Emergent abilities appear

We went from recognizing digits to passing the bar exam in 25 years

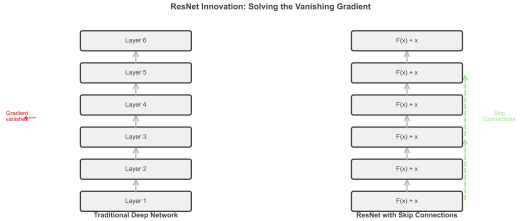
Problem: Networks Couldn't Get Deeper

The Vanishing Gradient:

- Gradients multiply through layers
- Become exponentially small
- Deep layers stop learning
- 20 layers was the limit

The Breakthrough: Skip Connections

- Add input directly to output
- $F(x) + x$ instead of just $F(x)$
- Gradients flow directly backward
- Can train 1000+ layers!



Why It Works:

- Learn residual (difference) only
- Identity mapping is easy default
- Gradients have direct path
- Each layer refines previous result

This simple trick enabled the deep learning revolution

Batch Normalization: Keeping Networks Stable

The Internal Covariate Shift Problem

The Issue:

- Each layer's input distribution changes
- As previous layers update
- Makes learning unstable
- Requires tiny learning rates

The Solution:

- Normalize inputs to each layer
- Mean = 0, Variance = 1
- Learn scale and shift parameters
- Apply during training and testing

BatchNorm Algorithm:

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2$$

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

$$y_i = \gamma \hat{x}_i + \beta$$

In plain words: 1) Find average, 2) Find spread, 3) Normalize to standard range, 4) Scale and shift as needed

Benefits:

- 10x faster training
- Higher learning rates OK
- Less sensitive to initialization
- Acts as regularization

Now standard in every deep network

2019: The Lottery Ticket Hypothesis

Most Network Weights Don't Matter!

The Discovery:

- Networks contain "winning tickets"
- Subnetworks that train well alone
- 90-95% of weights can be removed
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- Explains why big networks train better
- Pruning after training works
- Efficiency revolution starting
- Changes how we think about learning

A 1 billion parameter model might only need 50 million

Inductive Biases: Building in Assumptions

The Right Architecture for the Right Problem

What Are Inductive Biases?

- Assumptions built into architecture
- Guide learning toward solutions
- Trade flexibility for efficiency
- "Priors" about the problem

Examples:

- **CNN:** Spatial locality matters
- **RNN:** Order/time matters
- **GNN:** Graph structure matters
- **Transformer:** All positions can interact

Why They Matter:

- Reduce search space
- Faster convergence
- Better generalization
- Less data needed

The Tradeoff:

- Right bias = 10x better
- Wrong bias = 10x worse
- General architectures = safe but slow
- Specialized = fast but limited

Choosing the right inductive bias is still an art

Emergent Abilities: When Scale Creates Intelligence

Capabilities That Appear Suddenly with Scale

The Phenomenon:

- Small models: Can't do task at all
- Medium models: Still can't
- Large models: Suddenly can!
- No gradual improvement

Examples:

- 3-digit arithmetic (¿10B params)
- Chain-of-thought reasoning (¿50B)
- Code generation (¿20B)
- Multilingual translation (¿100B)

Why It Happens:

- Complex patterns need capacity
- Phase transitions in learning
- Composition of simpler abilities
- "Grokking" - sudden understanding

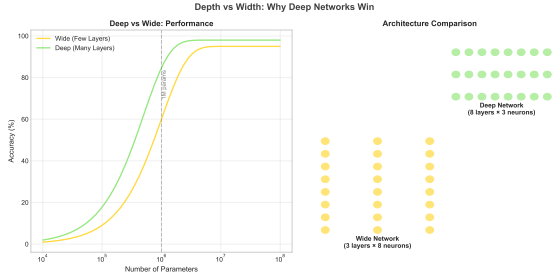
Implications:

- We can't predict what's next
- Scaling might unlock AGI
- Or hit fundamental limits
- Active area of research

GPT-3 showed abilities nobody expected or programmed

Architecture Choices: Deep vs Wide Networks

The Fundamental Tradeoff in Neural Architecture



Deep Networks (Many Layers):

