Understanding AI and Large Language Models

From Predictive Text to ChatGPT

A Journey into Modern AI

For Incoming College Students

Agenda

1. **Foundations** - Building blocks of AI
2. **The Revolution** - How transformers changed everything
3. **How LLMs Work** - The inner mechanics
4. **Beyond Text** - Diffusion models and multimodal AI
5. **Practical Considerations** - Real-world deployment
6. **Looking Forward** - The future of AI

Part 1: Foundations

Building Blocks of AI

Let's Start With Something Familiar

Open your phone and start typing a message...

> "I'll be there in..." → **"10" "minutes" "soon"**

This is **predictive text** - the ancestor of ChatGPT!

How it works:

- **N-grams**: Predicting next word based on previous words
- Counts word frequencies in large text collections
- "I'll be" → often followed by "there", "back", "late"

> **Key Insight:** What if we could predict not just words, but understand context and meaning?

Evolution: From Rules to Neural Networks

Era	Approach	Example
1950s-1980s	Rule-based	`if word == "Hello": suggest("World")`
1990s-2000s	Statistical (N-grams)	`P("world"|"hello") = 0.73`
2010s	Deep Learning	Neural networks learn patterns
2017-Present	Transformers	Attention mechanism changes everything!

Each era built on the previous, leading to today's AI revolution

What is a Model?

> "A model is just numbers (weights) arranged in a specific pattern"

Think of it like a recipe:

Ingredients

- Input text
- Training data
- Computing power

Instructions

- Neural network architecture
- Billions of weights
- Mathematical operations

Result: Output predictions!

These weights start random and get adjusted through training

Training vs Inference

Training

- Teaching the model patterns
- Adjusting billions of weights
- Like learning to ride a bike
- Happens **once**
- Very expensive ($$$)
- Takes weeks/months

Inference

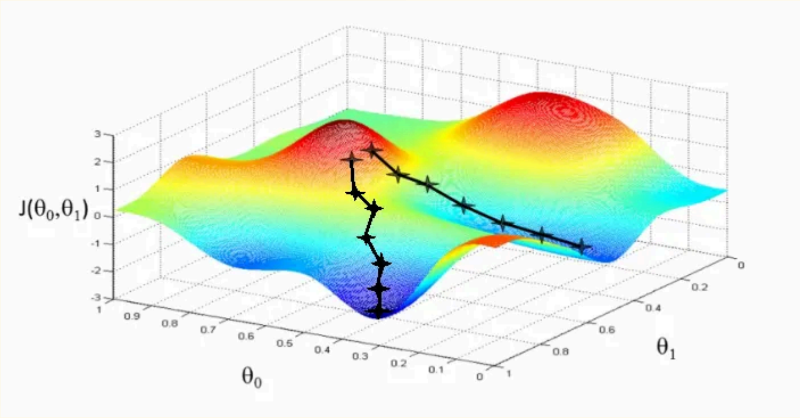
- Using what was learned
- Weights are frozen
- Actually riding the bike
- Happens **every chat**
- Relatively cheap
- Takes milliseconds

How Neural Networks Learn: Gradient Descent

The Training Process

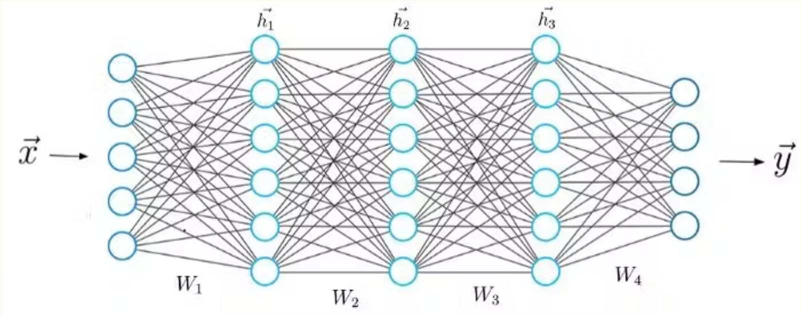
Gradient Descent - Like hiking down a mountain in the dark:

- Calculate the error (how wrong we are)
- Find the steepest downhill direction
- Take a small step in that direction
- Repeat millions of times



Training Loop:

1. **Forward Pass**: Input → Predictions
2. **Calculate Loss**: Compare to correct answers
3. **Backward Pass**: Calculate gradients
4. **Update Weights**: Adjust based on gradients
5. **Repeat**: Until model converges



