Lecture 14:

Pre-trained Language Models & LLM Era

Deep Learning for Natural Language Processing

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Lecture Contents

Part 1/9:

Introduction & Paradigm Shift

1. Review of Previous Lessons
2. Paradigm Shift in AI

NLP Evolution: From Rules to Neural Networks

Rule-Based Systems

Hand-crafted rules & feature engineering

RNN & LSTM

Sequential processing with memory

Seq2Seq Models

Encoder-decoder for translation

Word Embeddings

Word2Vec, GloVe semantic relationships

Attention Mechanism

Dynamic focus on relevant parts

Next Generation →

Transfer learning & deep context

⚠ Limitations

Shallow representations • Task-specific training

The Need

Better context understanding • Transfer learning capabilities

Paradigm Shift in AI

❌ Old Paradigm

Task-Specific Models

- 🎯 **Task-specific** models trained from scratch
- 📊 Requires **labeled data** for each task
- 🔧 Heavy **feature engineering** needed
- 📉 **Limited scale** and capabilities
- 🚧 No knowledge **transfer** between tasks

→

✨ New Paradigm

Foundation Models

- 🌐 **General-purpose** foundation models
- 🔄 **Pre-train** on massive text, then adapt
- 📚 **Self-supervised** learning from unlabeled data
- 🚀 **Scale matters:** emergent capabilities
- 🤝 **Democratization:** accessible to all

Part 2/9:

Pre-training Concepts

3. What is Pre-training?
4. Language Modeling Objective Function
5. The Importance of Scale

Pre-training → Fine-tuning Pipeline

1

Pre-training

Self-Supervised Learning

Learn from **massive text corpora**
No manual labels required
Predict masked/next words

→

2

Fine-tuning

Task Adaptation

Adapt to **specific tasks**
Requires minimal data
Pre-train once, fine-tune many

Captures **syntax & semantics**

Learns **world knowledge**

Creates **universal extractors**

Reduces **data requirements**

Key Advantages

✓ General language representations ✓ Two-stage learning process ✓ Efficient transfer to downstream tasks

Language Modeling Objective Functions

Autoregressive LM

Causal / Left-to-Right

The cat sat on ?

↓

$P(w_t \mid w_1, \ldots, w_{t-1})$

→ Predict **next token**

⚡ **Causal masking** (uni-directional)

✏️ Good for **generation** tasks

📝 GPT-style models

Masked LM

Bidirectional Context

The cat [MASK] on the

↓

$P(w_{masked} \mid context)$

🎯 Predict **masked tokens**

↔️ **Bidirectional** context (left+right)