- Complex hierarchical features
- Exponential expressiveness growth
- Harder to train (vanishing gradients)
- Better for vision, NLP

Wide Networks (Many Neurons):

- More parallel processing
- Easier optimization landscape

The Sweet Spot:

- Vision: Deep (100+ layers)
- Language: Very deep (24-96 layers)
- Tabular: Wide and shallow (2-4 layers)
- Time series: Moderate (5-10 layers)

Modern Insights:

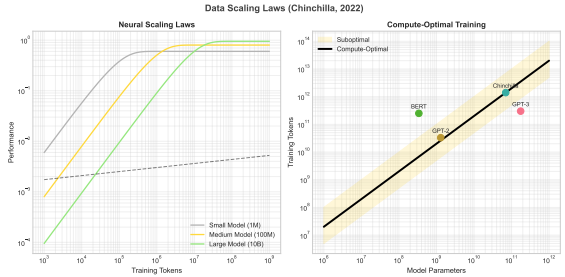
- Depth beats width for same parameters
- Skip connections enable extreme depth
- Width helps with memorization
- Depth helps with generalization

Scaling Laws:

- Performance $\propto$ depth$^{0.8}$
- Performance $\propto$ width$^{0.5}$

Scaling Laws: How Performance Grows with Data

The Predictable Relationship Between Data, Model Size, and Performance



The Chinchilla Law (2022):

- Optimal ratio: 20 tokens per parameter
- 10B model needs 200B tokens
- Most models are undertrained
- Data quality matters more than quantity

Power Law Scaling:

$$\text{Loss} = A \cdot N^{-\alpha} + B \cdot D^{-\beta} + C$$

Practical Implications:

- 10x data → 2x performance
- 10x parameters → 1.7x performance
- 10x compute → 3x performance
- Diminishing returns always

Data Efficiency Tricks:

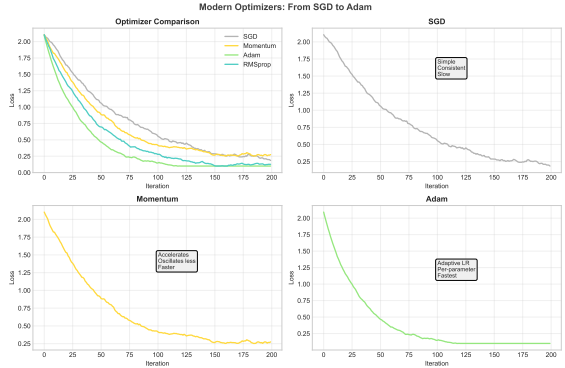
- Data augmentation
- Synthetic data generation
- Active learning
- Curriculum learning
- Multi-task training

Why it matters: These laws predict costs before training

Current Limits:

- Internet has ~10T tokens

The Evolution of Gradient Descent



SGD (1951):

- Basic gradient descent
- Learning rate: Fixed
- Slow but reliable
- Still used for fine-tuning

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- Adaptive learning rates per parameter
- Combines momentum + RMSprop
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Modern Variants:

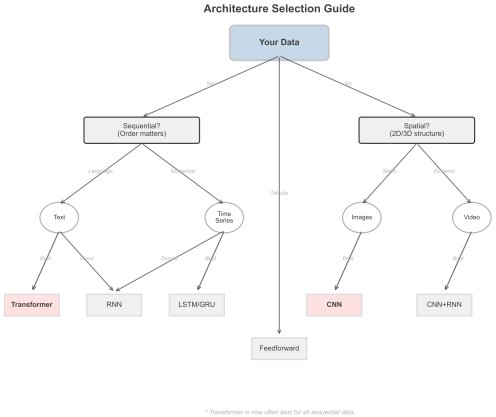
- **AdamW:** Decoupled weight decay
- **RAdam:** Rectified Adam
- **LAMB:** Large batch training
- **Sophia:** 2nd-order approximation

Choosing an Optimizer:

- Start with Adam (lr=3e-4)
- Large batch: LAMB

Quick Guide: Choosing Your Architecture

Which Network Should You Use?



Decision Questions:

1. Is your data sequential?
2. Does position matter?
3. Is it images/spatial?
4. Fixed or variable size?

Quick Rules:

- Images → CNN
- Text → Transformer/RNN
- Tabular → Feedforward
- Audio → CNN or RNN
- Video → CNN + RNN

Common Confusion: Transformers now dominate most tasks, but specialized architectures still win for specific problems!

