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

1950s: The Mail Sorting Crisis

The Challenge:

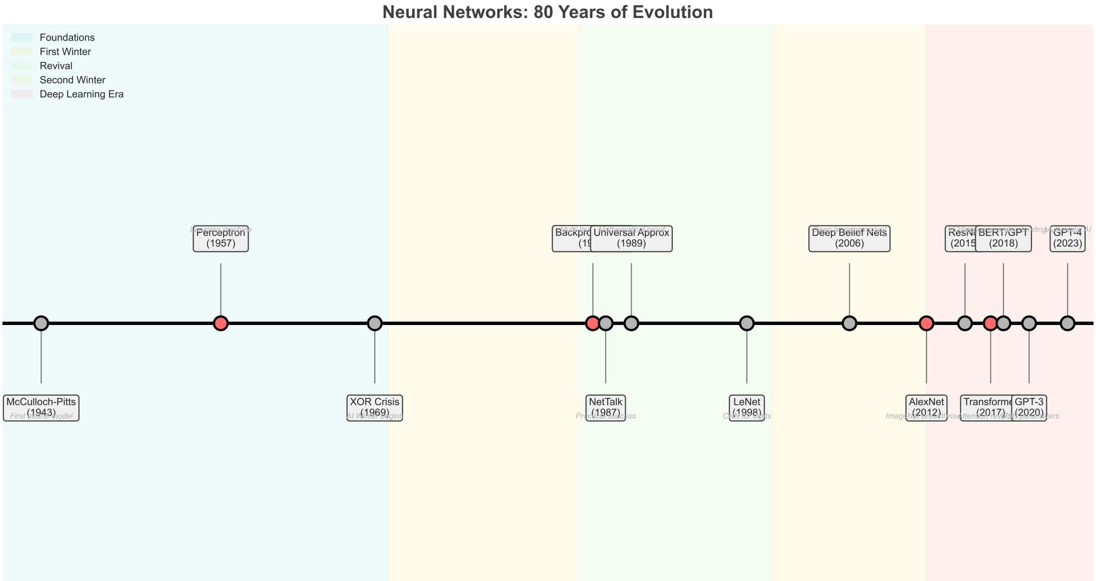
- 150 million letters per day
- Hand-written addresses
- Human sorters: slow, expensive, error-prone
- Traditional programming: useless

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?

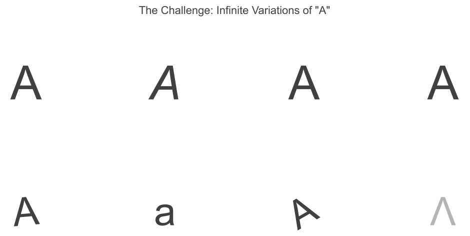
Problem: Recognize the Letter "A"

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?



Just for the letter "A", we'd need thousands of rules!

The breakthrough: What if machines could learn patterns like children do?

1943: The First Spark - McCulloch & Pitts

The Birth of Computational Neuroscience

The Revolutionary Paper:

- "A Logical Calculus of Ideas Immanent in Nervous Activity"
- First mathematical model of neurons
- Proved: Networks can compute ANY logical function
- Inspired von Neumann's computer architecture

Key Insight:

- Neurons = Logic gates
- Brain = Computing machine
- Thinking = Computation

The Model:

- Binary neurons (0 or 1)
- Threshold activation
- Fixed connections
- No learning yet!

Historical Impact:

- Founded field of neural networks
- Influenced cybernetics movement
- Set stage for AI research
- "The brain is a computer" metaphor

14 years later, Rosenblatt would add the missing piece: learning

1957: The First Learning Machine - The Perceptron

Frank Rosenblatt's Radical Idea: Neurons That Learn

Beyond McCulloch-Pitts:

- Adjustable weights (not fixed!)
- Learning from mistakes
- Physical machine built (Mark I)
- Could recognize simple patterns

The Hardware:

- 400 photocells (20×20 "retina")
- 512 motor-driven potentiometers
- Weights adjusted by electric motors
- Took 5 minutes to learn patterns

