Advanced Transformers

Week 7 - T5, GPT-3, and the Era of Scale

NLP Course 2025

September 21, 2025

From BERT to GPT-3: The Scaling Revolution

Week 7: The Era of Giant Models

When Size Started to Matter

The Discovery

- Scaling changes everything
- Emergent abilities appear
- **Quality** from quantity
- Power laws rule

The Models

- T5: 11B parameters
- GPT-3: 175B parameters
- Switch: 1.6T parameters
- Compute as currency

The Impact

- Few-shot learning works
- In-context learning emerges
- Task-agnostic models
- AI becomes mainstream

The moment language models became foundation models

Bigger is Different

The Kaplan Scaling Laws (2020)

$$L = aN^{-\alpha} + bD^{-\beta} + L_\infty$$

Where:

- N = number of parameters
- D = dataset size (tokens)
- $\alpha \approx 0.076$, $\beta \approx 0.095$
- Loss decreases predictably with scale

The Chinchilla Laws (2022)

Compute-optimal training: $N \propto D^{0.5}$

Key insight:

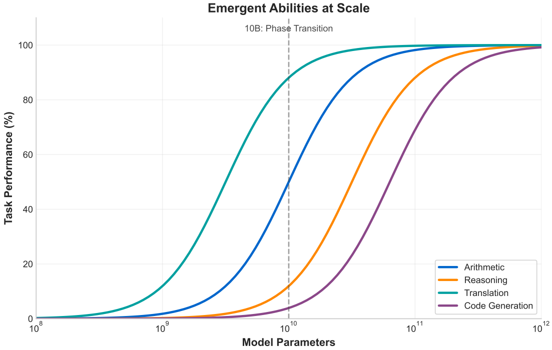
- Most models are undertrained
- Need 20 tokens per parameter
- Smaller models + more data = better
- Changes entire industry approach

From "make it bigger" to "train it longer"

Emergent Abilities: The Phase Transition

What Are Emergent Abilities?
Capabilities that:

- Appear **suddenly** at scale
- Were not explicitly trained
- Show sharp phase transitions
- Cannot be predicted from smaller models



Examples at Different Scales

Parameters	Emergent Ability
1B	Basic syntax
10B	Multi-step reasoning
50B	Chain-of-thought
100B+	In-context learning

The Mystery
Nobody knows why:

- Sharp transitions occur
- Specific scales matter
- Some tasks need 100B+
- Others emerge at 1B

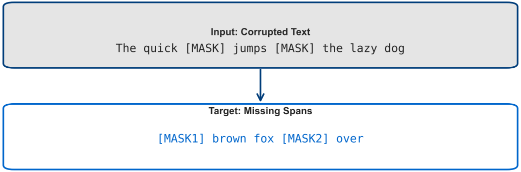
T5: Everything is Text Generation

The Unified Framework

Every task as text-to-text:

- Translation: "translate English to French: hello"
- Summarization: "summarize: [article]"
- Question: "question: what is NLP?"
- Classification: "sentiment: great movie"

Key Innovation: Span Corruption



Architecture Choices

Component	Decision
Model	Encoder-decoder
Size	60M to 11B
Objective	Span corruption
Dataset	C4 (750GB text)

Performance Impact

- SOTA on 20+ benchmarks
- Single model, many tasks
- Better than task-specific models
- Scales predictably

Google's answer to GPT: unify everything

GPT-3: The Model That Changed Everything

The Scale

Metric	Value
Parameters	175 billion
Layers	96
Hidden size	12,288
Attention heads	96
Training tokens	300 billion
Training cost	$4.6 million

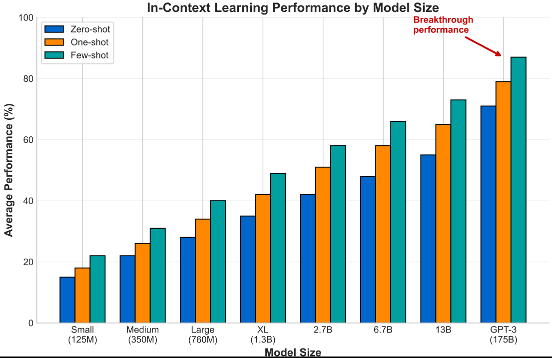
Few-Shot Learning

No gradient updates needed:

- 0-shot: Just describe task
- 1-shot: One example
- Few-shot: 2-10 examples
- Works surprisingly well!