Try It Yourself: You have 10,000 customer reviews to classify as positive/negative. Which architecture? Why?

Answer: Transformer or RNN - text is sequential and context matters

The Journey So Far

Core Concepts:

1. **Neurons:** $y = f(\sum w_i x_i + b)$
2. **Learning:** Adjust weights to minimize error
3. **Depth:** Each layer adds abstraction
4. **Backpropagation:** Distribute error backwards
5. **Non-linearity:** Enables complex functions

Historical Lessons:

1. Every limitation spawned innovation
2. Simple ideas + scale = revolution
3. Biology inspires but doesn't limit
4. Persistence through AI winters
5. Theory + engineering = breakthroughs

You now understand the fundamentals that power all modern AI

Epilogue: Your First Neural Network in 5 Minutes

Let's Build Something Real!

Complete MNIST Classifier:

```
import torch
import torch.nn as nn
from torchvision import datasets, transforms
from torch.utils.data import DataLoader

# 1. Define Network
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(784, 128)
        self.fc2 = nn.Linear(128, 64)
        self.fc3 = nn.Linear(64, 10)

    def forward(self, x):
        x = x.view(-1, 784)  # Flatten
        x = torch.relu(self.fc1(x))
        x = torch.relu(self.fc2(x))
        return self.fc3(x)

# 2. Load Data
transform = transforms.ToTensor()
train_data = datasets.MNIST('.', train=True,
                            download=True,
                            transform=transform)
train_loader = DataLoader(train_data,
                          batch_size=64,
                          shuffle=True)

# 3. Setup Training
model = Net()
optimizer = torch.optim.Adam(model.parameters())

# 4. Training Loop
for epoch in range(3):
    for batch_idx, (data, target) in
                enumerate(train_loader):
        # Forward pass
        output = model(data)
        loss = criterion(output, target)

        # Backward pass
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # Print progress
        if batch_idx % 100 == 0:
            print(f'Epoch {epoch}: {loss:.4f}')

# 5. Test One Example
model.eval()
test_image = train_data[0][0]
prediction = model(test_image.unsqueeze(0))
print(f"Predicted: {prediction.argmax()}")
```

What You Just Built:

- 3-layer neural network
- 60K training images
- 97% accuracy in 3 epochs
- Running on your laptop

Where to Go Next: Your Learning Path

Continue Your Neural Network Journey

Next Topics to Learn:

1. **CNNs:** Computer vision
2. **RNNs/LSTMs:** Sequences
3. **Transformers:** Modern NLP
4. **GANs:** Generation
5. **RL:** Decision making

Practical Projects:

- Image classifier for your photos
- Sentiment analysis of tweets
- Chatbot for customer service
- Style transfer for art
- Game-playing agent

Resources:

- **Fast.ai:** Practical deep learning
- **PyTorch Tutorials:** Official guides
- **Papers with Code:** Latest research
- **Kaggle:** Competitions and datasets
- **3Blue1Brown:** Visual explanations

Remember:

- Start simple, build up
- Theory + practice together
- Join communities
- Build projects you care about
- Share what you learn

You've learned how humanity taught machines to think.
Now it's your turn to push the boundaries!

The future of AI is being written now - be part of it!

Additional Material for Deep Dive

- Appendix A: Advanced Topics
- Appendix B: Extended History

Deep Dives for the Curious

This section contains advanced material that goes beyond the core BSc curriculum.

Topics covered:

- The Lottery Ticket Hypothesis
- Inductive Biases in Neural Architectures
- Scaling Laws and Performance Prediction
- Deep vs Wide Network Architectures
- Emergent Abilities at Scale
- Advanced Optimization Algorithms

These topics are valuable for understanding state-of-the-art research but not essential for getting started with neural networks.