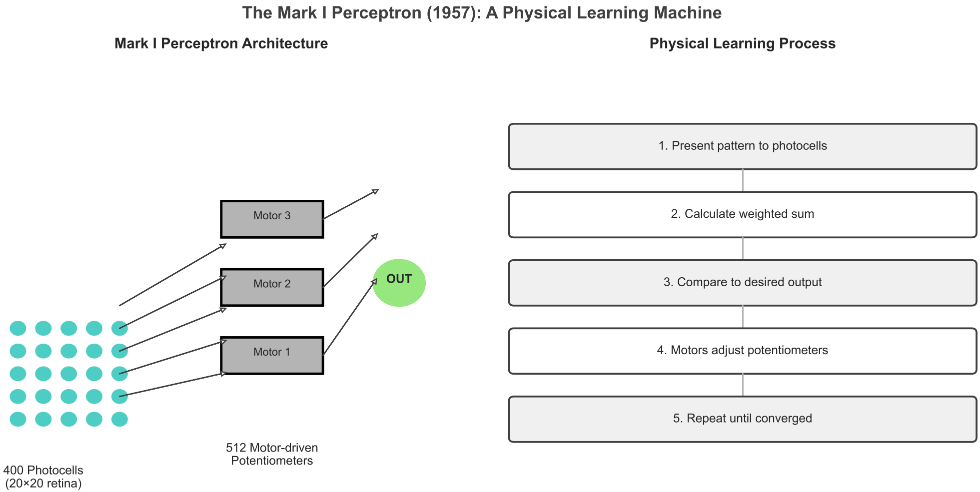
Mathematical Model:

- Inputs: $x_1, x_2, ..., x_n$
- Weights: $w_1, w_2, ..., w_n$
- Sum: $z = \sum_{i=1}^{n} w_i x_i + b$
- Output: $y = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{if } z \leq 0 \end{cases}$

Learning Rule: If wrong: $w_i = w_i + \eta \cdot error \cdot x_i$

The New York Times, 1958: "The Navy revealed the embryo of an electronic computer that will be able to walk, talk, see, write, reproduce itself and be conscious of its existence."

The Mark I Perceptron: A Physical Learning Machine



The first neural network wasn't software—it was a room-sized machine with motors physically adjusting weights

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:

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

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

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...

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

1969: The Crisis - XOR Problem

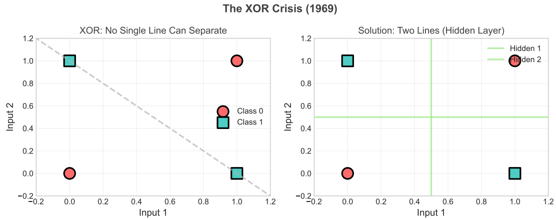
Minsky & Papert's Devastating Discovery

XOR (Exclusive OR):

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

The Problem:

- Can't draw a single line to separate
- Perceptron only learns linear boundaries
- Real-world problems are non-linear!



Impact:

- Funding dried up
- "AI Winter" begins
- Neural networks abandoned

The field would be dormant for over a decade...

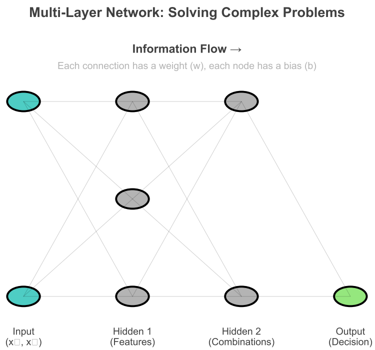
1980s: The Hidden Layer Revolution

The Insight:

- Stack multiple layers!
- First layer: detect simple features
- Hidden layer: combine features
- Output layer: final decision

Solving XOR:

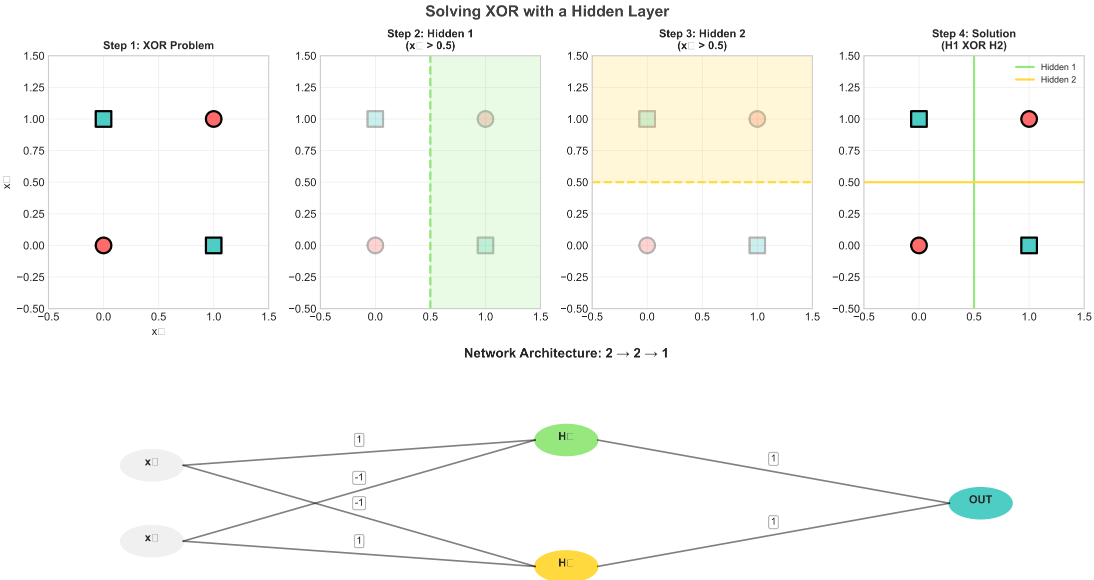
- Hidden neuron 1: Is it (0,1)?
- Hidden neuron 2: Is it (1,0)?
- Output: OR of hidden neurons



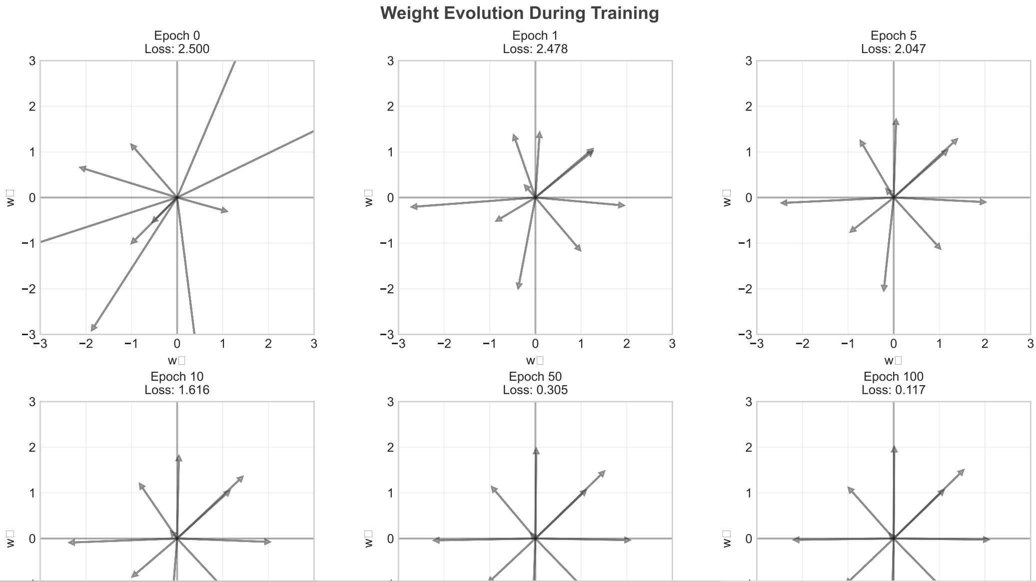
New Architecture:

- Input layer: raw data
- Hidden layer(s): feature extraction

Solving XOR: Step-by-Step with Hidden Layers



Learning in Action: Weight Evolution



1986: Backpropagation - Teaching Networks to Learn

The Credit Assignment Problem: Who's to Blame?

The Challenge:

- Network makes error at output
- Many neurons contributed
- Which weights should change?
- By how much?

The Solution: Chain Rule

- Calculate error at output
- Propagate error backwards
- Each layer gets its "share of blame"
- Adjust weights proportionally

Mathematical Insight:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial out_j} \cdot \frac{\partial out_j}{\partial net_j} \cdot \frac{\partial net_j}{\partial w_{ij}}$$

In Simple Terms:

1. How wrong were we? (Error)
2. How sensitive is error to this weight?
3. Adjust weight in opposite direction
4. Repeat for all weights, back to front

This algorithm is still the foundation of all deep learning today

1987: NetTalk - Networks Learn to Speak

Sejnowski & Rosenberg's Speaking Network

The Challenge:

- English pronunciation is irregular
- "though" vs "through" vs "tough"
- Rule-based systems failed
- Can a network learn from examples?