🧠 Better **understanding**

📖 BERT-style models

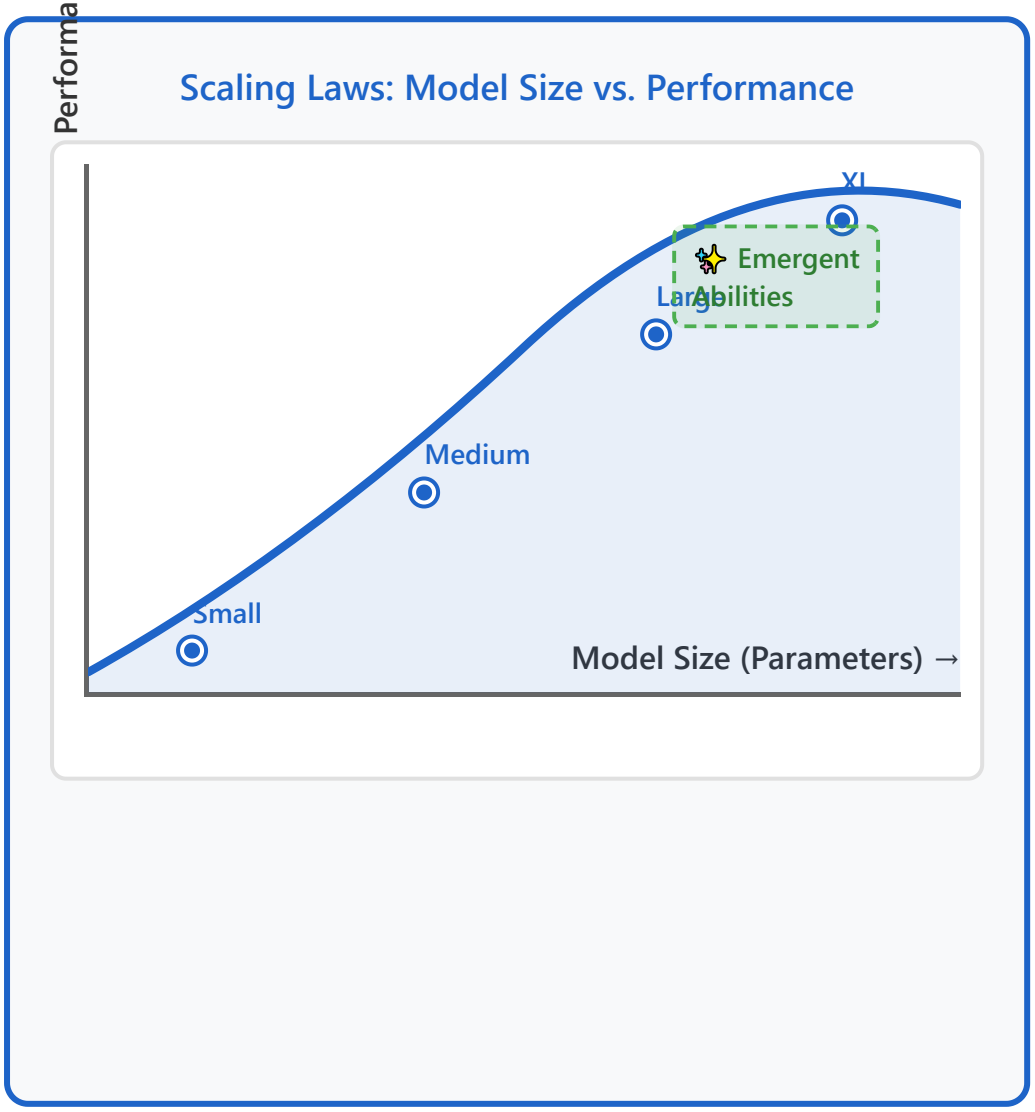
🎓 Training Approach

Self-supervision enables learning from unlimited text using **cross-entropy loss**

🔧 Architecture Fit

Different objectives suit different architectures and **downstream tasks**

The Importance of Scale



Predictable Growth
Performance improves **predictably** with size

More Parameters
Capture **more patterns** & knowledge

Larger Datasets
Richer knowledge coverage

Emergent Abilities
New capabilities at **scale thresholds**

Few-shot Learning
Dramatically **improves** with scale

Trade-off
Performance vs. **Efficiency & Accessibility**

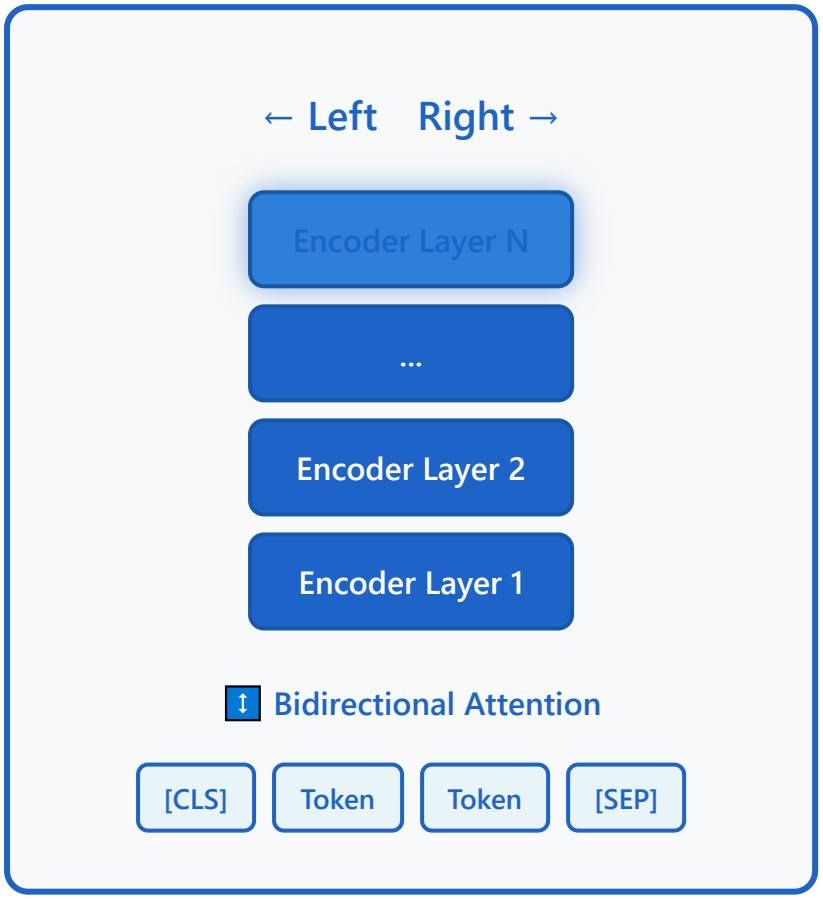
Part 3/9:

BERT - Encoder-based Models

6. Introduction to BERT
7. BERT Pre-training
8. BERT Fine-tuning
9. BERT Family Models

BERT: Bidirectional Encoder Representations from Transformers

Google, 2018 - Revolutionary NLP Model



Base: 110M params **Large:** 340M params

Dataset: BooksCorpus + Wikipedia (3.3B words)

Bidirectional Context

Deep **bidirectional** understanding from both directions

Transformer Encoder

Stack of **Transformer encoders** with self-attention

Pre-training Corpus

Trained on **BooksCorpus** and **Wikipedia**

Two Model Sizes

BERT-Base (110M) and BERT-Large (340M) parameters

State-of-the-Art Performance

Achieved SOTA on **11 NLP benchmarks**
Revolutionized NLP in 2018

🎓 BERT Pre-Training Process

1 Input Preparation

Tokenize the input text and add special tokens. [CLS] marks the start of the sentence, and [SEP] marks the end.

📝 **Example Input:**

```
"The cat sat on the mat"
→ [CLS] The cat sat on the mat [SEP]
```

2 Masked Language Modeling (MLM)

Randomly mask 15% of input tokens. The model learns to predict masked words using bidirectional context.