Part 2: The Revolution

How Transformers Changed Everything

"Attention is All You Need" (2017)

The paper that launched the modern AI era

Key Innovation: Attention Mechanism

The model can "focus" on relevant parts of the input

> **Analogy:** Reading a book and being able to instantly refer back to any previous page, understanding how every word relates to every other word

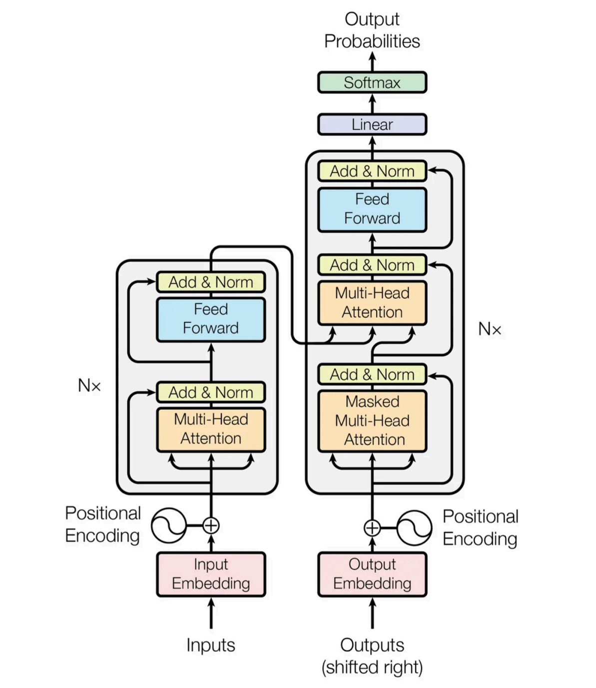


Figure 1: The Transformer - model architecture.

Why Transformers Matter

Feature	Impact	Result
Parallel Processing	Process all words simultaneously	100x faster training
Long-range Dependencies	Connect ideas across documents	Better understanding
Scalability	Performance improves with size	Predictable scaling
Transfer Learning	Pre-train once, use many tasks	Cost efficiency

Transformers solved the fundamental problems that held back previous approaches

Large Language Models (LLMs)

Transformer models trained on massive amounts of text

Model	Parameters	Training Data	Context Window
GPT-2 (2019)	1.5 Billion	40GB text	1K tokens
GPT-3 (2020)	175 Billion	570GB text	2K tokens
GPT-4 (2023)	~1.7 Trillion*	~13T tokens	128K tokens
Claude 3 (2024)	Not disclosed	Not disclosed	200K tokens

*Estimated, not officially disclosed

> **Scaling Law:** 10x more parameters → Predictable improvement

> **But:** 10x parameters → 100x training cost!

Part 3: How LLMs Work

The Inner Mechanics

Tokenization: Breaking Down Language

Models don't see words, they see **tokens**

Example:

"Understanding AI" becomes:
[Under] [standing] [AI]

Vocabulary Sizes:

- **GPT-3:** ~50,000 tokens
- **Claude:** ~100,000 tokens
- **Llama:** ~32,000 tokens

> **Note:** Different tokenization = Different costs!

Autoregressive Generation

Models generate one token at a time, using ALL previous tokens

Message 1: "Hello"
→ Process: "Hello"

Message 2: "How are you?"
→ Process: "Hello" + "How are you?"

Message 3: "Tell me about AI"
→ Process: ALL previous + new

Implications:

- Longer conversations = More computation
- Each response considers entire history
- Context window limits conversation length
- Cost increases with conversation length

Context Windows

The maximum amount of text a model can "remember"

Model	Context Window	Equivalent
GPT-3.5	4K tokens	~3,000 words (~6 pages)
GPT-4	8K-128K tokens	~6-100 pages
Claude 3	200K tokens	~150,000 words (a novel!)
Gemini 1.5	1M tokens	~750,000 words (7 novels!)