The Architecture:

- Input: 7 letters (context window)
- Hidden: 80 neurons
- Output: 26 phonemes
- 18,000 total weights

The Results:

- Started: Random babbling
- After 10 epochs: Consonants/vowels
- After 30 epochs: Simple words
- After 50 epochs: 95% correct!

Why It Mattered:

- Proved backprop works on real problems
- Learned complex, irregular mappings
- No rules programmed!
- Sounded like a child learning to read

The network literally learned English pronunciation overnight

1989: Universal Approximation - The Mathematical Foundation

Cybenko's Theorem: Networks Can Learn ANY Function

The Theorem: "A feedforward network with:

- One hidden layer
- Finite neurons
- Sigmoid activation

can approximate ANY continuous function to arbitrary accuracy"

What This Means:

- Neural networks are universal
- Can solve any pattern recognition
- Just need enough neurons
- Mathematics guarantees it!

The Catch:

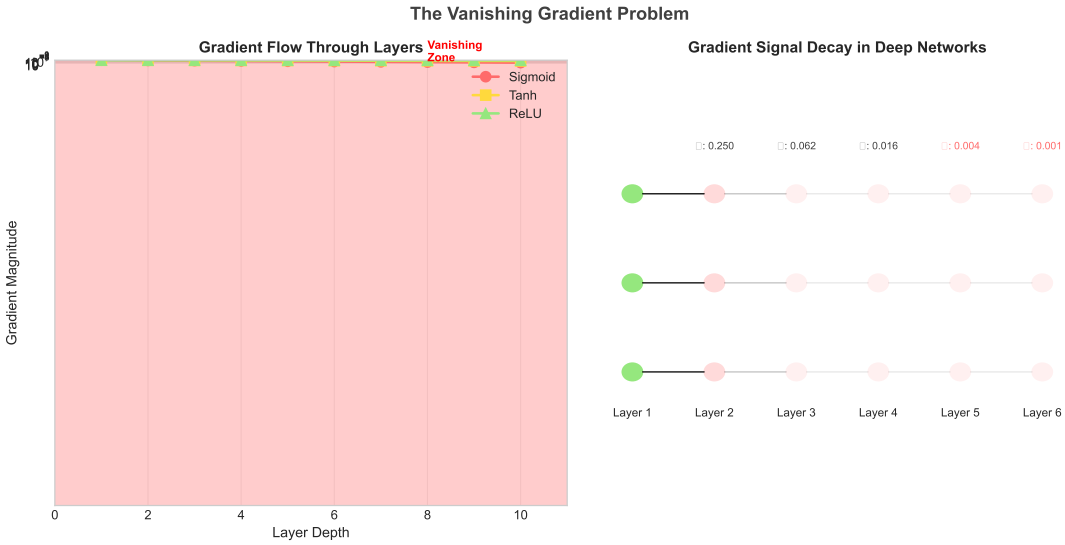
- Doesn't say HOW MANY neurons
- Doesn't say HOW to find weights
- Might need exponentially many
- Training might take forever

Historical Impact:

- Ended theoretical doubts
- Justified deep learning research
- Shifted focus to practical training
- "We know it's possible, now make it work"

This theorem convinced skeptics that neural networks were worth pursuing

The Vanishing Gradient Problem: Why Deep Was Hard



Gradients shrink exponentially through layers—this blocked deep learning until ReLU (2011)

Why Linear Doesn't Work: Activation Functions

The Need for Non-Linearity

Problem with Linear:

- Stack of linear layers = still linear!
- $f(g(x)) = (wx + b_1)w' + b_2 = w'wx + \ldots$
- 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
- **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

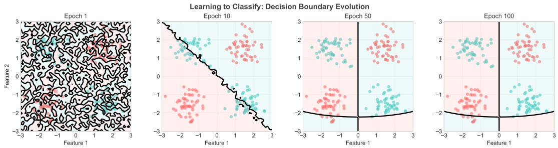
Teaching a Network to Separate Red from Blue Points

The Setup:

- Input: (x, y) coordinates
- Output: Red or Blue class
- Network: $2 \rightarrow 4 \rightarrow 2$ 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