🎭 **Masking Example:**

```
Input: [CLS] The cat sat on the mat [SEP]
Masked: [CLS] The [MASK] sat on the mat [SEP]
Target: Predict "cat"
```

💡 **Key Points**

- 80% replaced with [MASK]
- 10% replaced with random word
- 10% keep original word

3 Next Sentence Prediction (NSP)

Learn to determine whether two sentences are consecutive. This improves the ability to understand relationships between sentences.

🔗 NSP Example:

```
Case 1 (IsNext):
[CLS] The cat sat on the mat [SEP] It was sleeping [SEP]
Label: IsNext ✓

Case 2 (NotNext):
[CLS] The cat sat on the mat [SEP] Paris is beautiful [SEP]
Label: NotNext ✗
```

4 Training Objective

Train the model by simultaneously optimizing both MLM and NSP losses.

MLM Loss

Cross-Entropy Loss aiming for accurate prediction of masked tokens

NSP Loss

Binary Classification Loss for correctly judging sentence pair continuity

🎯 Total Loss

Loss = MLM Loss + NSP Loss

🎯 BERT Fine-tuning Process

1 Load Pre-trained Model

Load the pre-trained BERT model. It has already learned general patterns of language.

✨ Pre-trained Knowledge

- Understanding grammatical structure
- Capturing semantic relationships
- Bidirectional context comprehension

2 Add Task-Specific Layer

Add an output layer specific to the task. Different structures are used depending on the task.

📊 Classification

[CLS] token output + Softmax Layer
(Sentiment analysis, topic classification, etc.)

🏷️ Token Classification

Each token output + Classification Layer
(Named entity recognition, POS tagging, etc.)

❓ Question Answering

Start/End Position Prediction Layers
(SQuAD, reading comprehension, etc.)

🔄 Sequence Pairing

[CLS] token + Binary Classifier
(Natural language inference, sentence similarity, etc.)

3 Fine-tune on Task Data

Fine-tune the entire model with task-specific training data. Typically, 2-4 epochs are sufficient.

Sentiment Analysis Example:

```
Input: [CLS] This movie is amazing [SEP]
→ BERT Encoding →
→ Classification Layer →
Output: Positive (95% confidence)
```

Training Settings

- Learning Rate: 2e-5 ~ 5e-5
- Epochs: 2-4
- Batch Size: 16 or 32

4 Inference & Prediction

Use the fine-tuned model to make predictions on new data.

Prediction Pipeline:

```
Step 1: Tokenize new input
Step 2: Pass through fine-tuned BERT
Step 3: Apply task-specific head
Step 4: Generate prediction with confidence score
```

Final Output

Generate results in the appropriate format for the task:
Classification labels, token tags, answer spans, etc.

BERT revolutionized NLP by introducing bidirectional pre-training and transfer learning to the field.

BERT Pre-training: Two Main Tasks

1 Masked Language Model

MLM - 15% masking

Input:

[CLS] The cat [MASK] on the mat

↓

Predict: "sat"

Uses **bidirectional context** to predict masked tokens

2 Next Sentence Prediction

NSP - Binary classification

Input:

A: The man went to the store.

B: He bought a gallon of milk.

↓

IsNext ✓

[CLS] token for sentence-level representation

Tokenization

WordPiece
30K vocabulary

Special Tokens

[CLS] [SEP] [MASK] [PAD]

Training

4 days
on 4-16 Cloud TPUs

BERT Fine-tuning for Different Tasks

Pre-trained BERT (All Parameters)

+

Sequence Classification

Uses:

[CLS]

token representation

Sentiment Analysis, Text Classification

Token Classification

Uses:

T_1 T_2 T_3

each token's output

NER, POS Tagging

Question Answering

Predicts:

Start & End spans

SQuAD, Reading Comprehension

↓

End-to-End Fine-tuning

All parameters updated with task-specific data

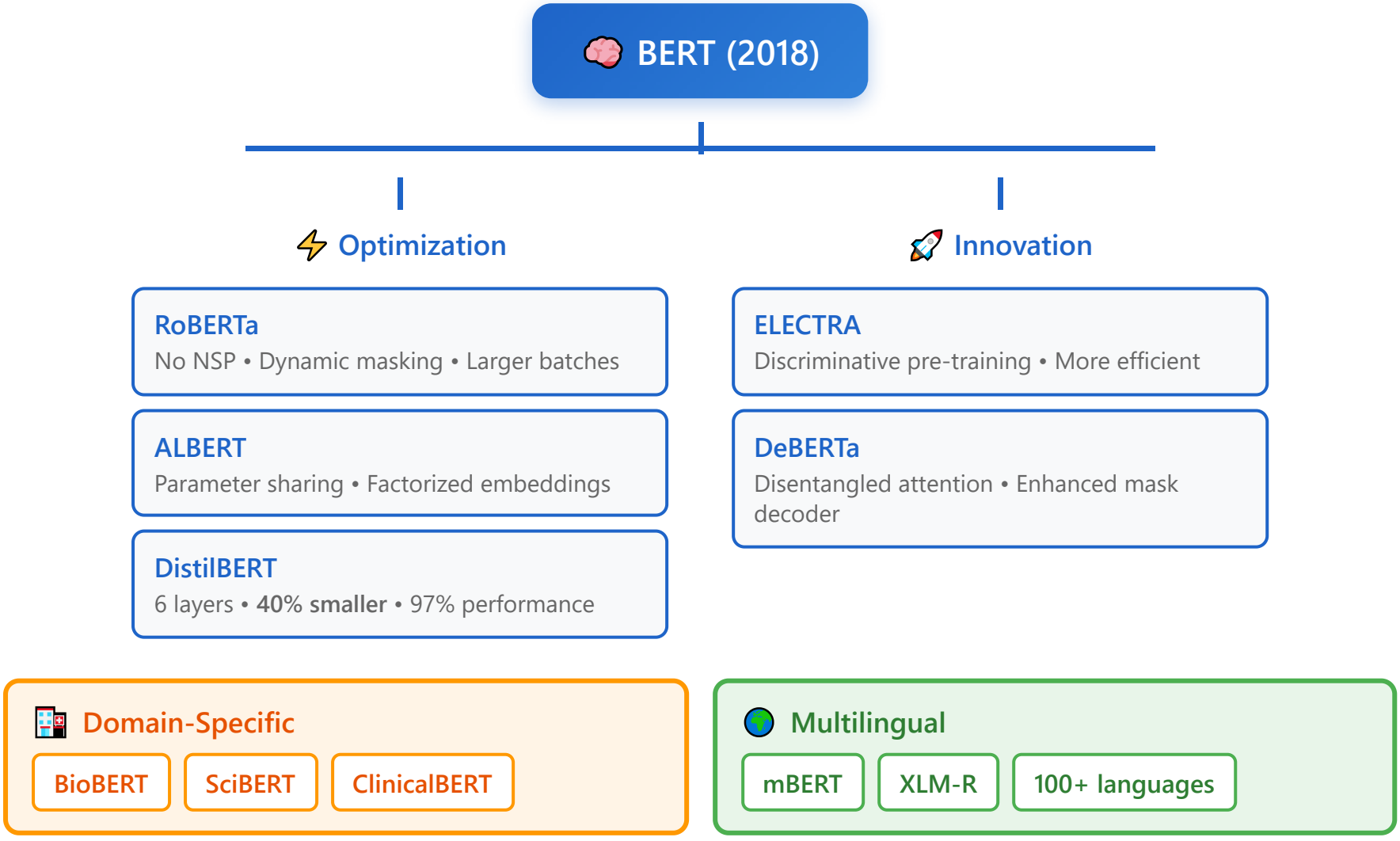
Fast Training	Task-Specific	Transfer Learning

Only **few epochs** needed

Add layer on **top of BERT**

Few-shot & zero-shot

BERT Family: Variants and Improvements



Part 4/9:

GPT - Decoder-based Models

10. Introduction to the GPT Series
11. GPT Pre-training
12. GPT-3 and Few-shot Learning
13. GPT Family Development

GPT: Generative Pre-trained Transformer

OpenAI - Autoregressive Decoder-only Architecture

Decoder-Only Architecture

Decoder Layer N

...

Decoder Layer 2

Decoder Layer 1

Causal Masking

Past → **Present** ✗ Future

Token 1 | Token 2 | Token 3 | Next →

Key Features

- → **Unidirectional** (left-to-right) attention
- Optimized for **text generation**
- **Autoregressive** prediction
- Decoder-only transformer stack

GPT Evolution

2018	**GPT-1**	117M params • Proof of concept
2019	**GPT-2**	1.5B params • Impressive generation
2020	**GPT-3**	175B params — ★ Paradigm Shift

🎓 Training Process (Pre-training)

1

Input Tokenization

Text is converted into tokens using vocabulary

```
"The cat sat" → [1045, 2635, 2068]
```

→

2

Forward Pass

Tokens pass through decoder layers with causal masking

```
Input → Embeddings → Decoder Stack → Logits
```

→

3

Predict Next Token

Model predicts probability distribution over vocabulary

$$P(\text{token}_4 \mid \text{token}_1, \text{token}_2, \text{token}_3)$$

→

4

Compute Loss

Compare prediction with actual next token using cross-entropy

```
Loss = CrossEntropy(predicted, actual)
```

→

5

Update Weights

Backpropagate gradients and update model parameters

$$\theta \leftarrow \theta - \alpha \nabla L(\theta)$$

🚀 Inference Process (Text Generation)

1

Input Prompt

User provides initial text prompt

```
"Once upon a time"
```

→

2

Tokenize & Encode

Convert prompt to token IDs and create embeddings

```
Tokens: [2949,
```

→

3

Autoregressive Generation

Generate one token at a time, appending each to input

```
Loop: predict → sample → append
```

→

4

Sampling Strategy

Use temperature, top-k, or top-p to select next token

```
Temperature = 0.7, Top-p = 0.9
```

→

5

Decode Output

Convert tokens back to text until stopping condition

```
Tokens → "there
```

2402, 257, 640]

lived a princess"

Step-by-Step Example

- Input: `"The weather is"`
- Step 1: `predict → "sunny"`
- Step 2: `"The weather is sunny" → predict → "today"`
- Step 3: `"The weather is sunny today" → predict → "."`
- Final Output: `"The weather is sunny today."`