Trade-offs:

Longer Context = More information
More Compute = Quadratic scaling
Higher Cost = More expensive

Latent Space: The Model's "Understanding"

Abstract representation of concepts inside the model

Think of it as a massive map where:

- "Cat" is close to "Dog" (both pets)
- "King" - "Man" + "Woman" ≈ "Queen"
- Similar concepts cluster together

This enables:

- Creative connections between ideas
- Understanding analogies and metaphors
- Transfer knowledge between domains
- Zero-shot learning (new tasks without training)

Part 4: Beyond Text

Diffusion Models and Multimodal AI

Diffusion Models for Images

Different approach from language models

The Process:

1. Start with random noise
2. Gradually remove noise (denoise)
3. Guide with text description
4. Result: Generated image

Popular Models:

- **DALL-E 3** - OpenAI
- **Midjourney** - Independent lab
- **Stable Diffusion** - Open source

> **Key Innovation:** Text embeddings from language models guide image generation

Multimodal AI: Connecting Everything

One model, many modalities

Current Capabilities:

- Text → Image (DALL-E)
- Image → Text (GPT-4V)
- Text → Audio (ElevenLabs)
- Audio → Text (Whisper)
- Text → Video (Sora)

Future Vision:

- Single model handles all modalities
- Seamless translation between formats
- Real-world understanding
- Embodied AI agents

Part 5: Practical Considerations

Real-World AI Deployment

Why Training is Expensive

GPT-4 Training: $100+ Million

Cost Breakdown:

Component	Details	Cost Factor
Hardware	10,000+ NVIDIA H100 GPUs @ $30K each	$300M+
Electricity	~50 GWh total (small city for months)	$5M+
Time	3-6 months continuous computation	Opportunity cost
Team	50+ researchers & engineers	$10M+
Data	Collection, cleaning, validation	$5M+

Customization: Context vs Fine-tuning

Context/Prompting 📝

When to use:

- Temporary instructions
- Document analysis
- Quick adaptations

Example:
You are a pirate. Answer
as a pirate would.

User: What is AI?
AI: Arr, AI be like...

Free, instant
Limited, temporary

Fine-tuning

When to use:

- Permanent changes
- Domain expertise
- Production deployment

Example:
```
model = finetune(
base="llama-2",
data="medical.txt",
epochs=3
)
```

Powerful, permanent
Expensive, complex

LoRA: Efficient Fine-tuning

Low-Rank Adaptation: Fine-tune without modifying all weights

Traditional fine-tuning (expensive)

W_new = W_original + ΔW # ΔW is huge!

LoRA (efficient)

W_new = W_original + A @ B # A and B are small!

Benefits:

- **1000x** fewer parameters to train
- **10x** faster training
- Multiple adapters can be swapped
- Run on consumer GPUs

Real-world use:

Open Source vs Closed Source

Aspect	Closed Source	Open Source
Examples	GPT-4, Claude, Gemini	Llama 3, Mistral, Qwen
Performance	State-of-the-art	~90% of closed models
Cost	$20/month or API fees	Free (need hardware)
Privacy	Data sent to provider	Run locally
Customization	Limited	Complete freedom
Transparency	Black box	See everything

> **Trend:** Gap narrowing rapidly. Llama 3.1 405B ≈ GPT-4 performance!

Part 6: Looking Forward

The Future of AI

Emerging Trends

Trend	Description	Impact
Multimodal Models	Text + Images + Audio + Video	Universal AI assistants
Edge AI	Models on phones/laptops	Privacy + No internet
AI Agents	Models that take actions	Automation revolution
Reasoning Models	Step-by-step thinking (o1, o3)	Complex problem solving
Scientific AI	Protein folding, drug discovery	Research acceleration

The pace of progress is accelerating exponentially

For College Students

Good Uses:

- Brainstorming and ideation
- Learning complex concepts
- Code assistance/debugging
- Research organization
- Writing feedback (not writing)
- Creating study materials
- Language practice

Avoid:

- Submitting AI work as yours
- Bypassing learning objectives
- Violating academic policies
- Over-relying on AI
- Not verifying AI output
- Using for exams/tests
- Plagiarism

> **Remember:** AI is a tool to enhance learning, not replace it!

Skills That Matter MORE With AI

Critical Thinking

Evaluating AI outputs, spotting errors, verification

Asking Good Questions

Prompt engineering, problem decomposition

Creativity

Using AI as a collaborator, not replacement

Human Skills

Empathy, leadership, communication, ethics

Domain Expertise

Deep knowledge AI can't replace

> **Key Insight:** AI handles routine → Humans focus on creative & strategic work

Key Takeaways

- AI models are just weights learned from data
- Transformers revolutionized AI with attention
- Bigger models work better but cost more
- Understanding tokenization and context is crucial
- Open source is democratizing AI
- AI is a tool - learn to use it wisely

> **The AI revolution is just beginning.**
>
> **You're entering college at the perfect time!**

Questions?

Let's explore your curiosities about AI!

Remember: There are no "dumb" questions when learning about AI

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