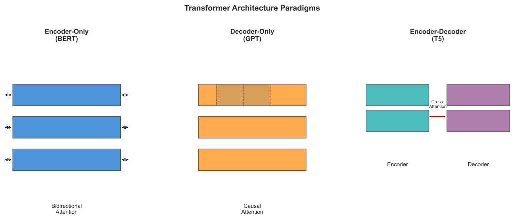
In-Context Learning Example

```
Translate to French:
sea otter -> loutre de mer
cheese -> fromage
peppermint ->
menthe poivrée
```



Architecture Evolution: From BERT to GPT-3

Three Paradigms



1. **Encoder-only** (BERT)
   - Bidirectional context
   - Best for understanding
   - Classification tasks
2. **Decoder-only** (GPT)
   - Autoregressive
   - Best for generation
   - Most scalable
3. **Encoder-Decoder** (T5)
   - Flexible input/output
   - Best for seq2seq
   - More parameters needed

The architecture debate is over: decoder-only won

Why Decoder-Only Won

Advantage	Reason
Simplicity	One stack vs two
Efficiency	Better GPU utilization
Scaling	More predictable
Generation	Natural fit
Training	Simpler objective

The Convergence

All roads lead to autoregressive:

- BERT team moves to decoder (PaLM)
- T5 team adopts decoder (Flan)
- Industry standardizes on GPT-style
- Even vision models follow (ViT-GPT)

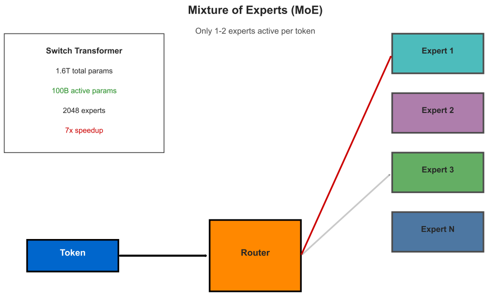
Mixture of Experts: Scaling Without Cost

The Problem with Dense Models

Every token uses ALL parameters:

- 175B params = 175B operations
- Linear scaling of compute
- Hit hardware limits quickly
- Unsustainable growth

The MoE Solution



Switch Transformer (2021)

Metric	Value
Total params	1.6 trillion
Active params	100B per token
Experts	2048
Speedup	7x

How It Works

1. Router selects experts
2. Each token → 1-2 experts
3. Experts specialize automatically
4. Load balancing critical

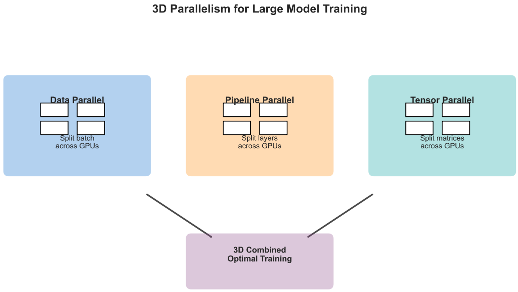
1.6T params, 100B compute cost!

Training Infrastructure: The Hidden Challenge

Model Parallelism Types

1. **Data Parallel**
   - Split batch across GPUs
   - Replicate model
   - Synchronize gradients
2. **Pipeline Parallel**
   - Split layers across GPUs
   - Micro-batching
   - Bubble overhead
3. **Tensor Parallel**
   - Split matrices across GPUs
   - High communication
   - Best for large layers

3D Parallelism: Combine all three!



GPT-3 Training Stats

Resource	Amount
GPUs	10,000 V100s
Training time	34 days
FLOPs	3.14×10^{23}
Power usage	1,287 MWh
CO_2 emissions	552 tons

From Research to Production

The API Revolution

No more training needed:

- OpenAI API (GPT-3)
- Google Cloud (PaLM)
- Anthropic (Claude)
- Cohere, AI21, etc.