GPT Pre-training: Causal Language Modeling

Autoregressive Prediction Process

1 The → cat — *Predict next token*

2 The cat → sat — *Use previous outputs*

3 The cat sat → on — *Continue generation*

Training Data
Diverse internet text: **Common Crawl, WebText**

Unidirectional Attention
Enables **efficient generation**

BPE Tokenization
Byte-pair encoding for vocabulary

No Explicit Fine-tuning
GPT-3: **Direct inference** capable

Pattern Learning

Massive Scale

Efficiency

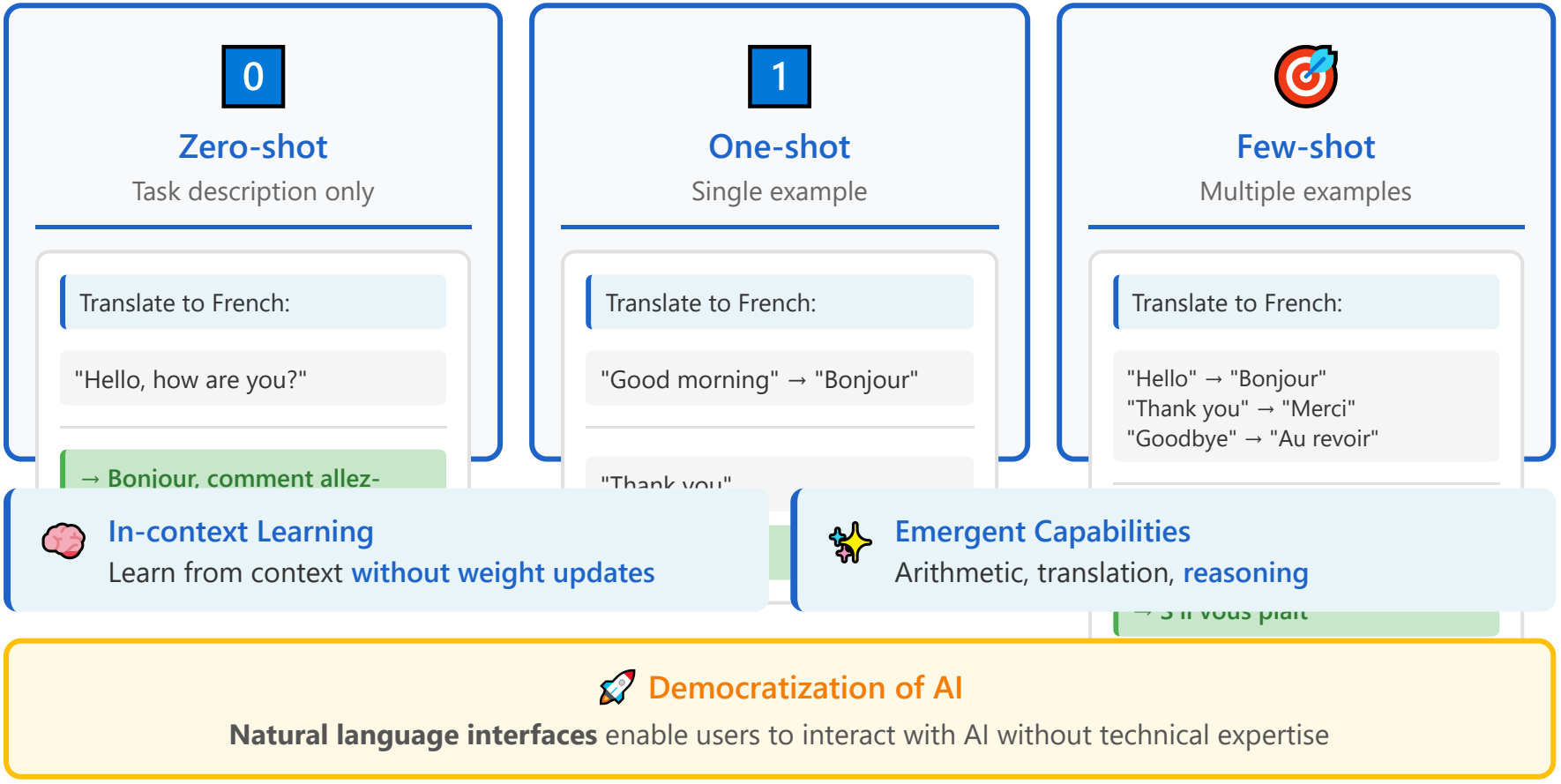
Learns patterns, facts, and reasoning from data

Unlocks in-context learning abilities

Fast generation through causal masking

GPT-3 and Few-shot Learning

175B parameters • 300B tokens • In-context Learning



GPT Family Development Timeline

Evolution & Innovations

InstructGPT

RLHF for instruction following

ChatGPT

Conversation-optimized with safety alignment

GPT-4

Multimodal • Improved reasoning & reliability

Codex

Code generation • Powers GitHub Copilot

Open Source Alternatives

- GPT-Neo
- GPT-J
- Bloom
- LLaMA

Safety

Continuous improvements

Accuracy

Enhanced reliability

API Access

Widespread development

Part 5/9:

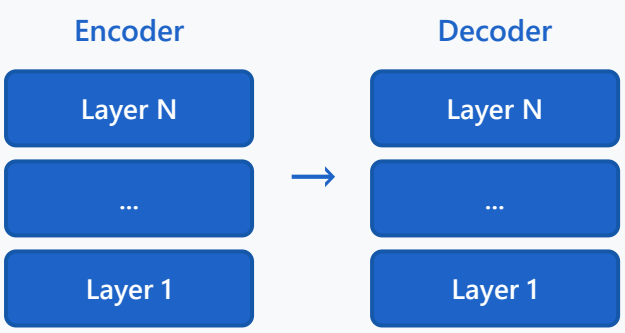
Encoder-Decoder Models

14. T5 - Text-to-Text Framework
15. BART and Other Models

T5: Text-to-Text Transfer Transformer

Google - Unified Framework for All NLP Tasks

Full Transformer



Pre-training

C4 corpus (750GB)
Span corruption objective

Scalability

T5-Base → T5-11B
Multiple model sizes

Performance

Strong results across diverse NLP tasks

All Tasks → Text Generation

translate English to German:
That is good. → Das ist gut.