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

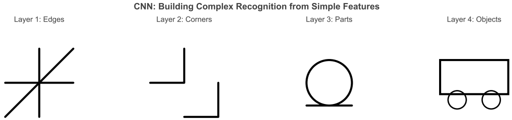
How We Actually Recognize Objects

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

The Mathematics of Learning: Gradient Descent

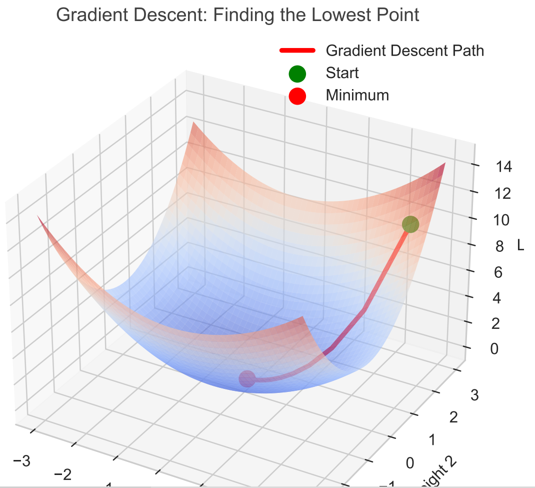
Finding the Best Weights: Like Hiking Down a Mountain

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: $w = w - \alpha \cdot \nabla L$
4. Repeat until bottom



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

The Overfitting Problem: When Learning Goes Too Far

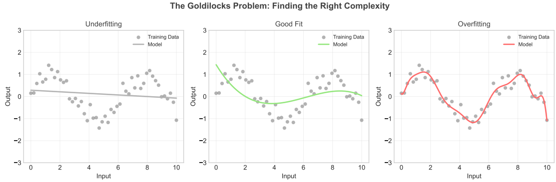
Memorization vs. Understanding

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

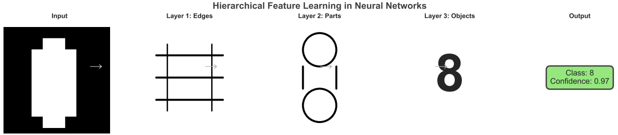


Solutions:

- **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:

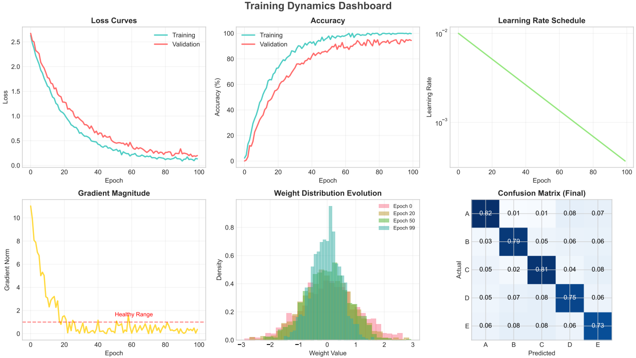
- Reusable features
- Efficient representation
- Transfer learning works
- Mimics visual cortex

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

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

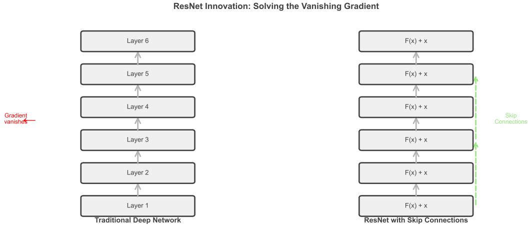
Problem: Networks Couldn't Get Deeper

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:

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

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

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

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

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
- Performance stays the same!

The Hypothesis: "Dense networks succeed because they contain sparse subnetworks that are capable of training effectively"

Implications:

- We massively overparameterize
- Training finds the needle in haystack
- Future: Train small from start?
- Mobile deployment possible

Why It Matters:

- 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

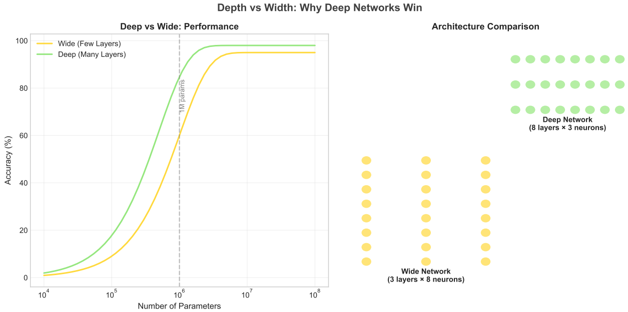
Implications:

- 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):

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:

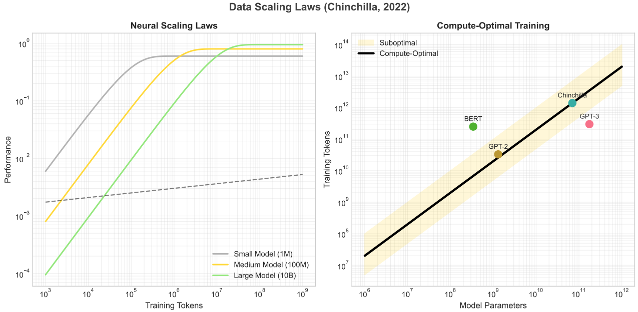
- Depth beats width for same parameters
- Skip connections enable extreme depth
- Width helps with memorization
- Depth helps with generalization

Scaling Laws:

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

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:

Practical Implications:

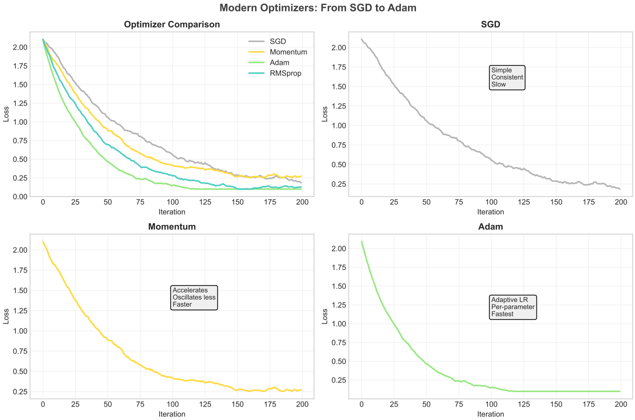
- 10x data → 2x performance
- 10x parameters → 1.7x performance
- 10x compute → 3x performance
- Diminishing returns always

Data Efficiency Tricks:

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

Current Limits:

The Evolution of Gradient Descent



SGD (1951):

- Basic gradient descent
- Learning rate: Fixed

Adam (2014):

- Adaptive learning rates per parameter
- Combines momentum + RMSprop
- De facto standard
- Works out-of-the-box

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)

Neural Network Architectures: Right Tool for Right Job

Feedforward Networks:

- Information flows forward only
- Fixed-size input and output
- Good for: Classification, regression

Convolutional (CNN):

- Spatial feature detection
- Translation invariance
- Good for: Images, video

Recurrent (RNN):

- Process sequences
- Maintain memory/state
- Good for: Text, time-series

Transformer:

- Attention mechanism
- Parallel processing
- Good for: Language, everything else

Each architecture encodes different assumptions about the data

Modern Training: Standing on Shoulders of Giants

Transfer Learning:

- Start with pre-trained network
- Fine-tune on your task
- 100x less data needed
- Days $\rightarrow$ Hours training

Data Augmentation:

- Create variations of training data
- Rotations, crops, color shifts
- Prevents overfitting
- Free performance boost

Advanced Optimizers:

- **SGD:** Basic gradient descent
- **Momentum:** Remember past gradients
- **Adam:** Adaptive learning rates
- **AdamW:** With weight decay

Mixed Precision:

- Use 16-bit floats where possible
- Keep 32-bit for critical ops
- 2-3x speedup
- Same accuracy

These techniques make deep learning practical for everyone

Why Deep Learning Exploded Now: The Perfect Storm

1. **Data Explosion:**
   - Internet = infinite training data
   - ImageNet: 14M labeled images
   - Common Crawl: 300TB of text
   - YouTube: 500 hours/minute
2. **Hardware Revolution:**
   - GPUs: 100x faster than CPUs
   - TPUs: Built for neural nets
   - Cloud computing: Rent supercomputers
   - Mobile chips with NPUs
3. **Algorithm Breakthroughs:**
   - ReLU activation (2011)
   - Batch normalization (2015)
   - Skip connections (2015)
   - Attention mechanism (2017)
4. **Open Source Culture:**
   - TensorFlow, PyTorch free
   - Pre-trained models shared
   - Papers with code
   - Collaborative research

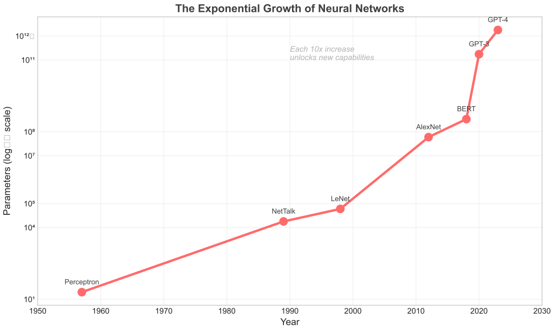
The same ideas from 1980s finally had the resources to work