Prompt Engineering

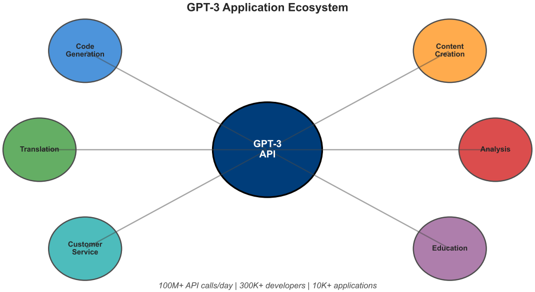
The new programming:

- Zero-shot prompts
- Few-shot examples
- Chain-of-thought
- Instruction following

Cost Per 1M Tokens

Model	Price
GPT-3 Ada	$0.40
GPT-3 Curie	$2.00
GPT-3 Davinci	$20.00

Real Applications (2021-2023)

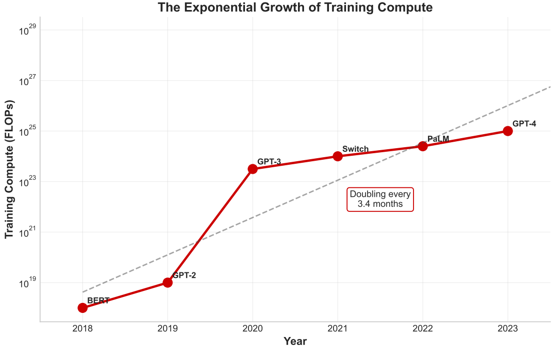


Success Stories

- GitHub Copilot: 40% of code
- Jasper.ai: $125M revenue
- Copy.ai: 10M users
- ChatGPT: 100M in 2 months

The Compute Race: Power Laws and Politics

Compute Requirements Over Time



Doubling every 3.4 months!

The Players (2023)

Company	Largest Model
OpenAI	GPT-4 (1T?)

The Hardware Arms Race

- NVIDIA A100: $10,000
- NVIDIA H100: $30,000
- TPU v4: Not for sale
- Custom chips emerging

National AI Strategies

- US: Export controls on chips
- China: $150B investment
- EU: Sovereign cloud initiative
- UK: Safety focus

Compute is the new oil

The Dark Side of Scale

Known Limitations

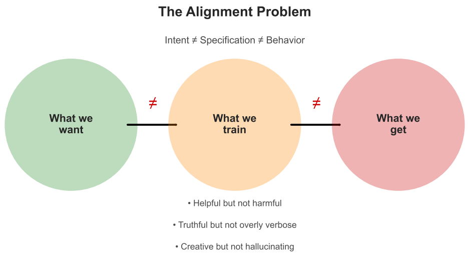
1. **Hallucinations**
   - Confident wrong answers
   - Made-up citations
   - No uncertainty estimates
2. **Reasoning Failures**
   - Simple math errors
   - Logic puzzles fail
   - Common sense gaps
3. **Control Problems**
   - Can't guarantee safety
   - Prompt injection attacks
   - Jailbreaking possible

Bigger models = bigger problems

The Cost Crisis

- Training GPT-4: \$100M+
- Running costs: \$700K/day
- Environmental impact huge
- Excludes most researchers

The Alignment Problem



The Road Ahead: What's Next?

Scaling Continues
GPT-5 and beyond:

- 10T parameters coming
- Multimodal by default
- Video understanding
- Reasoning breakthroughs?

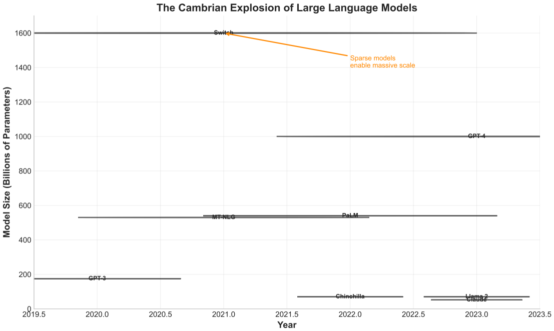
Efficiency Revolution
Making models smaller:

- Quantization (1-bit models!)
- Knowledge distillation
- Efficient architectures
- On-device inference

New Paradigms

- Retrieval-augmented generation
- Tool use and plugins
- Constitutional AI

The Cambrian Explosion



Open Questions

1. Will scaling laws hold forever?
2. Can we solve hallucinations?
3. Is AGI possible this way?
4. Who controls the models?
5. How do we ensure safety?

Key Takeaways

What We Learned About Scale

Technical Insights

- **Scale** brings emergence
- Decoder-only won
- Sparsity enables scale
- In-context learning works
- Compute is everything

Practical Lessons

- APIs democratize AI
- Prompting is programming
- Few-shot often enough
- Fine-tuning less needed
- Costs dropping fast

Future Challenges

- Hallucination problem
- Alignment crucial
- Efficiency needed
- Access inequality
- Safety concerns real

The scaling revolution changed everything. We're still figuring out what that means.

Next week: How these models actually read text (Tokenization)

References

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