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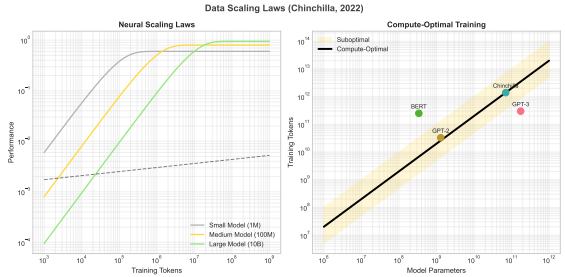

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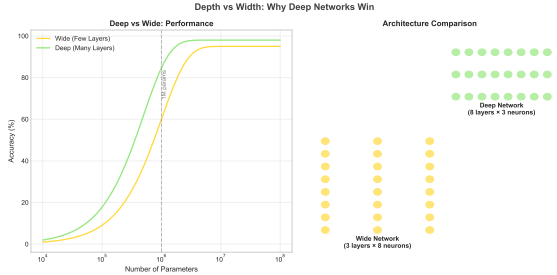

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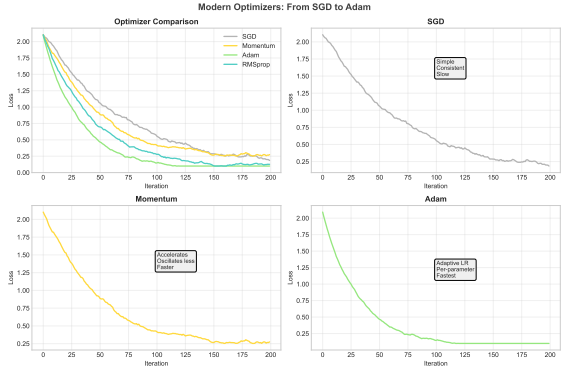

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The Full Story: Historical Deep Dives

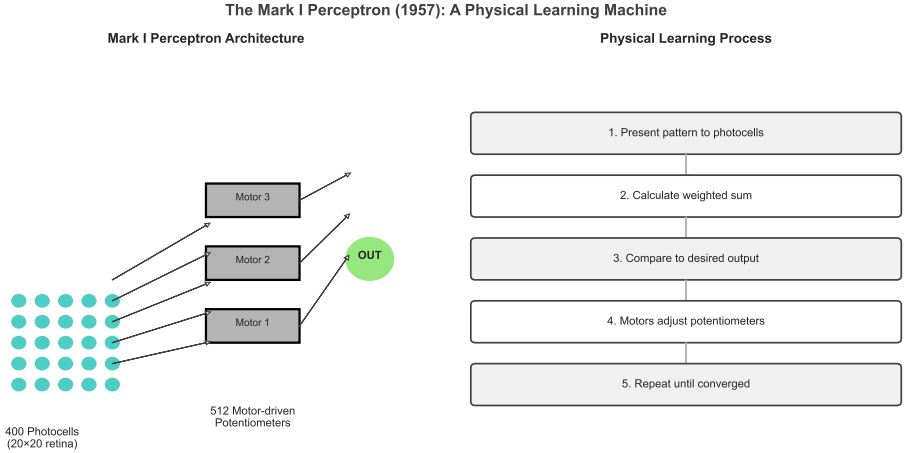
This section contains fascinating historical details that enrich the narrative but aren't essential for understanding the technical concepts.

Topics covered:

- The Mark I Perceptron: Physical Hardware
- NetTalk: Networks Learn to Speak (1987)
- Batch Normalization: Keeping Networks Stable

These stories show how each breakthrough built on previous work and overcame specific limitations.

The Mark I Perceptron: A Physical Learning Machine



The first neural network wasn't software—it was a room-sized machine with motors and photocells

1987: NetTalk - Networks Learn to Speak

Sejnowski & Rosenberg: The First Viral NN Demo

The Challenge:

- Convert written text to speech
- English is irregular (tough, though, through)
- Rule-based systems had 1000s of exceptions

The Network:

- 7×29 input (7-letter window)
- 80 hidden neurons
- 26 output phonemes
- Trained overnight on DEC workstation

The Magic:

- Started: Random babbling
- Hour 1: Vowel-consonant patterns
- Hour 5: Recognizable words
- Hour 10: 95% accuracy!

Hidden Neurons Learned:

- Vowel detectors
- Consonant clusters
- Word boundaries
- Nobody programmed these!

Common Confusion: The network discovered linguistic concepts on its own - features linguists took centuries to identify!

Media sensation: "Computer teaches itself to read aloud overnight"

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