Understanding Scale: From Perceptron to GPT-4

The Exponential Growth of Neural Networks

Parameter Growth:

- 1957 Perceptron: 20 weights
- 1987 NetTalk: 18,000
- 1998 LeNet: 60,000
- 2012 AlexNet: 60 million
- 2018 BERT: 340 million
- 2020 GPT-3: 175 billion
- 2023 GPT-4: 1.8 trillion



What Scale Brings:

- Emergent abilities
- Zero-shot learning
- Multi-task capability

Building a Digit Classifier in 10 Lines

PyTorch Implementation:

```
import torch
import torch.nn as nn

class SimpleNet(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(784, 128)
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = torch.relu(self.fc1(x))
        return self.fc2(x)

# Train
model = SimpleNet()
optimizer = torch.optim.Adam(model.parameters())
criterion = nn.CrossEntropyLoss()
```

What This Does:

- Input: 28×28 pixel image
- Hidden: 128 neurons
- Output: 10 digit classes
- Activation: ReLU
- Training: Adam optimizer

Training Loop:

- Forward pass
- Calculate loss
- Backward pass
- Update weights
- Repeat

This simple network achieves 97% accuracy on MNIST

Debugging Neural Networks: Detective Work

When Things Go Wrong (They Always Do)

Gradient Issues:

- **Exploding:** Gradients $\rightarrow$ infinity
  - Solution: Gradient clipping
- **Vanishing:** Gradients $\rightarrow 0$
  - Solution: Better initialization, ReLU
- **Dead ReLU:** Neurons never activate
  - Solution: LeakyReLU, smaller learning rate

Debugging Tools:

- TensorBoard: Visualize training
- Gradient histograms
- Activation distributions
- Weight evolution plots

Common Failure Modes:

- Loss not decreasing: Learning rate
- Loss NaN: Numerical instability
- Oscillating loss: LR too high
- Plateau: Local minimum or LR too small

Sanity Checks:

1. Overfit single batch first
2. Check gradient flow
3. Visualize first layer filters
4. Plot loss curves
5. Test on toy problem

"If it's not working, it's always the learning rate" - Andrej Karpathy

Common Pitfalls: Learn from Others' Mistakes

Data Problems:

- Not enough data
- Unbalanced classes
- Data leakage
- No validation set

Architecture Issues:

- Too deep without skip connections
- Wrong activation functions
- Incorrect output layer
- Bad initialization

Training Mistakes:

- Learning rate too high/low
- No normalization
- Overfitting ignored
- Wrong loss function

Debugging Tips:

- Start simple, add complexity
- Overfit single batch first
- Monitor gradients
- Visualize predictions

"It's not working" usually means one of these issues

The Future: What's Next?

Current Frontiers:

- Multimodal models (text+image+audio)
- Efficient models for phones
- Neuromorphic hardware
- Quantum neural networks

Unsolved Problems:

- True reasoning ability
- Learning from few examples
- Explaining decisions
- Energy efficiency

Next Breakthroughs?

- Models that update continuously
- Networks that program themselves
- Biological-digital hybrids
- AGI (Artificial General Intelligence)?

Your Role:

- This field is 70 years young
- Major breakthroughs every 2-3 years
- Anyone can contribute
- The best is yet to come

"We're still in the steam engine era of AI" - Geoffrey Hinton

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 pays (40-year problem!)
5. We're just getting started

Remember: Neural networks are just functions that learn from examples

Next: RNNs - Teaching networks to remember

From Here to RNNs and Beyond

What You Now Understand:

- Why traditional programming failed for pattern recognition
- How neurons compute: inputs $\rightarrow$ weights $\rightarrow$ sum $\rightarrow$ activation $\rightarrow$ output
- Why we need multiple layers and non-linearity
- How networks learn through backpropagation
- The historical journey from McCulloch-Pitts to GPT-4

Next Steps:

- **Week 3:** RNNs - Adding memory for sequences
- **Week 4:** Seq2Seq - Teaching translation
- **Week 5:** Transformers - The attention revolution
- **Week 6:** Pre-trained models - Standing on giants

"The question is not whether machines can think, but whether humans do" - B.F. Skinner