summarize:
Long article text... → Brief summary

sentiment:
I love this movie! → positive

question answering:
What is the capital? → Paris

Model Sizes:

T5-Small | T5-Base | T5-Large | T5-3B | T5-11B

BART and Other Encoder-Decoder Models

BART: Denoising Autoencoder

Combines BERT (Encoder) + GPT (Decoder)

1. **Corrupt Input** — Add noise
2. **Encode** — BERT-style
3. **Decode** — GPT-style
4. **Reconstruct** — Original text

Token Masking
`The [MASK] sat`

Token Deletion
`The _ sat`

Span Infilling
`The [X] mat`

Sentence Permutation
`Sent2 Sent1 Sent3`

Document Rotation
`...end → start...`

Text Infilling
`A B [Y] E F`

mBART

Multilingual BART for **50+ languages**

PEGASUS

Gap sentence generation for summarization

Marian

Efficient **neural machine translation**

BART Strengths

Particularly strong for **generation & summarization**

Encoder-Decoder Models

Best suited for **sequence-to-sequence tasks** • Translation • Summarization • Question Answering

Part 6/9:

Fine-tuning Strategies

16. Full Fine-tuning vs. Transfer Learning
17. Parameter-Efficient Fine-tuning
18. Fine-tuning Practical Tips

Fine-tuning Strategies Comparison

Full Fine-tuning

Update all parameters

- Task Head ✓
- Top Layers ✓
- Middle Layers ✓
- Bottom Layers ✓

✓ Best performance
⚠ Slower training
⚠ Risk of forgetting

Feature Extraction

Freeze base model

- Task Head ✓
- Top Layers ✗
- Middle Layers ✗
- Bottom Layers ✗

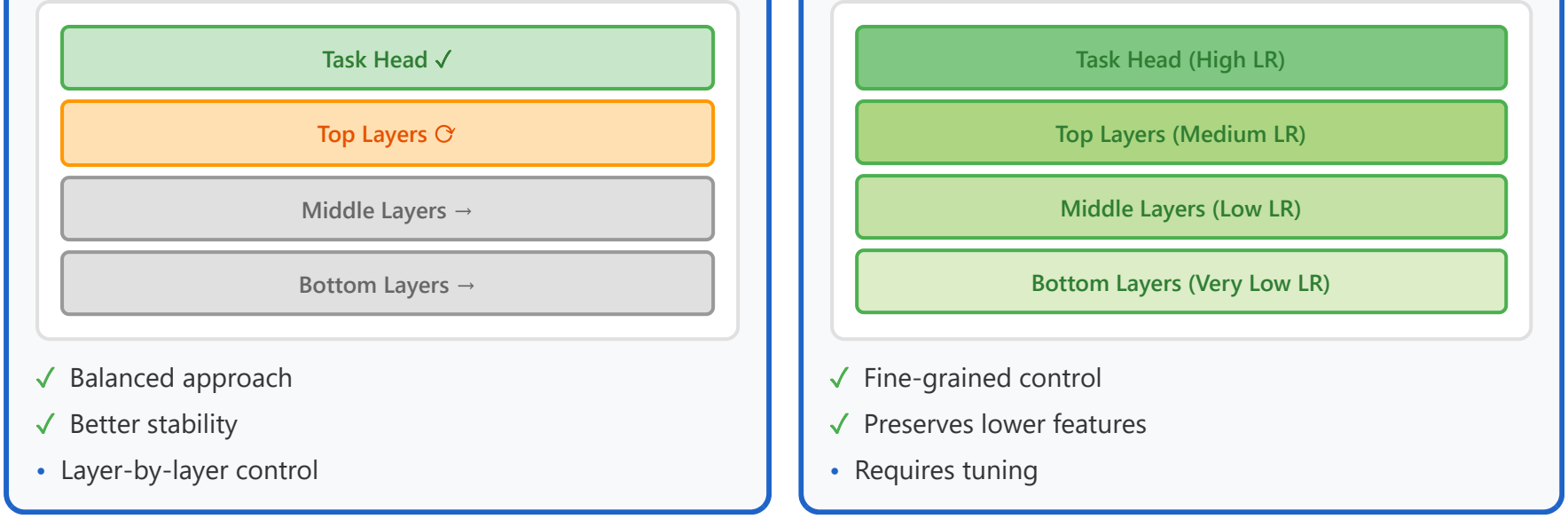
✓ Faster training
✓ No catastrophic forgetting
⚠ Lower performance

Gradual Unfreezing

Progressive unlocking

Discriminative LR

Different rates per layer



✓ Balanced approach
✓ Better stability
• Layer-by-layer control

✓ Fine-grained control
✓ Preserves lower features
• Requires tuning

🎯 Performance

Full FT: **Best**
Feature Ext: **Good**

⚡ Speed

Feature Ext: **Fastest**
Full FT: **Slowest**

💾 Memory

Feature Ext: **Low**
Full FT: **High**

💡 Decision Factors

Choice depends on **data size** and **computational budget** • Large data + resources → Full FT • Small data / limited resources → Feature Extraction

Parameter-Efficient Fine-tuning (PEFT)

LoRA

Low-Rank Adaptation

W (Frozen) + A × B

Low-rank matrices

$W' = W + AB$

<1% parameters trainable

Adapter Layers

Bottleneck Modules

Transformer Layer (Frozen)

↓

Adapter (Down → Up)

↓

Transformer Layer (Frozen)

↓

Adapter (Down → Up)

Small modules between layers

Prefix Tuning

Optimize **continuous prompt vectors**

Prompt Tuning

Learn **soft prompts**, freeze model

BitFit

Only tune **bias terms**, freeze weights

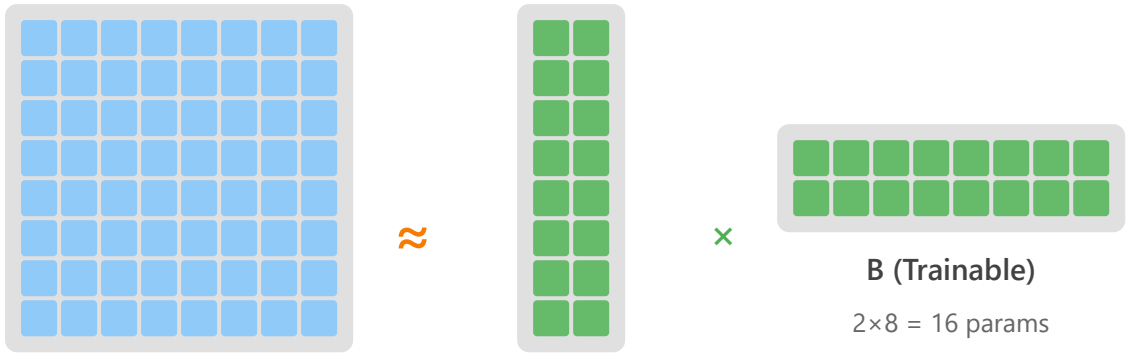
Single GPU Training

Fine-tune **large models** on limited hardware

High Efficiency

90-95% of full fine-tuning performance

Practical Example: LoRA Parameter Decomposition



W (Frozen)

8×8 = 64 parameters

A (Trainable)

8×2 = 16 params

B (Trainable)

2×8 = 16 params

64	32	50%
Original Parameters	LoRA Parameters (16 + 16)	Reduction

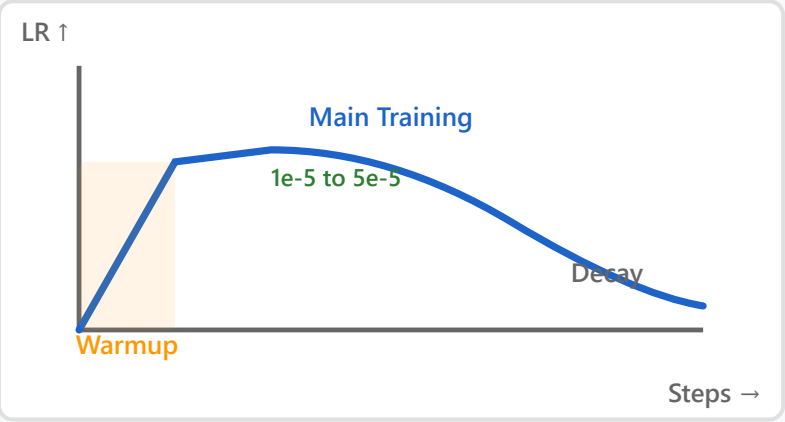
With Rank r = 2: (m×r) + (r×n) = (8×2) + (2×8) = 32

Lower rank = fewer parameters
(r=1: 16 params, r=2: 32 params, r=4: 64 params)

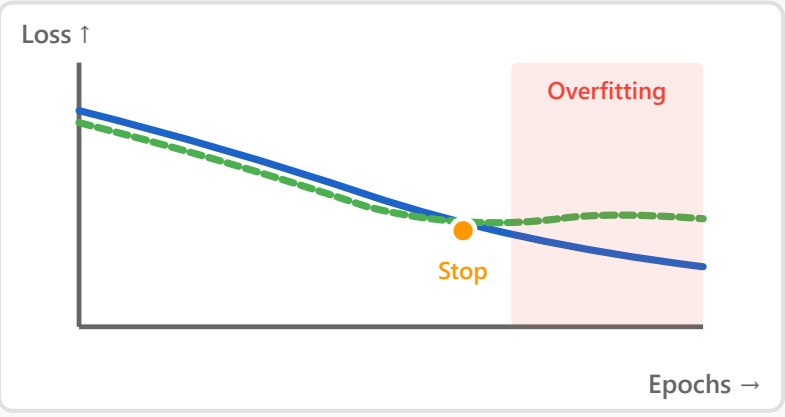
In large-scale models, over 99% parameter reduction is possible!

Fine-tuning Practical Tips

Learning Rate Schedule



Training & Validation Loss



1. **Learning Rate**
   Start with **1e-5 to 5e-5** range
2. **Warmup Steps**
   Use warmup to **stabilize training**
3. **Monitor Validation**
   Track validation loss to **prevent overfitting**
4. **Data Quality**
   Quality > Quantity for better results
5. **Batch Size**
   Affects **convergence & generalization**
6. **Early Stopping**
   Stop based on **validation metrics**
7. **Multi-task Learning**
   Consider for **related tasks**

Best Practice

Save checkpoints and test **multiple configurations** to find optimal settings

Part 7/9:

Prompting & In-Context Learning

19. Prompt Engineering Basics
20. Advanced Prompting Techniques
21. Fine-tuning vs. Prompting

Prompt Engineering: Good vs. Bad Examples

❌ Bad Prompts

📝 Example 1:

"Write something about AI."

⚠ Too vague

📝 Example 2:

✅ Good Prompts

📝 Example 1:

"You are an AI expert. Write a 3-paragraph explanation of machine learning for beginners, using simple analogies."

✓ Clear role & constraints

📝 Example 2:

"Summarize this article."

⚠ No context or format

Example 3:

"Translate to French."

⚠ Missing input text

"Summarize the following article in 3 bullet points, focusing on key findings. Format: • Point 1\n• Point 2\n• Point 3"

✓ Specific format & context

Example 3:

"Translate the following English text to French. Maintain a formal tone.\n\nText: 'Welcome to our conference.'"

✓ Complete with examples

Clear Instructions
Explicit & precise

Context
Background info

Format
Define structure

Role
"You are an expert"

Iterative refinement: Test and improve prompts

Consistency: Maintain format across examples

Advanced Prompting Techniques

Chain-of-Thought (CoT)

Question:

Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 balls. How many tennis balls does he have now?

Prompt:

"Let's think step by step."

1. Roger starts with **5 tennis balls**
2. He buys **2 cans** of tennis balls
3. Each can has **3 balls**, so 2 × 3 = **6 balls**
4. Total: 5 + 6 = **11 balls**

✓ Final Answer:

Other Advanced Techniques

Few-shot Learning

Provide **multiple examples** in prompt for pattern recognition

Self-consistency

Sample **multiple outputs** and vote for most consistent answer

Tree of Thoughts

Explore **multiple reasoning paths** simultaneously

ReAct

Reasoning and acting in interleaved manner

Auto Prompt Optimization

Use **evolutionary methods** to improve prompts

11 tennis balls

🎯 **Meta-prompting**

Prompts that generate prompts for different tasks

Fine-tuning vs. Prompting: When to Use Each?

Prompting

- **Quick** - No training needed
- **Flexible** - Easy to iterate
- **API-based** - Simple access
- Pay per API call

✓ Ideal for:

Prototyping | Few examples | Varied tasks | Quick experiments

Fine-tuning

- **Better performance** - Task-specific
- **Consistent** - Reliable outputs
- **Private data** - Full control
- Training infrastructure needed

✓ Ideal for:

Production | Large datasets | Low latency | Custom domains

Requirements

Consider **task complexity** & goals

Data

Evaluate **dataset size** & quality

Resources

Balance **cost & infrastructure**

Hybrid Approach

Prompt-based fine-tuning (instruction tuning) combines both benefits

Future Trend

Prompting becoming more powerful with larger models

Part 8/9:

Current Trends

22. RLHF and Instruction Tuning
23. Present and Future

RLHF and Instruction Tuning

Reinforcement Learning from Human Feedback

Three-Stage RLHF Pipeline

1 Supervised Fine-tuning

Train on high-quality demonstration data

→

2 Reward Model

Learn human preferences from comparisons

→

3 PPO Training

Optimize policy using reward model

Helpfulness

Better at following instructions

✓

Truthfulness

More accurate and reliable

Safety

Reduces harmful outputs

Instruction Tuning

Train on **diverse task instructions** to improve generalization

Constitutional AI

Self-improvement through principles and guidelines

Key to Success

RLHF and Instruction Tuning are fundamental to the success of **ChatGPT** and other assistant models

Present and Future: Current Trends in LLMs

Multimodal
Text, image, audio, video integration

Mixture of Experts
Sparse activation for efficiency

Long Context
100K+ tokens processing

Better Reasoning
Math, logic, commonsense

Retrieval Augmentation
Combining **LMs with knowledge bases** for accurate information

Smaller Efficient Models
On-device and **edge deployment** capabilities

Enhanced Capabilities
Improvements in **mathematical reasoning**, logical thinking, and commonsense understanding

Context Processing
Processing **100K+ tokens** enables handling entire books and documents

Specialized Domain Models
Medical | Legal | Scientific | Finance | Engineering

AGI Considerations
Focus on **capabilities**, **safety**, and **alignment** as we approach AGI

Part 9/9:

Ethics and Practice

Summary and Practical Considerations

🚀 Pre-trained LLMs Revolutionized the NLP Landscape

Choose Your Architecture

- **Encoder** — BERT-style
- **Decoder** — GPT-style
- **Both** — T5-style

- **Bias & Fairness**
- **Privacy**
- **Misinformation**
- **Environment**

- **Diverse Evaluation** — Test on diverse datasets and scenarios
- **Document Limitations** — Clearly state model capabilities and constraints
- **Transparency** — Open about model behavior and decisions
- **Human Oversight** — Maintain human-in-the-loop for critical tasks

- **Environmental Cost** — **Training emissions** and energy consumption
- **Accessibility** — **Democratization** vs. resource concentration
- **Continuous Learning** — Field evolves **rapidly**, stay updated

Responsible Deployment

Transparency • **Safety measures** • **Human oversight** in all deployments

Thank you

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